ENABLING ONLINE KNOWLEDGE EXCHANGE:

THEORY, PROGRESS AND APPLICATION

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STATEMENT OF ORIGINALITY

I declare that the content of this thesis is my original work. I have not submitted the work contained in this thesis for another degree or diploma at any other tertiary institution.

I have acknowledged all the assistance that I received in preparing this thesis and have made due references.

Yingnan Shi

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Chapter 1: Introduction & Background

As people enter a new era of the digital economy, the ability to create, utilise, reuse, and generate value from information and knowledge becomes a defining factor of success for all entities, irrespective of age, size, ethnicity, or country of origin (Hajkowicz et al., 2016). According to Abdallah et al. (2021), a digital economy introduces a range of novel disruptive business models and communication technologies. In this context, a wide array of economic activities are hinging on digitised information and knowledge as essential factors of production. Therefore, in the digital economy, mastery over knowledge handling—that is, the ability to collect, create, store, disseminate, and evaluate digital knowledge—forms a 'critical edge' or a decisive competitive advantage for individuals, organisations, and countries (Mizintseva & Gerbina, 2018).

In many organisations and societies, online knowledge exchange platforms have become an increasingly popular and also influential technological tool that empowers anyone to collect, create, evaluate, store, disseminate and accrue knowledge (Ihrig & MacMillan, 2015; Jan et al., 2017; Qiao et al., 2021; Z. J. Zhang et al., 2016). In fact, online knowledge exchange platforms have been recognised by many researchers and practitioners as a congruent part of knowledge management practices, and a growing body of literature has investigated this form of practice (Chen et al., 2010; Gazan, 2006; Harper, 2007; Lee et al., 2013; Nam et al., 2009; Raban & Harper, 2008; Ridings & Gefen, 2004; Shah et al., 2009; Yang et al., 2009). Additionally, online knowledge exchange platforms have also proven successful in firms' open innovation, organizational agility, and crowdsourcing activities. Also, some large businesses have built up and managed platforms to reach their customers so that they can gather inputs and feedback for new product and services developments, strengthening customer relationships, promoting brands, and enabling value co-creation and knowledge collaboration (Bilgihan et al., 2016; Randhawa et al., 2017; Y. Zhang et al., 2019). Knowledge exchange platforms also facilitate the dissemination of scientific knowledge, which is a foundation of the development of evidence-based policy, as well as help firms create opportunities and foster sustainability (Brownell et al., 2013; Olesk et al., 2019; Pauliuk, 2020; Y.

Zhang et al., 2019). A functional knowledge exchange platform, as Thomas-Hunt et al. (2003) argued, increases the effectiveness of creating knowledge by providing sufficient incentives, ensuring efficient matches between knowledge suppliers and receivers, and reducing the transaction cost (e.g., a knowledge seeker's time devoted to searching the right knowledge) involved in the knowledge exchange activities.

With the continuous development of information technology, a variety of knowledge exchange platforms, such as discussion forums, question answering sites, electronic bulletin boards, and wikis have been established (Pang et al., 2020; Sha et al., 2022a). These online knowledge exchange platforms have seen a tremendous rise in popularity and success, becoming a dependable source of knowledge sharing and acquisition for millions of users worldwide (Su et al., 2019; Yan et al., 2018). Their success is multifaceted; it is evident not only in their wide user adoption but also in the profitable business models they have inspired. In fact, many of these platforms rank among the 50 most visited sites on the web, testifying to their economic success and the role they play in the increasingly knowledge-driven society (Alexa, 2021). Here, the notion of "great success" encompasses not only financial profitability but also their impact in terms of providing widespread access to knowledge and serving as a constant resource for millions of users. Some of the platforms are private: Recognizing the so-called 'wisdom of the crowd', some organisations also create Intranet-enabled knowledge exchange platforms to foster knowledge sharing of explicit, and even tacit knowledge to speed up problem-solving processes and facilitate the exchange of knowledge (Cai et al., 2019; P. Huang et al., 2017; Sloan et al., 2015; Y. Zhang et al., 2019). For instance, SAP, a leading German multinational software corporation that develops enterprise software (e.g., ERP systems) to manage business operations and customer relations, established its own social knowledge exchange platform to allow all its stakeholders (e.g., partners, suppliers, customers, service providers) to post questions on the platform about system implementation, customization, and after-sale use evaluations. Thus, the company created an open pro-knowledge-exchange community where its active members can contribute and manage a wide range of knowledge exchange tools such as e-learning catalogues, technical libraries, code-sharing galleries, and wikis of different channels (P. Huang et al., 2018), and it has been recognized by some researchers and practitioners as one of the most successful open knowledge exchange platforms (Schmidl, 2012). There are also cases where firms build semi-open knowledge exchange platforms that extend beyond their boundaries to include various parties (such as customers, business partners and suppliers) in their value ecosystems, aiming to boost the productivity of R&D and increase the efficiency of using other intangible resources (P. Huang et al., 2017).

Despite their potential, all forms of knowledge exchange, including private, public, and hybrid, platforms often grapple with issues that lead to their failure. One of the reasons for this is that, after designing and initial development, it is difficult to sustain users' engagement to supply their knowledge and to do so at a favourable level. For instance, some platforms see a low participation rate—especially after they grow to a certain level (Butler, 2001; Tausczik et al., 2017). For these platforms, such a low participation rate can, in turn, cause a low contribution rate, which amplifies users' frustrations and further deters them from participating in it (Graham & Wright, 2010). Intuitively, the low participation rate reflects users' generally low tendency to contribute knowledge, which leads to problems such as knowledge starvation and degradation of the platform's overall effectiveness (Shtok et al., 2012). Other platforms have the reverse problem: they contain too much and often poorly written information that can overwhelm users which means that they have to spend considerable time searching for what they want and filtering out what they do not (Toba et al., 2014). These problems cause many of these platforms, both private and public ones, to lose a significant number of users and, subsequently, knowledge suppliers. As a result, they fail to grow into a vibrant community (Campanelli, 2006; Fang et al., 2018), and, sometimes, even cease to operate (Benbya, 2008; Chen et al., 2010).

In this research, as I summarised, addressing these challenges and improving the efficiency and quality of knowledge exchange involves pursuing three critical paths: introducing **incentives**, fostering **open** structures, and implementing **market-based** knowledge exchange practices. Besides that, conducting more empirical testing is considered necessary, as highlighted in the research philosophy chapter. The Post-positivist Worldview was selected as the overarching research approach, with quantitative research designs being employed to guide the studies conducted throughout the PhD research. Detailed justifications for this approach are provided in Chapter 3.

The first method is about **incentives**. Prior research around these platforms suggested the need to increase active engagement among users as a critical aim. For instance, some research focused on the outcomes of active engagement in those platforms (Cabrera et al., 2006; Centobelli et al., 2018; Lee & Cole, 2003; Z. Yan, 2018), and some focused on investigating the effective incentives driving up users' engagement so as to encourage contribution behaviours (Borck et al., 2006; Chen et al., 2017; Jeppesen & Lakhani, 2010; Qiao et al., 2021; Qiu & Kumar, 2017; Regner, 2004). However, it is challenging to increase users' active engagement and motivate knowledge suppliers to contribute more.

Although most prior research acknowledges that generally incentives[1] can increase contributors' engagement and therefore encourage relevant contribution behaviours on online knowledge exchange platforms (Kollock, 1999; Lin, 2002; Zhao et al., 2016), the effectiveness of incentivisation mechanisms is still a concern, as inconsistent results were often reported in such prior research. Users who actively engage in online knowledge-sharing platforms are either intrinsically motivated (e.g., by self-expression) or extrinsically motivated (e.g., by anticipated extrinsic rewards, points, badges, etc.) or both (X. Liu et al., 2020). Some researchers found that sometimes an incentivization mechanism provides its recipients with extrinsic motivations that represent a controlling, rather than motivating, factor and tend to decrease an individual's autonomy (Ke & Zhang, 2010). A decreased level of autonomy can result in a decreased level of sharing and contributing intentions, and some researchers theorise that the incentivisation mechanism is crowding out individuals' intrinsic motivations and, as a result, inhibiting them from sharing good knowledge (Bartol & Srivastava, 2002). This phenomenon has also been noted in many empirical studies (Bock

[1] Note that incentives can take many forms. Incentives, as Hsu, Ju et al. (2007) suggested, can be economy-based, identification-based, and information-based. Also, some prior researchers tend to subcategorise incentives that can encourage knowledge supplying behaviours into an external incentive, such as "fiat money" (e.g., dollar notes and vouchers) and "non-monetary currencies" (e.g., personal recognition, shared interests and goals, a higher score, and social status) (Bartol & Srivastava 2002; Bock et al., 2005; Kankanhalli, Tan et al., 2005).

& Kim, 2001; Bock et al., 2005). Some researchers argued that individuals supply knowledge because they perceive higher benefits than costs, though often people miscalculate the payoffs (Andreoni, 1995; Barachini, 2009; Z. Yan, 2018). Mis-calibrated and badly-designed incentivisation mechanisms may increase the possibility of these miscalculations and temper users' first-hand experiences, which negatively influences users' engagement and decreases their intention to contribute good quality knowledge pieces (X. Liu et al., 2020).

Researchers and practitioners call for well-designed incentivisation mechanisms that can increase individuals' intrinsic motivation by enhancing their perceived competence, which increases users' propensity and their capacity to make knowledge contributions, and also exert a spill-over effect on other non-incentivised engaging behaviours (Catersteel et al., 2017; P. Huang et al., 2017; Priharsari et al., 2020; Yu et al., 2018). The key to answer this call is to design a motivational feedback tool that can reduce the discrepancies between intended and actual behaviour, which would guide an individual's attention towards their intended performance and drive hedonic motivation (e.g., achievement-related gratification) and, therefore, cause desired behavioural changes (Hassan et al., 2019). In this regard, some researchers also argued that timely feedback can motivate knowledge contributors and elicit gratification, and it can also facilitate engagement and increase content contribution intentions (X. Liu et al., 2020). Like many other contemporary motivational information systems, feedback systems facilitate user engagement not only through providing users with accurate information but additionally through providing them with affective experiences (e.g., enjoyment and achievement) to further support both the utility and the self-purposefulness of use (Hassan et al., 2019; Koivisto & Hamari, 2019).

Second, besides incentivising contributors to produce good quality knowledge pieces, most public knowledge exchange platforms also need to maximise the knowledge's publicity and ensure that those quality knowledge pieces can be distributed to as many people in need as possible. This is especially true for platforms offering **open** knowledge platforms (esp. open science knowledge platforms). Open science encompasses a range of practices that emphasize the rapid and widespread sharing of scientific knowledge across various disciplines (Dawson, 2012). To achieve this, many research organisations build up public platforms for exchanging open scientific knowledge and, when they build these platforms, they highlight the notion of openness. It engenders an openness that enhances the value of the knowledge by allowing users to more easily find and access them: open scientific knowledge is considered as a prerequisite to improve people's livelihoods, well-being, and health and can accelerate these benefits as well as making innovation ecosystems more productive (Gans et al., 2017). Access to open science knowledge provides users with evidence-based, rigorously tested independent information, which also allows peer-reviews and verification, for interested individuals, institutional users and businesses, and public organisations (Olesk et al., 2019). Researchers can maximise the overall value of their research for society when openly sharing knowledge and when such knowledge is retrieved and reused (Sanderson a et al., 2017). Demand for open scientific knowledge from open knowledge exchange platforms continues to grow, particularly as new tools such as machine learning and artificial intelligence technologies increase their utility. On one hand, the users of open science knowledge require more access to quality scientific data to tackle global problems (Ylöstalo, 2020), while on the other hand, the owners of open science knowledge, such as not-for-profit public research organisations, need to prepare and manage their platforms, to increase usability, so that users can find and access their data. Making scientific knowledge easy to access, to read, and to reuse by both humans and machines is the basis of open science, and the underlying goal of open knowledge is to generate "transparency, democratising access and accelerating global synthesis" of science (Spasojevic et al., 2020).

To achieve high openness of scientific knowledge, many organisations build open science portals to transfer and distribute this type of knowledge and expect to create more impactful research outputs, but the management of open science data is highly complex. So far, little is known about how managers of these platforms can achieve this openness efficiently. The literature suggests that to increase openness, knowledge platforms' managers should increase their knowledge pieces' findability and accessibility (i.e., to increase the rate at which people retrieve knowledge). Managers of open science portals need good data-archiving policies. For instance, from an information technology perspective, common data-archiving approaches include ensuring meta-data richness and completeness (Lee et al., 2002), providing relevant documentation and information to potential retrievers, and requiring mandated open access (Curty & Qin, 2014; Niu, 2009). However, as Dunning et al. (2017) argued, the effectiveness of these approaches is often questioned for not being sufficient. In this regard, I argue there is a lack of empirical insights into why certain open science data are generating a higher impact than others.

Moreover, the optimality of enhancing the effectiveness and the efficiency of knowledge exchange through additional incentives shall also be assessed by considering the economic costs of establishing and maintaining those incentives. Many enterprises and organisations expect running a knowledge exchange platform to increase overall social and economic returns, but to reap these returns, the enterprises and organisations need to bear the cost of investing in relevant hardware and software and provisioning appropriate incentives to encourage participation and engagement. Also, the transaction costs of discovering, accessing, and using knowledge can be large. As Sanderson et al. (2017) posited, the key to building a successful knowledge exchange platform and sustaining a healthy value chain of information and knowledge is to ensure that costs, benefits and incentives optimise the efficient flow of knowledge pieces to where it can create the highest amount of value.

Third, to grasp this efficiency factor, many prior researchers have endorsed the idea of building **knowledge markets** and **marketized approaches** to foster knowledge exchange (Benbya & Leidner, 2017; Davenport & Prusak, 1998). As economists would argue, a knowledge market can potentially ensure that the scarce resource—in this instance, knowledge—is used efficiently. A knowledge market, as defined by Davenport and Prusak (1998), refers to a conceptual place where knowledge demanders (buyers) and suppliers (sellers) negotiate to reach a mutually satisfactory price for the goods exchanged. In a broader sense, as they described, a knowledge market is also a theoretical lens and a new type of economics. Using this lens, as Davenport and Prusak (1998) argued, researchers and practitioners can better understand and describe the exchange of knowledge goods among individuals and groups and seek optimal ways to distribute knowledge resources (Benbya & Leidner, 2017; Davenport & Prusak, 1998). Using this knowledge market lens, people can find and explain where and why the exchange of knowledge goods is sometimes flawed, and why the efficiency of such an exchange is often found limited. These problems can be seen as market failures due to problems such as high transaction costs, lack of market information, low number of market participants, market power, and unsuitable regulations (Diamond et al., 2010; Kafentzis et al., 2004; Malone et al., 2009; Van Alstyne, 2013). Knowledge markets also have the potential to help knowledge exchange platform managers address the inefficiencies of "underuse" and "under-provisioning" (Serrat, 2017). Overall, as Van Alstyne (2013) suggested, by understanding and mitigating those problems in knowledge markets, knowledge management scholars and practitioners can boost the effectiveness and the efficiency of inter-personal knowledge transfer by making quality knowledge resources to be more salient to the knowledge seekers' eyes because a knowledge market has the potential to self-adapt to knowledge consumers' needs and help balance the best use of everyone's time.

However, currently, there is still only a limited body of empirical research into the design of knowledge markets for internal and public knowledge exchanges. Bad designs, as Schmitt et al. (2012) concluded, can even cause a death spiral to occur where wrong incentives trigger distrust and low-quality knowledge resources, and platforms that contain distrusted knowledge resources demotivate users from using it, which further lessens the platform owners' ambition and motivation to keep investing in the platform. This reduces the quality and usefulness of the platform. Also, based on my review of the current literature, it is difficult to sustain a functional knowledge market that can keep incentivizing users to contribute more quality knowledge pieces and facilitate an efficient match among the knowledge suppliers and the knowledge seekers in the long term. Therefore, I conclude there is a need to observe and develop knowledge markets in a real-world setting to explore possible ways to develop functional knowledge markets.

Research problems

As described above, despite the significant progress in online knowledge exchange research in recent years, many unknowns remain about how to increase the efficiency of exchanging knowledge on knowledge exchange platforms. Specifically, this thesis mainly addresses three prominent research problems.

Online knowledge exchange platforms need continuous good quality knowledge contributions to sustain their development, so they usually set up various external motivation and incentivisation methods to encourage users' active engagement and participation behaviours—a vital antecedent of knowledge contribution behaviours. Not all research finds that external incentives produce favourable results for active engagement and participation. Although some studies have found that external incentivisation mechanisms can confer gratification and satisfaction to users and therefore produce a positive effect on active engagement and participation, other empirical studies show it can cause a negative effect or no effect. The mixed results and conclusions from those prior studies reflect the complexity of the nature of the incentivisation mechanisms, the complicatedness of people interacting with those mechanisms, and the level of uncertainty that researchers and practitioners are facing when they want to design a functional mechanism that can incentivise knowledge contribution behaviours. In this regard, this thesis aspires to produce a new, theoretically-sound, robust, and readily extensible design paradigm that can reconcile previous contradictory empirical results and suggest avenues for future research and designs of incentivisation mechanisms.

Even if knowledge suppliers keep contributing to a knowledge exchange platform with good quality knowledge contributions, the value of the knowledge contributions cannot be fully unlocked unless the knowledge contributions can be distributed efficiently. Prior research showed one of the effective ways to maximise the value of knowledge that is shared on the knowledge exchange platforms is to increase the knowledge pieces' findability and accessibility. However, current literature offers few insights on how organisations can help to unlock the value of knowledge. This thesis particularly looked at the open scientific knowledge, a special type of knowledge that contains a huge sum of hidden value and is increasingly being shared on knowledge exchange platforms after more and more experts and scientists joined these platforms and endeavoured to offer avenues for the communication and dissemination of scientific knowledge (Zhang et al., 2019). Offering open science knowledge online can extend the potential audience reach beyond the limits imposed by physical boundaries and, as a result, significantly expand the potential influence of scientific knowledge (Brownell et al., 2013); however, many organisations sometimes underinvest in open scientific knowledge-sharing practices and sometimes even provide wrong incentives for individuals and researchers. Therefore, there is a need to find the most important factors to efficiently increase the findability and accessibility of valuable open scientific knowledge. In this regard, this thesis draws on an empirical study based on the one of the largest open scientific data- and knowledge-sharing portals and investigates the attributes of open science data and knowledge and the enablers for users to access this type of data and knowledge.

A small but increasing number of researchers and practitioners are becoming interested in further optimising the distribution of knowledge contributions by adopting market-based knowledge exchange approaches. A market-based knowledge management system can provide adequate transaction mechanisms, dynamic and relevant market signals, and viable financial incentives. However, the extant literature has yet to show how to design an effective and efficient knowledge market to enable a sufficient and sustainable level of knowledge exchange. Few empirical studies exist in this field, and the few studies that do exist have focused only on large transnational enterprises (e.g., Simens, SAP, Allianz, and AECOM) and not on emerging companies nor public websites (Benbya, 2015; Desouza & Awazu, 2003; Dev et al., 2017; Van Alstyne, 2013). Consequently, it is unclear how a knowledge market can offer help in mitigating problems that block internal knowledge exchanging and in establishing an environment that makes the exchange of knowledge more efficient. In this regard, by designing and observing real-life knowledge markets, this thesis offers some insights that can advance people's understanding of the knowledge market.

Overall research objectives

The overarching purpose of this thesis is to enhance the efficiency and effectiveness of online knowledge exchange platforms. This aim encompasses an in-depth focus on knowledge-sharing behaviours, engagement tactics, and the optimisation of open knowledge retrieval and exchange mechanisms. In pursuit of these goals, this thesis seeks to achieve three research objectives:

1. Develop and Evaluate an Innovative Design Paradigm: This objective involves proposing a comprehensive, reliable, and rigorous design paradigm. The aim is not just to increase

contributors' knowledge-sharing and positive engagement behaviours but also to actively mitigate negative engagement behaviours. The effectiveness and applicability of this design will be assessed through meticulous evaluation processes, which will be detailed in the subsequent chapters of the thesis.

2. Identify Motivating Features for Open Knowledge Retrieval: The second objective is to pinpoint features that motivate users and practitioners to make the exchange of knowledge more open and more effectively and economically. Adopting more open arrangements can have significant benefits. It can increase the visibility and impact of research, facilitate interdisciplinary collaboration, and accelerate the pace of innovation. However, it also presents challenges, such as ensuring data quality, protecting privacy and intellectual property, and dealing with the vast volumes of data generated by scientific research, but problems also exist. My study is trying to mitigate the problem through an in-depth case study analysis of Australia's largest open science knowledge portal. The aim here is to derive practical insights that can aid in the cost-effective facilitation of knowledge retrieval.
3. Examine and Analyse Real-World Knowledge Exchange Cases and Market Practices: The third objective involves a detailed observation and analysis of actual online knowledge exchange instances and prevalent market practices. The objective is to investigate how knowledge market designs can aid in optimising the exchange of knowledge. By 'optimising', I aim to refine the knowledge exchange process to its most efficient and effective form, ensuring a seamless and beneficial interaction between knowledge contributors and seekers.

By fulfilling these objectives, the thesis intends to contribute to the development and understanding of online knowledge exchange platforms, focusing on the enhancement of user engagement, facilitation of knowledge retrieval, and optimisation of market practices.

An overview of the research methods

The above paragraphs identified several key research opportunities and research debates with regard to knowledge exchange research and practices. These opportunities and debates prompt the formulation of the research objectives, and this thesis mainly adopts three research methods to achieve these objectives.

First, a systematic literature review was conducted to identify the state-of-the-art theories, designs, and empirical implementations that are relevant to modern knowledge exchange and knowledge markets.

Second, an experimental research method was used to develop a new design paradigm to incentivise high-quality knowledge contributions. Specifically, a prototypical IS solution was designed to boost knowledge contributors' active engagement behaviours. The designing of this prototypical solution was guided by the Nudge theory and the Use and Gratification theory, and a series of rigorous post-hoc analyses were conducted to test the robustness of the solution designed. Thereafter, two subsequent empirical studies were also conducted to explore possible ways to better calibrate the solution and to confirm the external validity of the prototype.

Third, field studies were also conducted to understand how knowledge platforms (both market-based and non-market-based) work in real-world environments. Via observing three real knowledge markets, theoretical implications and practical road maps were determined which can be used to provide guidance to people who want to use knowledge market designs to improve knowledge exchanges.

Using the above-mentioned methods enables this thesis to produce both significant research implications and practical implications. This answers the call from Pan and Pee (2020) who argued that an information system's research output should be able to translate research findings for users into a practically applicable form, have both depth and breadth of use, and provide efficiency and effectiveness improvements for users.

Thesis Structure

After an overall introduction in Chapter 1, Chapter 2 presents a systematic review of the relevant literature whereby they are categorised into ten categories based on their research topics. Chapter 3 briefly overviews how the overarching research approach was selected for the studies presented in this thesis. Chapter 4 focuses on how to design a light-weighted software to incentivise knowledge contributors' willingness to contribute high-quality knowledge and to suggest how platform administrators can use the nudge design to guide software designs which can increase the quality of knowledge exchanged on their knowledge exchange platforms and reduce information overload problems and knowledge starvation problems. Chapter 5 modifies and confirms the effectiveness of the mechanism in a Massive Online Open Course forum, which indicates that the nudge proposed in this thesis has high external validity. Chapter 6 offers exploratory case analysis of Australia's largest open knowledge exchange portal, and provides insights to researchers and practitioners in data publishing communities of open science data about how to increase retrievability of open science data and knowledge. Chapter 7 gives a real-world use case analysis of an online course's market (edX.com) knowledge pricing structure, and this chapter helps the readers of this thesis understand some suboptimality problems that exist in current knowledge markets. In Chapter 8, I present an important empirical study of a real firm's internal knowledge market design which shows how the market-based mechanism can boost knowledge exchange in an emerging Chinese medium-sized company. Lastly, I summarise the research and draw conclusions in Chapter 9. Appendices and references are also provided.

In a rapidly evolving digital epoch, where knowledge functions as both a fulcrum and a keystone, this thesis endeavours to dissect the intricate tapestry of online knowledge exchange platforms. Situated at the confluence of rigorous academic scrutiny and pragmatic application, this work is more than a mere exploration—it is a testament to the ethos of digital knowledge sharing and an invocation for its enhancement.

Chapter 2: Literature review

Overview

At the heart of this thesis is the literature review—a profound exploration of the intellectual foundations that underpin modern knowledge exchanges and marketplaces. By circumscribing extant literature, theories, and empirical studies, it establishes a grounding narrative that precedes and informs the thesis's central inquiry: How can researchers elevate the overall efficiency of exchanging knowledge on these platforms?

Specifically, this chapter offers a comprehensive review of the literature relating to modern knowledge exchanges and knowledge marketplaces and their design. This review constitutes a first step in circumscribing extant literature, theories, and empirical studies before answering the central research question of this thesis: *How to increase the overall efficiency of exchanging knowledge on knowledge exchange platforms?* This review also intends to summarise current research findings from multidisciplinary backgrounds and to help future researchers to gain a deeper understanding of modern knowledge exchange issues.

The first part of this literature review will introduce the time and sources that I used for conducting this review, while the second part introduces the keywords framework that I used in this thesis. The third part introduces the forward and backward research method that I used for conducting this literature review. The fourth part clarifies the definitions of several key terms that are used in this thesis. Next, I categorised the literature that I reviewed into three general categories based on the three research problems that were introduced in the previous section of this thesis. In the figure below, I illustrate the structure of this literature review chapter.

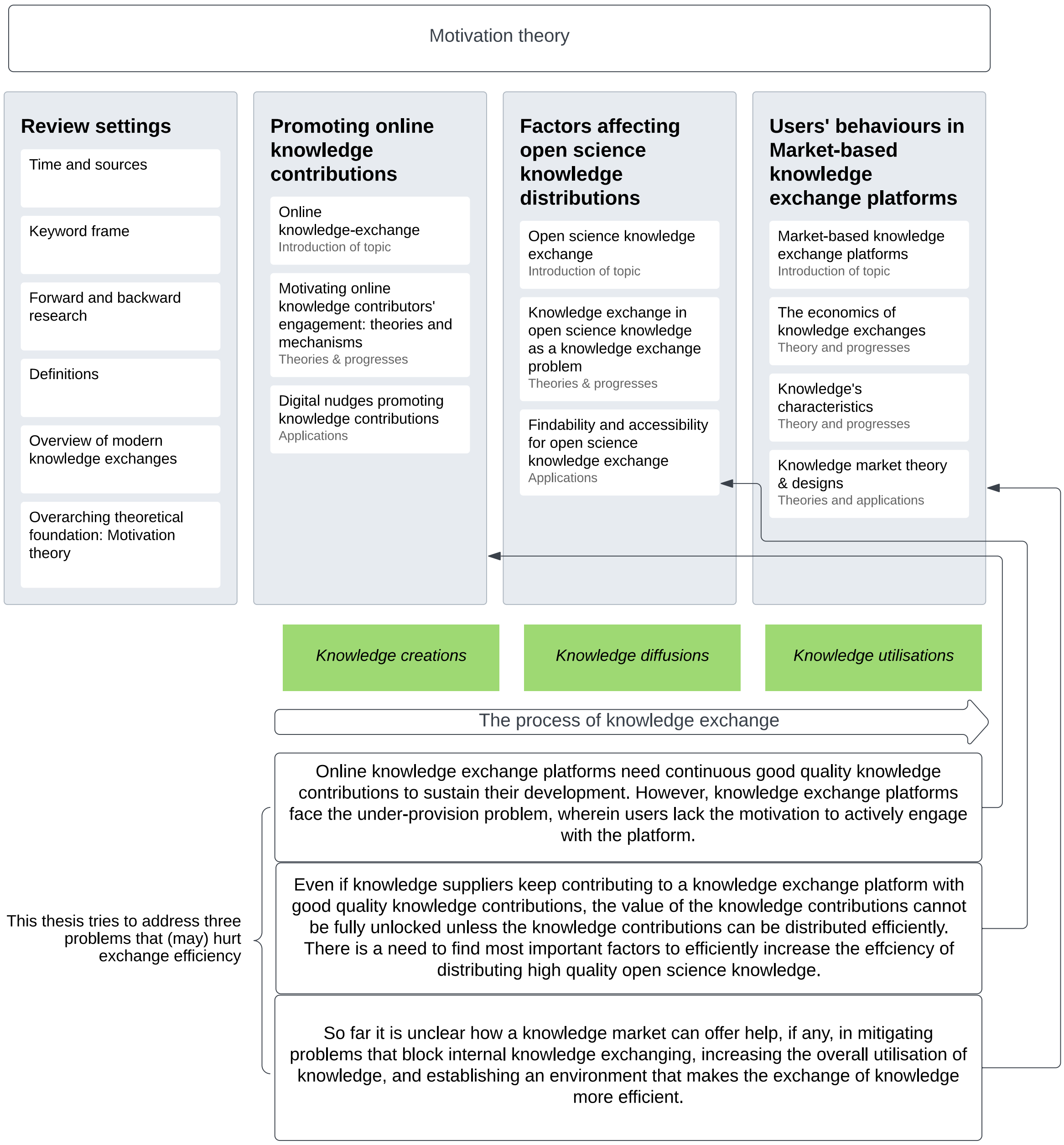


Figure 1. Structure of the literature review chapter

Time and sources

The scope of this review is restricted to: (1) scholarly and peer-reviewed journal publications (including papers to be published), (2) proceedings from established conferences, and (3) academic books published from 1997 to 2022. Publishers and conference organisers of the papers selected encompass Sage, Elsevier, Emerald, Springer, Routledge, IEEE, Wiley, arXiv, AAAI, and citeseerx.

The process of searching and selecting is empowered by the Australian National University's e-library, EBSCO, ProQuest, IEEE, and Google Scholar.

Keyword framework

To explore the key issues and potential answers regarding my research questions listed in the previous chapter, this thesis collected research literatures related to general knowledge exchange behaviours, the management of online knowledge platforms and portals to increase the exchange efficiency, technologies that can be used to boost knowledge exchange, and knowledge payment and market-based knowledge exchange.

I used a keyword search to retrieve articles. The keywords used for searching and selection were "knowledge exchange", "knowledge quality assessment", "knowledge platforms", "knowledge communities", "incentivizing knowledge exchange", "promoting knowledge exchange", "knowledge graph", "knowledge fusion", "knowledge retrieval", "knowledge trading", "knowledge market design", "knowledge payment", "knowledge transactions", "knowledge market", "knowledge valuation", and "knowledge pricing". It is noted that, with the continuous prosperity of the knowledge exchange topic, relevant research has flourished. For example, searching for the keyword "knowledge market design" on Google Scholar resulted in approximately 4,500,000 articles, as of November, 2021.

This keyword-based review established a primary broad review of relevant literature and positioned those basement-like literature regarding the abovementioned topics. To limit the scope, several criteria were established for screening useful papers.

First, the research literature was limited to English papers. Also, a selection was conducted based on the title and the abstract of the papers to find papers that were in the following ten areas:

- Online knowledge exchange and knowledge transfer
- Online knowledge exchange platforms
- Motivating knowledge contributions

- Digital nudges designs that can promote knowledge exchanges
- Open science knowledge exchange and open science knowledge exchange platforms
- Retrievals and distributions of open science knowledge
- Knowledge markets and knowledge trading
- Pricing strategies of knowledge
- Knowledge market designs
- Knowledge management technologies

There were 348 papers shortlisted at this point.

Then, I read the full text of the shortlisted paper and included only those that were highly relevant to the ten topics that I introduced previously. Ninety papers were obtained, and the papers selected after this selection process were called core papers.

Forward and backward research

After the primary broad review, based on the core papers, I adopted a series of "Forward" and "Backward" reference searches, which was helpful in terms of holistically identifying and following models, theories, constructs, and research streams (Levy & Ellis, 2006). The "Forward" method aims at identifying those new studies based on the existing research, so as to probe the topics more deeply, that is, the process was to find follow-up studies from the core papers. For example, using the "Cited by" feature in Google Scholar and cross-reference tracing functions offered by other digital databases, enables researchers to retrieve the most updated findings that relate back to the core papers. The "Backward" reference searching method, also called "Chain Searching", aims at finding those articles published before the core papers. Those prior publications are either cited in the core papers or written by the authors of the baseline papers at an earlier time. This chain searching process contributed to identifying the origin, the development, and the history of those topics. This is particularly important for this interdisciplinary research, as it helps me identify inconsistencies in theories, in constructs, and in terms used.

After these processes, this study contained 337 journal papers, 53 conference proceedings, 37 book sections, 7 research reports, and 7 PhD theses in total.

Definitions

Because this review encompasses many fields of research, some of the concepts and terms that are used in this review are often borrowed and used alternately across different fields, which sometimes leads to confusions and ambiguities. Therefore, in the following paragraph, I will provide the definitions for the key terms that are commonly used in this thesis by summarising their usages and meanings presented in literature.

Many papers in existing information systems (IS) and the Computer Science literature distinguish the concept of “knowledge” from “information” and “data”. However, there is no consensus on this hierarchy (Braganza, 2004; Wang & Noe, 2010). Typically, in the IS field, information and data are often objective terms defined as serialised bits and a flow of messages, whilst knowledge is more subjective, as it refers to the contextualised information including personal understandings and know-hows, typically followed by the sense-making of information (Argote et al., 2003; Davenport & Prusak, 1998; Nonaka, 1994).

In Thierauf's (1999) framework, data and information are defined as any objectively existing beings that can be digitalised and encoded as a stream of bits, whereas knowledge is the subjective and contextualised information containing a certain degree of personal understandings, know-how, and experiences. Notably, as this thesis mainly focuses on the exchange of knowledge, for simplicity, data and information are used interchangeably in this thesis, because there is not much practicality to make such distinctions as so far, the main focus in this thesis is knowledge.

Knowledge exchange, according to Beck et al. (2014), is a dyadic linguistic communication process between a knowledge contributor and a knowledge seeker. Knowledge transfer is an extremely similar term which has often been conceptualized as two behaviours: knowledge contribution (or supplying) behaviours and knowledge seeking (or access) behaviours (Benbya, 2016; Niu, 2009). According to Kuang (2019), knowledge exchange platforms are online platforms where individuals can share their knowledge, experience, and expertise by answering questions and posting articles. These platforms serve as knowledge repositories and also offer social engagement opportunities for users who share similar interests. Now, online knowledge exchange platforms such as Quora.com, StackOverflow.com, and Zhihu.com have gained widespread popularity and rapidly evolved into individuals' go-to places for knowledge exchanging. These platforms have attracted billions of users and have become valuable information technology artifacts for knowledge accruement, knowledge creation, knowledge seeking and online learning that are available to the public for free and for fee.

According to Davenport and Prusak (1998), there must exist a "market" for knowledge pieces to be exchanged and transferred on these platforms. In this market, knowledge pieces are packaged into knowledge goods. Although they are often intangible in nature, some of them may contain some tangible parts. However, the "core component" of a knowledge product is the codified knowledge embedded inside, so only the value of the core part is of concern to me. For example, an electronic book is a typical knowledge product, and its printed version, if any exist, would be the "tangible part" of that product, and the digitised codes are the "data and information", whilst the "expertise" and the "know-how", which can be gained by the "knowledge receivers" only after their further interpretations and personal understandings, are classified as "knowledge". Accounting and Finance journal articles also discussed knowledge goods, and they often refer to knowledge goods as Knowledge Assets (KA) and Intellectual Capital (IC), which are commonly used terms. Papers in those two areas often provide extra aides for the measuring and valuation of knowledge (Sudarsanam et al., 2003), so I also reviewed a small number of important studies in these two areas. To enable measuring, Accounting and Finance researchers and practitioners often require three prerequires for KA and IC: they need to (1) be identifiable; (2) be likely to generate future benefits, and (3) have measurable costs (Marr, 2005). Compared to the definitions from the IS fields, the scope of the aforesaid terms is much narrower, but it enables knowledge measurement and valuation from an asset perspective.

A Knowledge Market (KM), also termed knowledge marketplace, is a mechanism for distributing knowledge via summoning a collection of knowledge suppliers and consumers who, via interactions, collectively determine a price of the commercialised knowledge (Benbya, 2015). It consists of three core market components, namely players for participation, rules for the governance of the transactions, and spaces for the transaction (Desouza et al., 2005). Such market allows knowledge, which assumedly has its inherent value, to be evaluated and priced. The process of valuing KA and IC is named “knowledge valuation”. The valuation can be also utilised on KPs, in a much broader sense (Menon & Blount, 2003). A Virtual KM Platform is a digitised version of a traditional KM (Kafentzis et al., 2002). It is typically in the form of a non-centralised, IT-supported, and collaborative knowledge management system, aiming at matching knowledge seekers with knowledge sources. (Benbya & Van Alstyne, 2010) The advent of the Internet helps in making this process faster, more efficient, and with fewer transaction costs (Bakos, 1998; Ryan & Deci, 2020). Virtual KMs typically provide price-based and/or community-based services (Chen et al., 2010). If implemented internally, a KM is often the critical infrastructural element supporting a company’s knowledge management whose ultimate goal is to capture, to disseminate, and to accumulate knowledge assets and intellectual capitals (Hayaeian et al., 2021; Seleim & Khalil, 2011).

Overview of modern knowledge exchange

Now, the importance of having smooth processes for the exchange of knowledge has been recognized by both academia and knowledge management practitioners. For firms, knowledge has been deemed by many as an organization’s most important resource for staying competitive (Benbya, 2015), and an effective exchange of knowledge ensures smooth reconfiguration, and interpretation of knowledge among employees (Beck et al., 2014). For society, knowledge has also been identified as being central to the era of the digital economy and also a critical factor for influencing a country’s global competitiveness given that global competition is becoming increasingly knowledge-intensive (Dayasindhu, 2002; Ranta et al., 2021).

This thesis also adopts the traditional method of dividing the knowledge exchange process for exploration by breaking it down into three stages: knowledge creation, knowledge diffusion, and knowledge utilization (Estabrooks et al., 2008; Gera, 2012; Rich, 1991). Each stage presents unique challenges to knowledge management researchers and practitioners.

Firstly, I delve into the knowledge creation stage. Here, the struggle for many online knowledge exchange platforms is sourcing enough high-quality knowledge contributions for sustained development (Franke et al., 2006; P. Huang et al., 2018; P. Huang et al., 2017; Jeppesen & Lakhani, 2010). As many platforms cannot offer functional motivational mechanisms to attract enough active knowledge contributors, platforms may face a "knowledge starvation" problem, which leads to a degradation of the community's overall effectiveness and usability (Cheng et al., 2017; Shtok et al., 2012). This degradation often results in users even more lacking the motivation to actively engage with the platform, and sometimes it also causes low-quality, poorly written, destructive-oriented content to overwhelm users, which further reduce users' engagement activities (Matschke et al., 2012; Qi et al., 2021; Wolf et al., 2009; Yeh & Ku, 2019).

Secondly, it is also vital that knowledge platforms ensure a smooth knowledge diffusion stage, as even if knowledge suppliers keep contributing to a knowledge exchange platform with good quality knowledge contributions, the value of the knowledge contributions cannot be fully unlocked unless the knowledge contributions can be distributed efficiently (Fasbender et al., 2021; H. Liu, 2017). Moreover, after the dissemination and the receiving of existing knowledge, knowledge recipients process the knowledge and, against their own intuition and assumptions, test it for validity and reliability, transform it into a form that is usable, and finally apply it when making decisions (Rich, 1991).

Thirdly, in the knowledge utilization stage, knowledge recipients process the received information, testing its validity and reliability against their intuition and assumptions. The knowledge is then transformed into a usable form, ready for decision-making applications (Rich, 1991). Teece (1998), similarly, describes the process of knowledge utilisation as the identification of knowledge assets a firm possesses or needs, the identification of their possible knowledge clients, and the identification of knowledge products or services these clients need. Many scholars have recognized the importance of knowledge utilisation, but as Diehr and Gueldenberg (2017) pointed out, in practice, many firms found their utilisation of knowledge insufficient. Some researchers argue knowledge markets can encourage effective trading of intangible knowledge goods and services and realise most knowledge utilisation (Benbya, 2015; Diehr & Gueldenberg, 2017; Kafentzis et al., 2004). Many researchers and practitioners therefore explored the potential of knowledge markets for mitigating problems that block internal knowledge exchanging, thus increasing the overall utilisation of knowledge and establishing an environment that makes the exchange of knowledge more efficient (Powell, 2011; Serrat, 2017; Van Alstyne, 2013). However, previous knowledge market experiments and fieldworks have produced mixed results, indicating there is still a lack of insight into how to design an efficient knowledge market and understanding its various effects (Benbya, 2015; Carrillo, 2016).

Finally, I conclude with an overview of the four emerging trends in modern knowledge exchanges, as evidenced by a broad spectrum of research studies. These trends will be examined in detail in the subsequent sections. In this regard, a wide spectrum of research studies on knowledge exchange shows that modern knowledge exchanges show four trends.

For the first trend, recent decades have seen knowledge exchange platforms expanding at an unprecedented speed but also becoming more decentralized (Gao et al., 2011; Gautier et al., 2021; Pipek et al., 2012; Schneckenberg, 2009; Sultanov et al., 2021; Whelan, 2007). Notably, one of the underlying assumptions of the modern virtual knowledge market is that "knowledge is decentralised", and this decentralization automatically produces problems such as knowledge silos and idled knowledge resources which is extremely common in the knowledge management and exchange field. Originated by Hayek (1945) whose famous argument was, as quoted "practically every individual has some advantage over all others because he possesses unique information of which beneficial use might be made, but of which use can be made only if the decisions depending on it are left to him or are made with his active cooperation". Such philosophy, though it has attracted a lot of criticism, certainly influenced and enlightened the founders of many modern knowledge platforms, such as

Jimmy Wales and Larry Sanger, establishers of Wikipedia, and Jerry Yang and David Filo, creators of Yahoo! Answers (Barrett, 2008; Benbya, 2015). Indeed, one of the fundamental beliefs of the large-scale virtual knowledge exchange platforms, such as Yahoo!Answers, is “Everyone knows something” (Adamic et al., 2008). Also, as Hayek and his advocates acclaimed, the best way of communicating such knowledge is through a viable price system, and a virtual knowledge market provides such a system and, being similar to other markets, allows its participants to exchange knowledge resources to maximise their utilities based on its inherent price system (Desouza & Awazu, 2003).

The second trend is decentralization. Several factors contribute to the increasing decentralization of knowledge sharing and exchange. Firstly, there is a proliferation of knowledge exchange platforms such as Wikipedia, Quora, GitHub, and Stack Exchange. These platforms enable users to contribute and access knowledge from a global community, decentralizing knowledge sharing and challenging the traditional top-down management style of knowledge platforms. Yan et al. (2018) highlight the growing reliance of companies and organizations on digital platforms for knowledge exchange.

Secondly, there is a cultural shift towards open innovation and collaborative problem-solving, both in academia and industry. This shift fosters a decentralized approach to sharing and exchanging knowledge, as it is seen to promote innovation and creativity (Kayes et al., 2015).

Thirdly, organizations are facing an increasingly unpredictable and decentralized working environment, particularly in the aftermath of the COVID-19 pandemic. This necessitates knowledge management systems and platforms with high resilience and the ability to rapidly embrace new problems and changes. Teams are now spread across different geographical locations, requiring a system that facilitates easy remote sharing and access of knowledge (Nakash & Bouhnik, 2023).

Thereby, it is arguable that the traditional methods of managing knowledge, which focus on historical facts, may not effectively address problems that have not yet occurred. For instance, Benbya (2015) mentions the case of the Oyo Corporation, which, after a major earthquake, opted for a decentralized approach to connect people and rapidly solve problems, rather than relying on a centralized knowledge management system. This highlights the need for flexible and responsive knowledge-sharing mechanisms.

Moreover, the capture and codification of knowledge can be costly, and experts may struggle to meet the increasing demands of knowledge seekers. Market-based mechanisms, as demonstrated by NTT Software, have shown promising results in enabling rapid knowledge exchange and reducing redundant work (Benbya & Van Alstyne, 2010). Van Alstyne (2013) argues that companies should adopt the mindset of market makers in designing knowledge platforms, emphasizing special recognition for generous information contributors and creating pro-social design features to foster community-building and knowledge sharing.

Lastly, the rise of the gig economy has further emphasized the need for decentralized knowledge sharing. With people from various locations collaborating on the same projects or tasks, a decentralized approach ensures smooth collaboration and task completion (Yang & Ye, 2019; Yang et al., 2014). Decentralization is a significant trend in knowledge sharing and exchange, driven by factors such as the emergence of social-based platforms, cultural shifts, remote work, and the gig economy. This trend challenges traditional top-down approaches and necessitates flexible, decentralized mechanisms for effective knowledge sharing and collaboration.

Diving deeper into the heart of knowledge exchange platforms, the third trend observed reflects the integral role of voluntary participation and engagement. The following paragraph dissects the mechanisms and devices that inspire such user interaction and discusses the balance between extrinsic and intrinsic motivations driving knowledge suppliers. Many researchers and practitioners also agreed that voluntary attendance and participation are the keys for the success of social knowledge exchange platforms, and there is a need to design and implement appropriate devices and mechanisms to increase users' engagement and sustain voluntary attendance and participation (Qiao et al., 2021; Qiu & Kumar, 2017; Regner, 2004; W Chen, 2017). As Kafentzis et al. (2004) contended , altruism is one of the keys ensuring the success of a market-based internal knowledge transfer platform, and after launching the platform, knowledge suppliers can still be motivated by not only the market rewards (mostly offering extrinsic motivations) but also can be driven by intrinsic motivators such as desire to pass their knowledge to others and the love of their subjects. An efficient internal market-based knowledge exchange involves important social processes and mechanisms, and by changing the reward structure as well as the ways of using a knowledge platform, these processes and mechanisms, such as organization norms can also be influenced, which may impact overall knowledge sharing and transfer level in the company (Benbya, 2016). A knowledge market may bring a high level of satisfaction by giving users a higher level of exposure and perception of self-efficacy, which are important intrinsic motivations (Ergün & Avcı, 2018). The enhancement of intrinsic motivation can further increase users' social interactions, which eventually boost users' engagement level and therefore their voluntary participation (Chiu et al., 2006; Hung et al., 2011; Yan et al., 2018).

Navigating to the fourth emerging trend, I delve into the intricate landscape of modern market-based knowledge exchange platforms. Their complexity and non-linearity posit a stark contrast to the unitary, atomistic, and individualistic approaches found in earlier literature. As emphasized by Song (2019), these platforms require evolutionary, socially interactive, and non-linear mechanisms. Henceforth, as Benbya et al. (2020) and Tanriverdi et al. (2010) argued, the daunting task of optimizing interactions on these complex systems to encourage more knowledge exchanges. Even well-intended strategies like employing recommendation systems and digital nudges for guiding micro-decisions, such as pro-knowledge-sharing behaviours. As Brown (2021) and Malgonde et al. (2020) stated, researchers and practitioners can use approaches such as recommendation systems and digital nudges, to guide users' micro-decisions (e.g., individuals' pro-knowledge-sharing behaviours), but such designs may sometimes lose their power when they are placed into a macro-level context, because complex systems have complex problems and these problems are encountered by diverse agents with different objectives, preferences, constraints, learning abilities, connectedness, and dependencies. Also, these problems can interact with each other in nonlinear ways, self-organize, and produce emergent macro-level behaviours that differ in scale and kind from the micro-level behaviours (Tanriverdi et al., 2010). Market-based knowledge exchange platforms' high complexity can cause irreducible uncertainty for participants towards matching a transaction, though facilitating transaction-matching between knowledge buyers and sellers is one of the main reasons that knowledge exchange platforms exist (Serrat, 2017). In the face of irreducible uncertainty, consequently, the focus shifts from “reducing” to “taming” the irreducible uncertainty (Malgonde et al., 2020). Song (2019) recommended researchers investigating such platforms should not treat the term ‘marketplace’ as a catch-all phrase and should examine the complex set of interactions in it. There are also interactions that are harder to classify along the lines of financial return, such value creation and innovative activities.

Modern knowledge exchange platforms are more reliant on self-organised monitoring which is often not sufficient to monitor the quality of knowledge that is contributed, transferred, and shared. For example, Khansa et al. (2015) showed that some online knowledge exchange platforms opt for a decentralized control system supported by coordination among individual end users. However, since communications and interactions play a centre role in these platforms, once hindered, a significant number of users and, subsequently, knowledge suppliers, are lost. When users lose engagement, the platforms fail to grow into a vibrant community, and, sometimes, even cease to exist (Campanelli, 2006; Fang et al., 2018). Moreover, modern knowledge exchange platforms often entail high transaction costs. The platforms typically allow a vastly higher number of users to participate and make contributions, which also often lowers the findability and accessibility of the right knowledge contributions, causing too many (and often poorly produced) contributions that can overwhelm users and mean that they have to spend considerable time searching for what they want and filtering out what they do not (Toba et al., 2014). This also creates problems for platform managers because they are supposed to be responsible for effectively mediating between knowledge suppliers and receivers, both enabling and constraining the uses that can be made of those knowledge contributions (Borgman et al., 2019). This is especially true for portals that offer open scientific knowledge because this type of knowledge is highly important and valuable in terms of extending research collaboration among researchers, popularizing science and educating the public, and expanding the potential influence of scientific communication (Claussen & Osborne, 2013; Y. Zhang et al., 2019). However, although modern knowledge exchange platforms allow more contributors to produce knowledge contributions and enable these contributions to be more available for knowledge seekers, the distribution of open science knowledge is still often deemed as “lacking” by many platform managers, because they often find open science knowledge is not well received by the knowledge seekers who need them.

Overarching theoretical foundation: Motivation theory

The importance of user motivation in knowledge exchange platforms has been widely recognized (Milton, 2010). However, the effectiveness of such platforms depends on users actually engaging with them. Motivation theory, which distinguishes between intrinsic and extrinsic motivations, has been used to explain the relationship between user behaviors and motivations (Thomas & Gupta, 2022). The motivation theory usually distinguishes motivations into two types: 1) intrinsic motivation and 2) extrinsic motivations (Deci & Ryan, 2013; Ryan & Deci, 2020).

Intrinsic motivation occurs “when acting without any obvious external rewards” and involves simply enjoying “an activity” or taking “an opportunity to explore, learn, and actualize one’s potential” (Coon & Mitterer, 2012). For example, individuals might want to simply provide help in general (e.g., do more knowledge contribution activities to help the community), achieve something specific (e.g., produce high-quality answers), or gain self-efficacy and/or a sense of autonomy (Lin, 2007; Reeson & Tisdell, 2007). Hung et al. (2011) have found that highly intrinsic motivations, such as altruism, significantly correlated with the perceived satisfaction that individuals had with the knowledge they shared. However, they also found that altruistic motivations had no significant correlation with the quantity or the quality of knowledge that individuals shared.

In contrast, with extrinsic motivations, individuals act in order to gain an external incentive, such as “fiat money” (e.g., dollar notes and vouchers) or “non-monetary currencies” (e.g., recognition, a higher score, and social status) (Bartol & Srivastava, 2002; Bock et al., 2005; Hsu et al., 2007; Kankanhalli et al., 2005). Theoretically, extrinsic motivations represent a controlling factor and tend to decrease an individual’s autonomy (Ryan & Deci, 2020). Ke and Zhang (2010) used Self-Determination Theory to decompose extrinsic motivations into four types: 1) external, 2) introjected, 3) identified, and 4) integrated. Here, “external” refers to motivations to obtain a desired consequence or prevent an undesired one); “introjected” refers to motivations that depend on self-esteem;

“identified” refers to motivations to achieve something one has identified as a personal goal; and “integrated”, the most autonomous form of extrinsic motivation, refers to motivations to become self-determined but still for a presumed instrumental value.

Research has shown mixed findings regarding the impact of extrinsic motivations on knowledge sharing. Extrinsic motivations can either crowd out or crowd in intrinsic motivations. Frey and Jegen (2001) and Osterloh and Frey (2000) found that extrinsic motivations sometimes “crowd out” and sometimes “crowd in” intrinsic motivations. Other studies noted that they found no significant correlation between “outcome-based rewards” and “intention to share knowledge” (Kwok & Gao, 2005; Lin, 2007). Specifically, Wasko and Faraj (2005) tentatively argued that promoting knowledge exchanges via leveraging extrinsic motivations may have more salient effects on individuals than intrinsic motivations. If users perceive an extrinsic motivator as a acknowledging factor, the extrinsic motivator is more likely to impose a positive feeling for individuals and make them become more confident about their competency and not lose their perceived self-determination (Osterloh & Frey, 2000). However, an extrinsic motivator may also crowd out individuals’ intrinsic motivations and, as a result, inhibit them from contributing, sharing, transferring and spending time on searching for good knowledge, if the extrinsic motivator is considered dominating (Bartol & Srivastava, 2002). Anticipated extrinsic rewards have been found to negatively affect attitudes toward knowledge contribution, transfer, and retrieval, potentially reducing the intention to use knowledge exchange platforms (Bock & Kim, 2001; Bock et al., 2005). Deci et al. (1999) proposed that unless rewards establish a positive feedback loop, it is challenging to assert that extrinsic motivational factors directly result in improved knowledge exchange behaviors. The process of definitively linking extrinsic motivational factors to enhanced knowledge exchange behaviors is intricate and multifaceted.

Overall, user motivation plays a crucial role in the success of knowledge exchange platforms. Some researchers suggested that users consider the motivators (e.g., financial incentives, social recognitions, peer supports, etc.) and demotivators (e.g., psychological costs, costs of time and energy, etc.) before using a knowledge exchange platform. To attract users and drive up their continuous use, knowledge platform owners should implement mechanisms that can enlarge the effect from motivators and decrease the effect from demotivators (Bock et al., 2006; Davenport & Prusak, 1998). Yan et al. (2018) maintained that users generally have a threshold for motivation, and if their motivation level is higher than the threshold, they can establish an active engagement with the platform and perform positive knowledge exchange behaviours, such as writing high quality knowledge contributions, actively interacting with others in the exchange platforms, and continuously retrieving knowledge from the exchange platform. Yan et al. (2018) also said that, if a mechanism can increase users' motivation level above the threshold, desired behaviours can be incentivised, and if after the receiving the incentivisation of the mechanism, users' motivation level is still below the threshold, the mechanism would be useless. A mechanism can even cause a negative impact (e.g., in scenarios where external incentives causing a crowding-out effect on desired knowledge exchange behaviours), users' motivation levels will be further reduced and even some users may adopt detachment and destructive behaviours (Dolan et al., 2016; Oye et al., 2011). Therefore, when designing and implementing those mechanisms, knowledge platform owners should provide an environment that makes the power of motivators for performing knowledge exchange behaviours exceed the threshold value.

Promoting online knowledge contributions

The first research topic that this thesis discusses is the knowledge contributions' engagement problems which have been commonly encountered by knowledge exchange platforms nowadays. In the rest of this section, I will firstly introduce the online knowledge-exchange platforms. Then the second part of this section will discuss the theories that previous studies have discussed in terms of motivating online knowledge contributors' engagement. In the third section, I will review the current progress in the literature on finding the right motivational mechanisms for promoting knowledge contribution behaviours. Lastly, I will review the Nudge theory which is the guiding theory for one of the studies presented in this thesis.

Online knowledge exchange platforms

Online knowledge-exchange platforms like StackOverflow, TripAdvisor, Quora, and Wikipedia are crucial for daily knowledge sharing and can take varied forms including forums, question-answer platforms, electronic boards, and wikis (Li & Du, 2011; Qi et al., 2019; Charband & Navimipour, 2016; J. Liu et al., 2019). They allow for exchange of a broad spectrum of explicit knowledge from mundane queries to complex expert insights. One of the most influential and popular forms is Community-based Question & Answering (CQA), also known as Social Question & Answering (SQA) platforms. Many of these platforms have become popular ways for information retrieval, knowledge marketing, and social networking (Chen et al., 2010; Gazan, 2006; Harper, 2007; Lee et al., 2013; Nam et al., 2009; Raban & Harper, 2008; Ridings & Gefen, 2004; Shah et al., 2009; Yang et al., 2009). A typical CQA platform was Google Answers, a price-based CQA, where question-owners paid rewards, donations, bounties or tips for high-quality answers. Another platform, Quora, founded in 2010, is an innovative CQA site which successfully embeds many social network elements into its basic structure and has rapidly attracted huge participation from both common users and domain experts (Wang et al., 2013). Also, on Zhihu, initially a Quora copycat, users can not only ask and answer questions as they do on traditional CQAs but can also enjoy a set of knowledge services via online consulting sessions offered from an intended experienced user. Knowledge owners on Zhihu can sell their knowledge via Zhihu Live, typically a one-hour “lecture-like” or a “TED-talk-like” session. Each session has a topic, with some of the most popular topics being “how to attain financial freedom”, “strategies of pricing bitcoins”, “how to get a good body shape”, etc. On average the unit price for a session is about 50 RMB (approx. 7 USD as of 28th, Oct 2021) per person and knowledge contributors can earn about RMB 8,300 (approx. 1,200 USD) for each session (Feng, 2017). According to Cai et al. (2018), in China, knowledge exchange is a promising market whose scale reached 30-50 billion RMB (approx. 7.2 billion USD) in 2017. Also, in 2017, it was estimated that the number of users who were willing to pay for online knowledge products in China was approximately 188 million, but this number escalated to around 477 million in 2021, with an average annual growth rate of 26.21% (Thomala, 2022).

Some online consultation services facilitate the knowledge exchange among domain experts and knowledge seekers. Typical examples include Whale, Fenda, Zaihang-Yidian, Doctorondemand, and AskDr. Compared with traditional fee-based offline consultation services, Qi et al., (2019) argued that these online consultation services providers have extra benefits in the following aspects: beyond geographic proximity, 24hr availability, cost and time savings, lack of embarrassment, more reliable privacy protection, convenient retrieval of information and the ability to make an appointment of commutation with a specific expert.

Recognising the so-called ‘wisdom of the crowd’, some organisations create web-enabled platforms to foster the knowledge exchange of explicit, and even tacit, knowledge to speed up problem-solving processes, improve community members’ engagement levels and facilitate the exchange of intra-organisational and inter-organisational knowledge (Cai et al., 2019; P. Huang et al., 2017; Kapoor et al., 2018; Sloan et al., 2015; Y. Zhang et al., 2019). Such online knowledge exchanging platforms have also proven successful in open innovation, organisational agility, and crowdsourcing activities, and some large businesses have built and managed such sites and platforms to reach their customers so that they can gather input and feedback for new product and service developments, strengthen customer relationships, promote their brand and enable value co-creation and knowledge collaboration (Bilgihan et al., 2016; Randhawa et al., 2017; Sha et al., 2022b; Y. Zhang et al., 2019).

Motivating online knowledge contributors' engagement: theories and mechanisms

A great deal of prior research has recognised the importance of using motivational mechanisms to boost user contributions and people’s rational reactions towards those extrinsic and intrinsic mechanisms. Some of these studies are more theoretical-oriented, extensively drawing on a variety of well-established theories (e.g., Social exchange theory, Economic exchange theory, Equity theory, etc.) to investigate and develop useful mechanisms that can foster a pro-knowledge exchange culture and boost active knowledge exchange behaviours (Burtch et al., 2018; Jan et al., 2018; S. G. Lee et al., 2018; Lu et al., 2018; Yan et al., 2018). Some are more focused on the practical factors, focusing on issues that involve the designing, validation and implementation of the mechanisms that can lead to better exchange behaviours, for example, high quality contributions, pro-social behaviours, friendly responses, etc. (Davlembayeva et al., 2021; Kankanhalli et al., 2005).

Similar to this thesis, many previous studies used Motivation Theory to explain the motivation driving knowledge contributors’ engagement behaviours, arguing that motivational mechanisms should offer rewards that create a positive feedback loop between intrinsic and extrinsic motivations for their recipients, otherwise it would be difficult to establish an extrinsic or an intrinsic motivational factor that can deterministically translate into enhanced knowledge exchange intentions and behaviours (e.g., writing better contributions). As Wang and Noe (2010) noted, prior studies have produced inconsistent findings about how motivations influence individuals’ knowledge contribution-related behaviours. Frey and Jegen (2001) and Osterloh and Frey (2000) found that extrinsic motivations sometimes “crowd out” and sometimes “crowd in” intrinsic motivations. Other studies noted that they found no significant correlation between “outcome-based rewards” and “intention to share knowledge” (Kwok & Gao, 2005; Lin, 2007).

Theories of goal-oriented actions are widely employed in social psychology, marketing, and information systems literature to examine how engagement translates into purposeful behaviors, such as generating knowledge and content online (Kim et al., 2005). These theories categorize purposive behaviors into three types: goal setting, goal pursuit, and automatic activation of goals. In the goal setting stage, individuals determine why they want to achieve a particular goal. Goal pursuers then develop detailed action plans to attain their goals during the goal pursuit stage. Finally, in the automatic goal activation stage, actions are performed, consequences are experienced, and subsequent actions are influenced.

Khansa et al. (2015) built upon this theory to analyze users' active engagement in knowledge platforms, identifying three distinct but interconnected activities: goal setting, goal pursuit, and automatic goal activation. They discovered that users' engagement behaviors were significantly influenced by the way a knowledge exchange platform provided external incentives, as these incentives could manipulate users' goal-setting processes. In the goal setting stage, the design of reasonable incentives that reorganize users' personal goal structures was found to be critical in influencing their level of engagement and contribution behaviors. Ling et al. (2005) also suggested that explicitly specifying and achievable goal structures tend to yield better performance from contributors.

During the goal pursuit stage, Khansa et al. (2015) argued that membership status within a knowledge exchange platform serves as a valuable indicator of individuals' commitment to achieving their goals. Many modern platforms adopt level-based systems to incentivize contributors, encouraging them to contribute more and progress to higher levels. Theories of goal-oriented actions propose that a well-designed incentivization mechanism should provide clear guidance on the points needed for the next level-up, particularly when users are near the threshold of advancing to the next level.

In the automatic goal activation stage, users develop habitual behaviors by visiting knowledge exchange platforms regularly, transforming engagement and participation into daily routines. Kraut et al. (1999) and Hobbiss et al. (2021) noted that online environments are conducive to cultivating habitual behaviors, and online knowledge exchange activities exhibit strong correlations between past and future use. Contributors who habitually contribute to a knowledge exchange platform are less likely to disengage in the future (Khansa et al., 2015).

Goal setting theory is often used in conjunction with other theories in research. For example, Goes et al. (2016) integrated goal setting theory and status hierarchy theory to investigate contributors' efforts in knowledge exchange platforms. They found that three factors—before goal attainment, after goal attainment, and rank on the incentive hierarchy—jointly influence users' knowledge contribution behaviors. While glory-based incentives may initially motivate users to contribute more, the positive effect is temporary and diminishes over time, particularly for contributors with higher ranks. In this regard, theories of goal-oriented actions provide a framework to understand how engagement translates into purposeful behaviors. By examining goal setting, goal pursuit, and automatic goal activation stages, researchers can gain insights into the factors influencing users' engagement levels, contribution behaviors, and the role of incentives in knowledge exchange platforms.

Many information systems designers used affordance theory to find methods to motivate platform engagement and knowledge contributions. In this theory, affordance takes a focal point; it refers to the general actionable attributes of an object that can gratify users' particular needs (Gibson, 1977). As Gibson (1977) argued, an affordance combines actual and perceived properties of a thing that determines how it would be utilised in a specific context. In the knowledge exchange context, as L. Chen et al. (2019) explained, information systems designers shall make their affordances invoke intrinsic motivations, such as interest and enjoyment, and by doing so, their affordances can further promote desired behavioural outcomes, such as contributors' continued engagement and more good quality contributions. According to this theory, different users perceive affordance very differently even if the technological capability that affordances provide are the same (Treem & Leonardi, 2013; Utz & Levordashka, 2017). For example, drawing on the framework of successful gamification against a backdrop of affordance theory, Suh and Wagner (2017) conducted research and found that, although reputation scores could increase employees' knowledge contribution in an internal enterprise collaboration system, the reasons for the increase are different: Some users viewed reputation scores as a kind of achievement, while others regarded them as a sense of recognition of their expertise. L. Chen et al. (2019) reported that, while maintaining content quality is important, negative motivational affordances (i.e., down voting) can reduce sustained contributions.

Equity theory is also a widely used theory to explain users' contribution behaviours in knowledge exchange platforms. This theory argues that people contribute knowledge because they want to restore equity if they sense that they will be rewarded (Huseman et al., 1987). When users feel they are over-rewarded, the extra rewards might lead to a feeling of indebtedness which motivates them to complete more reciprocating activities. If users' sense that they are under-rewarded, they will also make corresponding efforts to restore equity (Adams, 1963). In online knowledge exchange scenarios, as Qi et al. (2021a) and Kuang et al. (2019) argued, individuals manage their relationships with others and assess the ratio of their outputs and inputs to the relationships when they are participating in knowledge exchange platforms. They argue that, when users receive an extra number of extrinsic rewards for knowledge exchange activities, the feeling of indebtedness incurs, which eventually can be translated into knowledge contribution behaviours. Moreover, as Feng and Ye (2016) argued, people tend to avoid being seen as selfish by performing reciprocal behaviours, such as voluntary knowledge sharing, knowledge seeking, and social engagement, when they are participating in knowledge exchange platforms, and under this context, if there is an extra amount of extrinsic incentive, according to the equity theory, they would voluntarily contribute extra time and effort to the knowledge exchange platform (Kuang et al., 2019).

Framing theory suggests that how a "frame" is presented to the audience influences the choices people make about how to process that information (Carnahan et al., 2019). Frames are abstractions that work to organize or structure message meaning in a way that it can draw people's attention towards certain aspects and, at the same time, draw people's attention away from other aspects (Goffman, 1974). As a consequence of this presentational difference, individuals' attitudes can be changed and become more aligned with framed information, leading to more message-consistent effects; this is referred to as a framing effect (Cacciatore et al., 2016). According to Bateson (2000), the concept of framing was first posited in 1972, but, as Huang et al. (2019) argued, researchers have explored more than 100 years of research about the use of performance feedback interventions to motivate the transfer of knowledge and learning of knowledge. Motivating users to contribute knowledge content can be achieved by well-selected feedback message framings that speak to different motives for knowledge contribution, though this process is nuanced and highly contextual (Huang et al., 2019). For example, as Wozniak (2012) and Srivastava and Rangarajan (2008) argued, there are several factors, such as personal traits of the framing messages' recipients and the ways framing messages are provided, that can affect the effects of framing.

Many researchers used Self-determination theory to understand how online knowledge platforms' contributors perceive incentives and how incentives can affect contributors' engagement levels and behaviours. The Self-determination theory focuses on social-contextual conditions that promote versus undermine the process of self-motivation, social functioning, and positive human potentials (Deci & Ryan, 2008). The theory stresses three basic psychological needs that drive continuing motivations for competence (one's personal development and achievement), connection (one's social development and achievement) as well as autonomy (one's perception that his or her life is going well) (Ryan & Deci, 2000). Similar to Motivation theory, Self-determination theory also differentiates intrinsic motivation and extrinsic motivation, but focuses more on intrinsic sources of motivation which pertain to principal sources of inherent satisfaction and enjoyment (Ryan & Deci, 2000). As L. Chen et al. (2019) argued, Self-determination theory is most applicable to explaining why some contributors are proactive and engaged in online exchange platforms even if there are seldom tangible economic benefits or monetary reimbursement for the time and effort they spent on their services. Using this theory, Yoon and Rolland (2012) postulated that knowledge contributors keep contributing to virtual platforms because of perceived competence and perceived connectedness; perceived autonomy, however, has no influence.

Social cognitive theory is also a widely used theory for studies that focus on individual behaviours in this area. The theory was derived from social learning theory which was proposed by Miller (1945). The theory argues that people's behaviours are shaped and manipulated by their cognition in a social environment: (Bandura, 1990; Locke, 1997). Knowledge exchange researchers who draw on this theory tend to highlight the importance of social interactions and the set of resources embedded within the network, and articulate that online knowledge exchange platforms are social networks where people interact with others who share common interests, goals, or practices so their knowledge exchange behaviours, such as contributing, sharing of knowledge, will be influenced not only by personal experiences but also by the actions of others, and environmental factors (Chiu et al., 2006). Knowledge contributors, before inputting efforts, calculate the expected outcomes of behaviour change such as personal gains (e.g., gaining more respect and making more friends in the knowledge exchange platform) and community-related gain, for example, the impact of knowledge contributions that they author on the knowledge exchange platform (Lin & Chang, 2018). Also, if one's belief about his/her capability confidence to contribute to knowledge exchange platforms is impaired by the situational factors, the person's intention to contribute would be lowered significantly especially for novice participants. Therefore, the researchers suggested that knowledge exchange platforms administrators shall offer easier motivations to those without any prior experience to contribute (Kuo et al., 2020).

According to Guan et al. (2018), the social exchange theory is the most popular theory in terms of investigating users' communication and content generation behaviours on online communities/social media. Also, as Chen and Hung (2010) and Ye et al. (2015) indicated, this theory has been widely adopted and extended to develop integrative models for explaining the knowledge exchange phenomenon in organizations and in online public communities. This theory was proposed by Homans (1958) whose initial purpose was to study people's social behaviour in economic affairs. Theorists argue that social-exchange-related behaviours starts when people expect others will pay something back and stops when the paying back activities cease. Unlike daily economic exchange behaviours, social exchanges involve less rationality and calculation in terms of analysing and quantifying the benefits and costs of taking a transaction because it is more difficult to do so when doing social exchanges activities (Foa et al., 1993). Phang et al. (2009) further argued that exchange knowledge for social purposes can be regarded as social exchanges and when these exchanges happen, there will be resources considered as currency of social exchange which may constitute the costs (resources given away) or benefits (resources received) for exchange. Wasko and Faraj (2005) and Kankanhalli et al. (2005) also used this theory to set up a framework that differentiates knowledge contribution motivators (bringing pertinent benefits) and demotivators (costs-related factors). Nonetheless, when people conduct knowledge contribution behaviours in social media, they are mostly long-term oriented, and people tend to pay attention to common benefits in the long run (Guan et al., 2018). As suggested, people exchanging knowledge online need to go through a dynamic process where the person's social relationship with other members in the platform is developed and maintained over time, which differentiates itself from pure economic exchanges because their processes are more simultaneous and discrete. As Rui and Whinston (2012) contended, knowledge contributors trade knowledge for attention when exchanging knowledge with others on social Q&A communities. Also using social exchange theory, Chen and Hung (2010) explained how the norm of reciprocity and interpersonal trust can significantly impact knowledge sharers' contribution intentions and behaviours. Ye et al. (2010) used this theory and found that knowledge suppliers make contributors because they expect fair exchange, and this intention can be reinforced by norms for reciprocal exchange. Later, also using social exchange theory, Ye et al. (2015) further proposed four antecedents (pro-sharing norms, information need fulfilment, perceived recognition from leader, and perceived co-presence of leader) that are distinctly linked to knowledge contributions.

Social capital theory is also used by some researchers. The theory evolved from new economic sociology, and was proposed by French sociologist Bourdieu (2018). Social capital is defined as "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit" (Nahapiet & Ghoshal, 1998). The concept of social capital has been borrowed by knowledge management researchers for many years to explain the role of relational resources embedded in dyadic or network relationships involving knowledge resource exchange and knowledge management practices (Hau et al., 2013). It is also widely accepted that social capital is a key facilitator of organizational knowledge creation and sharing (Inkpen & Tsang, 2005). For instance, Chow and Chan (2008) surveyed 190 managers from Hong Kong firms and found that two social capital factors (social network and shared goals) significantly contributed to a person's volition to contribute and share knowledge, but another type of social capital factor, social trust, showed no such effect. Yang and Farn (2009) used social capital theory and conceptualised social capital as strong interpersonal connections and extensive investment in interpersonal relationship. Hey also hypothesised that individuals who have a stronger social capital in his/her social network will be more likely to transfer tacit knowledge with his/her co-workers because he/she has a stronger need to maintain an interpersonal friendship in their social network. Wang et al. (2011) investigated employees in a Chinese bank and found team-level social capital interacted with individual-level social capital in influencing knowledge transfer; they found that once a knowledge contribution created, people with a better social capital (i.e., having a shorter distance from the knowledge source and a more equivalent network position to the knowledge source) tend to acquire the knowledge contribution more easily, but these influences are softened by team-level social capital characteristics. Zhao et al. (2012) indicated that there are three factors (i.e., familiarity with other members, perceived similarity with other members, and trust in other members) that relate to the three dimensions (i.e., structural dimension, cognitive dimension, and cognitive dimension) of social capital in online knowledge exchange platforms, and all three factors positively correlated with users' sense of belonging to knowledge exchange platforms, which affects their intentions to retrieve and contribute knowledge.

There is a small but increasing number of researcher who have used community commitment theory, a relatively new theory, to explain users' continued contribution behaviours. As Bateman et al. (2011) and Greer (2013) argued, participants develop psychological bonds to a particular online platform because of three types of commitments: need commitment (also called continuance commitment), affect commitment (also called emotional attachment), and obligation commitment (also called normative commitment), and each commitment usually causes a different impact on different knowledge-exchange-related actions. Need-based commitment predicts thread-reading behaviours, affect-based commitment predicts commenting behaviours, and discussion-moderating behaviours, and obligation-based commitment predicts only moderating behaviours. Generally, according to Jeong et al. (2016) when members consider themselves to have commitments to a community (e.g., a knowledge exchange platform can be seen as a community for exchanging knowledge), users will continue to show engagement behaviours with the community and actively participate in it. This is because they are certain their engagement behaviours are conducive to community development. Drawing on this theory, Wei et al. (2015) found that a user's reputation does not directly motivate contribution behaviours but the relative reputation (ranking) does. They further imply that online knowledge exchange platforms can use built-in reputation systems to strengthen contributors' commitments—it is important to use peer effect to make the strengthening stronger. X. Zhang et al. (2021) used community commitment theory to explore social loafing behaviours (i.e., users reduce their active efforts, that is, write good knowledge contributions and play a "free rider" role). They found community commitment plays a mediating role between community supports and explore social loafing behaviours, but the different commitment type's impact is different: Specifically, affective commitment negatively affects social loafing behaviours, normative commitment exacerbates social loafing behaviours and continuance commitment has no influence on social loafing behaviours.

Use and gratification theory is also popular in knowledge contribution studies. Platform owners generally want their users to actively engage with the platforms to create value through positive interactions and contributions and do not want their users to only consume content passively (Dolan et al., 2019; Silic & Lowry, 2020; Yan et al., 2018). Use and Gratification Theory, which originated in the communication field, elucidates why users actively seek out and use specific media to fulfil needs, explains users' motivations and predicts users' engaging behaviours (such as continuous content-contributing behaviours) on knowledge-sharing platforms (X. Liu et al., 2020; Muntinga et al., 2011; Shah, 2006). Gratification refers to satisfaction perceived by users when they purposefully access a certain media. Different levels of gratification lead to different levels of engagement behaviours (Chua et al., 2012). For instance, as Dolan et al. (2016) summarised, high gratification can lead to positive-valanced engagement behaviours such as value co-creation and positive contributions whilst low gratification provokes negative contributions and co-destruction.

There are some researchers who have used the affective response model to explain the relationship between knowledge contribution and users' engagement. This theoretical model is often used to explain people's instant knowledge and information-sharing behaviours (Li et al., 2017; Stieglitz & Dang-Xuan, 2013). Because instant knowledge and information sharing are usually more emotional and impulsive but less rational and deliberate, the theory suggests that if one wants to promote knowledge contributors to make more of this type of knowledge contribution, there is a need to provide and reinforce affective cues to the contributors (Li et al., 2017). Affective cues are environmental signals, characteristics or features that manifest the affective quality of the stimuli and are able to influence emotions (P. Zhang, 2013). This is because affective cues contain affective information, such as characteristics of time, product, ambience, design, and society, which can trigger people's emotional reactions (Chang et al., 2011; Graa & Dani, 2012). There are three types of affective cues (i.e., information uniqueness, information crowding, and social interactivity) and all these cues can have significant impacts on contributors' positive emotions, which sparks an urge to knowledge sharers to contribute and share knowledge and information (Li et al., 2017). In another research, Feng et al. (2021) further found negative emotional words can also be naturally seen as affective cues that will generate arousal and action tendencies, and people who receive affective cues brought by negative emotional words will reduce their knowledge exchange intentions and behaviours such as knowledge contribution and knowledge diffusion.

Similarly, the IS literature has utilized signalling theory to examine online knowledge exchange behaviors. Originally an economics theory, signalling theory explains how sellers and buyers can engage in transactions by using and transmitting signals that reveal relevant information to the other party in situations where market information is uncertain and highly asymmetric (Connelly et al., 2011; Spence, 1976). A signal, as defined by Rao et al. (1999), is a quality cue that sellers use to credibly convey information about unobservable product quality to buyers. According to the theory, one party must decide whether and how to transmit a signal, while the other party must determine how to interpret the signal (Spence, 2002).

Given that the online environment separates buyers and sellers in terms of time and space, the problem of information asymmetry is even more pronounced in online platforms (Ghose, 2009). Online knowledge exchange platforms are no exception. A robust signalling environment between knowledge contributors and seekers is crucial for facilitating the efficient flow of knowledge, as signals indicate where knowledge is located and how to access it (Lai & Hsieh, 2021). To mitigate the risks arising from information uncertainty, knowledge contributors need to employ signals to convey quality cues for their knowledge contributions, as without such signals, their contributions may not receive sufficient attention from knowledge seekers (Merchant et al., 2019). Zheng et al. (2013) suggest that this effect operates in a self-reinforcing manner, where knowledge seekers easily and quickly find more useful knowledge by pursuing quality cues, leading contributors of well-crafted knowledge to gain more attention from knowledge seekers. As a result, these individuals may further contribute high-quality knowledge to enhance the overall knowledge stored in exchange platforms.

Furthermore, signalling theory suggests that knowledge exchange platforms should incorporate well-designed features that present visible quality cues related to the system. These cues aid knowledge seekers in searching for and reusing specific knowledge pieces (Lai & Hsieh, 2021). Searchability, an important system quality cue, plays a role in determining how frequently a knowledge seeker utilizes a knowledge management system for retrieving knowledge (Alavi & Leidner, 2001; Ahmed & Elhag, 2017).

Previous studies have also examined the effectiveness of the signalling process in relation to the characteristics of knowledge seekers. Connelly et al. (2011) found that individuals vary in their attention to signals when browsing online information. Some people may disregard signals entirely, rendering the signalling process ineffective. Analysing weak signal cases, where signals may or may not be ignored, is more common but can be challenging (Ilmola & Kuusi, 2006; Taj, 2016). Moreover, research on the relative strength of quality signals is limited (Sha et al., 2022a).

Generally, there are many empirical studies claiming that their mechanisms can exert a positive effect on encouraging knowledge contributors' engagement levels and on causing better exchange behaviours (e.g., high quality contributions, pro-social behaviours, friendly responses, etc.) when they are exchanging knowledge online (Davlembayeva et al., 2021; Kankanhalli et al., 2005). For example, Chua et al. (2012) designed a mobile content-sharing application, MobiTOP, and they found that users' mobile content-contribution intentions were positively associated with two gratification factors: easy access and entertainment. Tang (2012) investigated the designing of a revenue sharing scheme and reputation scores, and found when they are used together both can motivate content contribution. Sutanto and Jiang (2013) conducted an empirical study which investigated the effect of a 'semantic score' (i.e., a rate calculated by a 'sophisticated' knowledge-management system to evaluate shared online knowledge) on knowledge contributors' frequency and tendency to share knowledge on electronic knowledge repositories. All the knowledge items that contributed to the knowledge base were transferred to a third-party organisation to calculate the semantic score, and the researchers found that this explicit rating had a positive effect on knowledge suppliers' contribution quality but not frequency. Guided by Self-determination theory, Lou et al. (2013) sent out a questionnaire and analysed the reward system utilised in Baidu Knows, one of the largest knowledge exchange platforms in China, and found that it is partially effective to implement that particular reward system to recognise community users' knowledge contributions. Specifically, they found that the reward system can be effective in enhancing knowledge contribution quantity, but the system has limited power on enhancing knowledge contributions' quality. The researchers suggested that the system should add some embedded tools and modules to facilitate user's learning in the community because they demonstrated that learning can be a significant driver of both quantity and quality of knowledge contributions. Guided by Framing theory, Huang et al. (2019) found that using a deliberately motivational framing message, as an inexpensive extrinsic motivator, can strengthen knowledge contribution intentions when sharing. Yoo et al. (2021) performed an empirical research on YouTube and reported that overall, removing negative incentives (e.g., downvotes) can positively influence the discussion culture on the platform and boost users' content sharing behaviours. Burtch et al. (2021) conducted another research and found that peer awards, which are widely considered as a type of extrinsic motivator, are more likely to foster and maintain recipients' intrinsic motivations when sharing knowledge online. Suh and Wagner (2017) argued that gamified affordances added on motivational mechanisms that are designed for promoting contributors' intention to write more knowledge content can be effective in increasing the quantity and quality of knowledge pieces contributed by users, but simply incorporating game artifacts does not guarantee this effect. Instead, it is critical assessing, monitoring and diagnosing what affordances users perceive from the use of a gamified system.

There are also a large number of empirical studies that have found a negative relationship. For instance, Bock et al. (2005) introduced cases in which introducing an extrinsic motivational mechanism can negatively influence people's knowledge-sharing and exchanging behaviours. In another instance, Shah et al. (2009) also empirically found that mechanisms that provide extrinsic motivations can both increase the quality and the quantity of knowledge in communities such as Yahoo!Answers and Google answers. Some researchers argued even weak forms of extrinsic motivations, such as virtual points, have proven useful in online question answering communities to promote knowledge-sharing behaviours (Kollock, 1999; Lin, 2002; Zhao et al., 2016). Also, some researchers proclaimed that group-level incentives are more effective than individual-based rewards, while the latter ones' effects are more volatile (Bordia et al., 2006; Jarvenpaa & Staples, 2000; Wasko & Faraj, 2000). However, there is also another stream of research that supports the opposite view (Lee & Ahn, 2007). Thus, as Wang and Noe (2010) noted, prior studies have produced inconsistent findings about how motivational factors influence individuals' knowledge-sharing behaviours. The following Table 1 summarises the important findings in this realm for the last three decades.

Author(s)	**The effect of motivational mechanism**	**Type of research**
Kohn (1993)	Rewards' positive effect only exists in a short run but exhibits a negative effect in the long run because rewards only buy temporary compliance but do not create a lasting commitment.	Summary of empirical research
Weiss (1999)	Incentives do not support devoting time to do knowledge exchange behaviours (namely, "non-billable" activities) unless the incentives are designed in such a way that they are aligned with the goals of creating a knowledge-sharing organization	Interviews-based research
Alavi and Leidner (2001)	Incentives are important to overcome two knowledge-sharing barriers (i.e., employees lacking time to contribute their knowledge and a corporate culture lacking a history of rewarding knowledge contributions)	Review of literature
Goh (2002)	If a reward system focused purely on financial results or outcomes, it may cause fierce competition and therefore cause a negative impact on knowledge sharing and team cooperation.	Theoretical research

Ipe (2003)	Individuals generally are inclined to share knowledge especially when the value attributed to such knowledge is very high. However, if incentives are sufficient then people may be motivated to share that knowledge. Even if the knowledge exchange platform offers significant incentives, when the opportunities to share are insufficient and when the culture of the organization/community attributes power to those who are perceived to possess certain knowledge, the incentive by itself may not cause knowledge sharing.	Theoretical research
Bock et al. (2005)	Extrinsic rewards can exert a negative effect on individuals' knowledge-sharing attitude	Theoretical + Empirical (questionnaire)
Kwok and Gao (2005)	Extrinsic rewards have no significant effect	Student sample experiment
Roberts et al. (2006)	Extrinsic rewards have a positive impact on knowledge sharing among open-source software developers	A longitudinal study on open-source software developers
Lin (2007)	Extrinsic rewards have no significant effect on knowledge-sharing behaviours	Empirical research
Lee and Ahn (2007)	Theoretically, reward systems and other organizational factors can complement each other and exert positive impact on knowledge sharing. A firm can efficiently capitalize on its knowledge assets by using a simple linear reward system, but it	Conceptual research

	is also not necessarily desirable to encourage workers to share as much knowledge as possible	
Raban and Harper (2008)	Positive, and the effect of financial rewards is higher than intrinsic rewards and social rewards	Empirical research (Crawled data)
Shah et al. (2009)	Monetary compensation is an important motivator for contributing knowledge on social Q&A sites	Review of literature
Jeon et al. (2010)	Financial rewards increase the likelihood of a knowledge seeker receiving an answer but generally do not assure high answer quality	Empirical research
Zheng et al. (2011)	Extrinsic rewards have no significant effect on knowledge-sharing behaviours	Empirical research (Crawled data)
Lee et al. (2013)	Knowledge contributors are rarely motivated by social factors but are predominately motivated by financial incentives as well as intrinsic motives on a mobile pay-for-answer Q&A platform	Empirical research (Crawled data and survey)
Lou et al. (2013)	No indication of a relationship between rewards and knowledge contribution quality but the motive of rewards-gaining is only significant on quantity	Empirical research (Questionnaire-based)
J. Yang et al. (2014)	Extrinsic rewards have positive effect on users' knowledge contribution behaviours	Empirical research (Crawled data)
Huang et al. (2019)	Framing message, as an inexpensive extrinsic motivator, can strengthen knowledge contribution intentions when sharing.	Empirical research
Yoo et al. (2021)	Overall, removing negative incentives (e.g., downvotes) can positively influence the discussion	Empirical research

	culture on the platform and boost users' content sharing behaviours.	
Zhang and Liu (2021)	For UGC contributors, if monetary incentives are used as a proportional mechanism (i.e., the monetary rewards for each contributor are proportional to the audience attracted), the incentives' impact are generally positive, but if monetary incentives are used as a quality control mechanism (i.e., only if a contributor can attract an audience larger than a threshold, then the contributor can get monetary rewards), the impact will be negative.	Empirical research

Table 1. Important Findings Regarding the Effect of Motivational Mechanisms for the Last Three Decades

Digital nudges promoting knowledge contributions

It is of great importance to design an incentive system that guarantees effective knowledge exchanging. Potentially, there are a variety of options open for firms to use, and the firms may flexibly choose strategies and mechanisms that combines and maximises the incentivisation power from both the extrinsic rewards and intrinsic recognitions. As aforementioned, researchers and practitioners in this field, using different research approaches, theoretical underpinnings, and methodologies, have implemented an extensive amount of investigations to understand the effect of motivators on promoting knowledge exchange behaviours. As Li and Du (2011) argued, when producing knowledge contributions, knowledge contributors consider factors such as the size of the rewards, social networks improvements, trust in the community, types of content to be shared, and the perceived value of their contributions. Finding a mechanism that can give acceptably sufficient consciously perceivable rewards to contributors that satisfy those needs has been extensively studied in the past several decades (Chang & Chuang, 2011; Charband & Navimipour, 2016; He & Wei, 2009; Jung et al., 2021; Kuem et al., 2020; Mitton et al., 2007; Sutanto & Jiang, 2013; Y. Zhang et al., 2019). Yet, by reviewing the literature, I also noticed that prior studies reported many inconsistent findings. To reconcile those conclusions, I argue it is important to investigate the subconscious elements of motivational mechanisms, design new motivational mechanisms that highlight the importance of subconscious elements and evaluate the effect of the new designs.

Human behaviour is heavily guided by non-conscious cognition and can be influenced by seemingly subconscious elements in the environment (Khansa et al., 2015). Recent research has shown that subliminally presented reward incentives can be effective, even without conscious awareness of those incentives (Bargh et al., 2001; Custers & Aarts, 2005; Hartig & Zhao, 2009; Hinze et al., 2021). The Nudge theory is one approach that researchers and practitioners can use to promote desired knowledge exchange behaviors, by emphasizing the importance of subconscious elements during the knowledge contribution stage. A 'nudge', as defined by Thaler and Sunstein (2019), is any aspect of the choice architecture that predictably alters people's behaviour, without forbidding any options or significantly altering their economic incentives. As Peer et al. (2020) explained, the Nudge theory focuses on non-conscious heuristics and irrational elements that can be exploited to encourage desired behavioural outcomes, benefiting both individual users and society as a whole. Purposeful interface designs can help a system influence users' behaviors by exploiting well-known biases in human decision-making in predictable ways (Acquisti et al., 2017; Schneider et al., 2018). For example, in a field experiment of a leading online education and career knowledge-sharing community in China, N. Huang et al. (2018) demonstrated how a digital nudge that used both monetary incentive and framing effect—a common cognitive bias wherein an individual's choice from a set of options is influenced more by how the information is worded than by the information itself (Saposnik et al., 2016)—can cause a significant positive effect on users’ sharing behaviours. However, the authors also reported that a nudge message with only a simple request for sharing reduced sharing behaviours, indicating that the suboptimal design of digital nudges may decrease, rather than increase, desired behavioural outcomes. This also indicates that nudges, if not curated and designed properly, cannot trigger desired knowledge-sharing behaviours.

The key to designing a well-functioning digital nudge that can facilitate the knowledge exchange process is to find an applicable bias. To do that, there is a need to understand why people make positive, high-quality knowledge contributions. Some researchers examined the Use and Gratification theory, a popular theory in information sciences literature used to explain human knowledge contribution behaviours. According to Dolan et al. (2016), users' high gratification levels stimulate effective engagement and positive contributions, whereas low gratification levels lead to user detachment and negative contributions. As Davenport and Prusak (1998) argued, people's time, energy and knowledge are limited such that, before deciding to contribute to a knowledge management system (e.g., a knowledge exchange platform) people consider whether the value of their knowledge contribution is rewarded. Moreover, as Yan et al. (2018) contended, knowledge contributors generally have a threshold for their motivation, and only an incentive that brings external gratification that exceeds their motivation threshold value can have a positive effect on their contribution behaviour, meaning that an incentive that is below this threshold will not have a positive effect and might even have a negative effect. However, online knowledge exchange platforms provide an environment that usually involves a significant time lag between a user sharing knowledge and receiving gratification, feedback, and motivational recognition (Kang, 2022). When sharing, contributors often do not know whether they are doing well, feel unsure of the value and use of their contribution, and do not receive a sufficient level of guidance (Ma & Agarwal, 2007). Sometimes, this delay can be months, which discourages users from sharing more knowledge. This lack of synchronicity further attenuates the positive effect that gratification can have on the motivation threshold.

The present-time bias (i.e., people prefer immediate gratification over delayed gratification is one of the common biases shared by many people (Adusumalli et al., 2020). Prior research in Behavioural Economics shows that a motivational reward's perceived value depends on when an individual receives that reward, that is, a reward's relative value decreases if an individual receives the reward later—referred to as 'delay discounting' or 'time discounting' (Frederick et al., 2002). Moreover, Keren and Roelofsma (1995) and Li et al. (2010) also demonstrated that most people prefer ‘smaller but sooner’ to ‘larger but later’ external motivations. In addition, as the research of Adusumalli et al. (2020) suggested, most people have present-time bias, which means that a nudge that provides real-time feedback should have increased motivational power in promoting desirable behaviours for most people, though this time preference effect may exhibit a significant culture difference (Shi & Li, 2017). For instance, based on a research on 53 countries, people from all countries exhibited hyperbolic discounting patterns, but nationals from countries that have a culture of high uncertainty avoidance have stronger hyperbolic discounting (M. Wang et al., 2015). Further, a higher degree of individualism and long-term orientation shows low time preference (M. Wang et al., 2015).

Also, a nudge applying the present-time bias can foster the sense of connectedness and involvement between members if the platform has a feedback mechanism characterised by high automaticity and a sense of naturality and instancy. Sending and receiving gratification in immediate time creates the sense of connectedness and involvement as well as the feeling of social presence, which have a positive influence on users’ motivation to gain further gratification (Chen & Cheung, 2019; Han et al., 2015). As previous literature emphasised, these senses and feelings can also promote intrinsic motivation and hedonic values in users, enabling an interventional nudge to be more effective, and eventually elicit the desired behaviour change intended to be produced by the nudge (Gerdenitsch et al., 2020; Hamari, 2015; Luo et al., 2021).

A successfully designed nudge provides salient cues in the user interface to influence users and thereby increase the likelihood of desired actions by minimising decision frictions, reducing cognitive load, and increasing the power of intrinsic and extrinsic motivations (Acquisti et al., 2017; Luo et al., 2021). Specifically, designing a good nudge that can promote knowledge contribution is important in managing online knowledge exchange communities because it can address two prominent user-management problems that have been identified in the literature: 1) decreasing user engagement; and 2) low-quality contributions. First, decreasing user engagement is a problem that often manifests in unison with a growth of the number of users in a community (Butler, 2001; Tausczik et al., 2017). Low user engagement then leads to issues such as ‘knowledge starvation’ and a degradation of the community's overall effectiveness and usability (Cheng et al., 2017; Shtok et al., 2012). Second, low-quality contributions are often a consequence of the loss of user engagement. A knowledge exchange community platform typically receives excessive poorly written, low-quality or even irrelevant contributions that can overwhelm other users, who need to filter out redundant knowledge (N. Huang et al., 2017). This is a major problem for knowledge exchange communities because it leads to users adopting increasingly passive behaviours, such as detaching from the community. Ultimately, a knowledge exchange platform then risks users disengaging, which can even lead to a community losing its purpose and value proposition for users (Guo et al., 2020; P. K. Roy, Ahmad, Singh, Alryalat, Rana & Dwivedi, 2018).

However, my literature review also shows that most of the designs of motivators and digital nudges reported in the literature do not provide immediate feedback, and evidence of the effect of the immediacy factor on changing user behaviours is not sufficiently conclusive. For example, in Huang et al.'s (2019) study, they found firstly, that by providing immediate framing-based performance feedback messages (e.g., 'you are in the top 5%' and 'your contribution helped 2,000 people'), contributors' content quality increased significantly, and secondly, that gender moderated this motivational effect—specifically, female users were more motivated by pro-social feedback, while male users were more motivated by messages that aroused competition. However, these normative feedback messages were purposefully fake and did not really evaluate the quality of the knowledge content. In addition, other research such as Li et al.'s (2017) examined the antecedents and mechanisms of users' immediate information-sharing behaviours on microblogs, but not the motivational effects of immediate feedback on users' information-sharing nor knowledge-contributing behaviours. Additionally, considering the best form for a nudge, Luo et al. (2021) suggested that a graphic intervention targeting perception seems to have a satisfactory effect on reducing friction in providing informational feedback to promote desirable behaviours.

With the development of the technologies such as natural language processing, textual-based content evaluation, and schema-based knowledge classification, it is highly possible that a dynamic system can be invented to assess the value of knowledge at run time, thereby developing more advance nudges to boost knowledge suppliers' contribution intentions and mitigating the problem of the Inspection Paradox for knowledge seekers.

The ultimate objective of knowledge marketplaces is to ensure incentives can be correctly placed to boost provisions and to optimally allocate knowledge resources to the knowledge seekers. One of the directions to achieve this optimization is to understand the knowledge content semantically. Previous studies mostly focused on the syntax and grammar features of knowledge content when using machines to undertake knowledge evaluation tasks (Hirschberg & Manning, 2015; Pérez-Nicolás et al., 2021; Raban, 2007). However, most of the current studies focused on the syntax features when evaluating knowledge content, but the semantic features were under-utilised (Fu & Oh, 2019). I argue that Named Entity Recognition (NER) can provide valuable assistance. NER is a key semantic tool in the Natural Language Processing (NLP) technique family for question answering and information management by automatically identifying and annotating named entities such as persons, locations, organizations, drug types, times, clinical procedures, or biological proteins (Yadav & Bethard, 2019). After naming the entities, researchers can use the recognized entities to perform other calculations such as identifying spam, as well as insulting, inflammatory, and obscene posts (Papasavva et al., 2020), conducting people portrayal (Field et al., 2019), characterizing collective attentions (Stewart et al., 2020), and so on. Most NER-applications perform quality evaluation tasks in the pre-processing stage, but it can be also used for overall quality estimation. To name a few Baralis et al.'s (2013) Yago-KB-based summarizer and Qiang et al.'s (2016) pattern-based summarizers are used to evaluate and extract the most representative sentences in documents. The performance of NER is often better than other tagging tools, such as POS Tagger and chunking (Cao et al., 2012; Goyal et al., 2018; Ritter et al., 2011). NER can also be used to discover associations among entities and clustering entities and documents. For instance, Zhang et al., (2013) introduced a Suffix Tree Clustering with Named Entity Recognition (STC-NER) to cluster keywords and entities into four groups (places, organizations, time expressions, and names of person); the authors used semantic features to evaluate and identify reduplicative documents; they also argued that by presenting a smaller number of reduplicative documents to users, users' burden can be reduced, and the timeliness and the richness of knowledge retrieval can be increased.

There is also a need to acquire knowledge from the Internet where there exists a vast number of semi-structured data, as well as unstructured data, so it is essential to use content extraction systems to screen out irrelevant contents (B. Liu, 2007). After the extraction, Natural Language Processing (NLP) techniques are needed to recognise the ontologies in the extracted content. This is where a group of large knowledge bases are needed. During the process of information extraction and knowledge acquisition, Named Entity Recognition (NER) is often needed where techniques including Part-of-Speech tagging (POS tagging), Distributed Representation which is commonly used in deep learning fields, and Linear Discriminant Analysis (LDA) and/or Support Vector Machine- (SVM) based classification mechanisms are usually utilised. As indicated by Y. Wang et al. (2015), via Open Web-oriented large-scale knowledge bases, rich knowledge can be obtained, allowing for semantic-based information retrieving, knowledge mining, clue mining, query extension, semantic question answering, relationship referencing, ontology relationship deducing, and so on (Dong et al., 2014). After the recognition of ontologies, Knowledge Fusion (KF) and Ontology Fusion (OF) is often the next step for further integration of information taken from heterogeneous sources (Boury-Brisset, 2003), which often depends on methods such as ontology mapping (Gu & Zhou, 2006). This acquisition and fusion process often generates a tremendous amount of data, which typically requires NoSQL databases for effective storage and allocation and retrieval. Spark and Hadoop are often the best solutions for fast computations under such scenarios (Bello-Orgaz et al., 2016).

Using the ontology-based context model, according to Wang et al. (2004), enables computational entities to interact with each other so as to enhance Knowledge Sharing and Knowledge Reuse. Schema Matching can be utilised in knowledge-based scenarios, facilitating the alignment of ontologies by finding the data that are semantically equivalent at different "places" and therefore enhancing the integration of heterogeneous databases (Bernstein et al., 2011). It is expected that an advanced schema matching algorithm, with its faster-processing speed, may greatly reduce the redundancies ratio of the knowledge market, cut down the codification costs of the knowledge suppliers, and accelerate the value-assessing process. According to Otero-Cerdeira et al. (2015) matchings can also be utilised for linking knowledge across different languages (e.g., ConceptNet.com), linking based on synonymy or hyponymy (e.g., BabelNet.com), and linking structured data (e.g., Wikidata, Yago, and DBpedia).

Knowledge Graph technologies hold great promise in facilitating a more effective, rapid, and resilient knowledge market, primarily centred around knowledge acquisition and fusion. They enable the construction of a comprehensive knowledge base that can fill informational gaps autonomously, thereby significantly supporting knowledge market dynamics and the valuation of knowledge. This support extends across various domains, such as expert systems, knowledge management systems, and QA systems (Q. Wang et al., 2015).

Through the lens of artificial intelligence, these technologies pave the way for enhancing the quality of knowledge exchange, steering contributors towards knowledge-sharing behaviours, elevating the motivation levels of sharers, improving the match between knowledge seekers and providers, and curbing transaction costs associated with knowledge exchange. Yet, it's important to also consider potential unintended consequences. For instance, users may experience discomfort or annoyance if they perceive these technologies as intrusive or overly monitoring (Helbing, 2019).

This dynamic, multifaceted landscape underscores the need for an interdisciplinary approach to studying knowledge markets. Collaboration between experts in Computer Science, specifically those in Knowledge Graph technologies, and scholars in Business can yield a richer understanding of how these technologies are implemented in knowledge exchanges and the issues surrounding knowledge evaluation. To date, such interdisciplinary research has been limited, underlining a compelling opportunity for further exploration in this area.

Factors affecting open science knowledge distributions

Open science knowledge has significant value, and there are many open science knowledge portals established to facilitate the exchange of open science knowledge. The value of open science knowledge cannot be realised if the knowledge is not accessible, findable, disseminated and reused.

However, it is unclear how to motivate knowledge users to find, retrieve and reuse those valuable open science knowledge contributions. In the following sections, this thesis will first present my review on open science knowledge in general. Then, it will discuss several problems that exist in the current literature regarding knowledge exchange in major open science knowledge portals. The last subsection discussed issues regarding the issues with findability and accessibility (i.e., to increase the rate at which people retrieve data) for open science knowledge exchange.

Open science knowledge and open science knowledge platforms

Scientific knowledge drives innovation, enables the development of evidence-based policy (Olesk et al., 2019), and helps firms create opportunities (Cohen & Levinthal, 1990). Scientific knowledge is also needed to foster sustainability (Pauliuk & Heeren, 2020), to engage in overcoming some of the biggest challenges that humankind is facing such as global climate change and environmental protection (Overpeck et al., 2011). Most importantly, scientific knowledge is the prerequisite to improving people's livelihoods, well-being and health. Open science knowledge accelerates these benefits and makes innovation ecosystems more productive (Gans et al., 2017). Access to open science knowledge provides users with evidence-based, rigorously tested, independent information, which also allows peer-reviews and verification, for interested individuals, institutional users and businesses and public organisations (Olesk et al., 2019). Researchers can maximise the overall value of their research for society when openly sharing knowledge and when such knowledge is retrieved and reused (Sanderson et al., 2017). Faems et al. (2007) explained that in a research and development (R&D) sharing environment, science data first need to be disseminated and made available by the 'expert partner'. In a second step, scientific knowledge is then retrieved and assimilated by the receiver.

Demand for scientific knowledge continues to grow, particularly as new tools such as machine learning and artificial intelligence technologies increase their utility. With the growth of the Web, and the push for open access, science knowledge is increasingly disclosed and disseminated openly by knowledge holders via the Web, e.g., via their own websites or public sharing platforms. From an open science knowledge perspective, the receiver can either be another organisation (inter-organisational knowledge exchange) or the broader public (organisation-public knowledge exchange). Open data, as Molloy (2011) stated, is a critical element of open science knowledge.

Open science knowledge users require increased access to high-quality scientific data to address global challenges (Ylöstalo, 2020), but on the other hand, knowledge holders, such as not-for-profit research organizations, must prepare and manage their platforms to enhance usability and facilitate data discovery for users. Ensuring ease of access, readability, and reuse of scientific knowledge by both humans and machines is fundamental to open science, with the ultimate goal of promoting transparency, democratizing access, and accelerating global synthesis of science (R. Gallagher et al., 2020; R. V. Gallagher et al., 2020; Scheuer et al., 2021). The development of digital technology has enabled organizations to create open science portals, facilitating the exchange and distribution of scientific knowledge and promoting more impactful research outputs. Overall, these portals serve as platforms for collaboration, knowledge sharing, and advancing scientific progress.

Knowledge exchange in open science knowledge as a knowledge exchange problem

The management of open science data presents numerous complexities, and various barriers can hinder knowledge holders from sharing their data and knowledge (Bonn & Pinxten, 2020). Challenges identified in the literature include issues related to data management operations, such as absorptive capacity of users and open portal management, as well as legal concerns and intellectual property (Gans et al., 2017 ;Arzberger et al., 2004; Sá & Grieco, 2016). Moreover, the "privatization of scientific commons" and the trade-off between advancing science and careers contribute to the lack of openness in transferring open science knowledge (Nelson, 2004). Bonn and Pinxten (2020) argued that this lack of openness in transferring open science knowledge is because of a trade-off between advancing science and advancing careers. Further, they suggest that researchers could dedicate more time to improve the data. Although enhancing open data quality is important or even essential in advancing science, performance in this area remains rather low as, in practice, researchers often have little time for extra administrative duties. Extra role activities that are not performance-related such as depositing, preparing and sharing data perceivably take a lot of effort, are often not performed and form the strongest barrier to share ((Kim, 2017).

These challenges highlight the pressing issue faced by managers of open science platforms regarding the enhancement of data set value and the motivation of users to retrieve and utilize them effectively (Davenport & Prusak, 1998; Zander & Kogut, 1995). While knowledge exchange involves the sharing of knowledge between holders and recipients, many knowledge exchange platforms struggle to foster continuous user contributions and ensure the efficient retrieval of valuable knowledge contributions. Consequently, even if knowledge suppliers consistently provide high-quality contributions, the full value of these contributions cannot be realized unless they can be effectively retrieved and reused. Therefore, the untapped potential of knowledge contributions persists until they can be easily accessed and repurposed.

Motivating knowledge retrieval and reuse requires addressing the findability and accessibility of knowledge contributions. Drawing on the technology acceptance model (TAM) and motivation theory, Allam et al. (2019) theoretically explained that individuals' behavioural intention to use a technology (e.g., retrieve some content from a knowledge exchange platform) is determined by users' attitudes towards using the technology, which in turn is decided by extrinsic motivation factors and intrinsic motivation factors. The original TAM research model adopted a utilitarian perspective and the related constructs (i.e., perceived usefulness and perceived ease) are extrinsic motivations. However, Moon and Kim (2001) extended the TAM model for the World-Wide-Web context and argued that an intrinsic motivation factor—perceived playfulness—is also an important factor in attracting and altering users' attitudes towards technology use. Moon and Kim (2001) also postulated that the intrinsic motivational factors have more influence on attitude than the extrinsic ones to build positive attitude in the World-Wide-Web context. According to Allam et al. (2019), systems whose knowledge contributions' findability and accessibility are high are more likely to trigger users' intrinsic motivations, such as perceived enjoyment, perceived curiosity, and perceived explorability, which are important ingredients of the hedonic state that users experience when they browsing. As Ames and Naaman (2007) maintained, knowledge contributions should be easy to retrieve, easy to search, and easy to recall by names of event, person, situation, and place; as van Velsen and Melenhorst (2009) reasoned, a platform using a good tagging mechanism can increase the findability and search-ability of knowledge items stored in the platform, which can help its users decide quickly on the items' relevance, and eventually motivate users to do more serendipitous browsing activities on the platform and retrieve more items from that platform.

Open scientific knowledge advocates also emphasize the importance of open research data as a foundational aspect of open science. The open data movement primarily focuses on enhancing public accessibility and findability of research data and knowledge (Sá & Grieco, 2016).

Increasing open science knowledge exchange

There is a need to find the most important factors to efficiently increase the efficiency of distributing high quality open science knowledge. Arguably, it is vital to know which factors form barriers for users to access this data, and contribute to an area of research, but as Gregory et al. (2019) claimed, that still remains a nascent field. Wolfram (2015) conceptualised the typical knowledge exchange process from a user perspective, explaining that users first *identify* the data needs and context; second, they *find* possible data sources and adopt search strategies *to access* the data. Third, users then evaluate the *retrieved* datasets (Wolfram, 2015). During this process, data providers need to manage both the platform and the proper documentation of data so that users can retrieve the information (Niu, 2009). But to date little is understood on how open knowledge managers can effectively organise the knowledge exchange processes and manage their open data platforms so that users can best find and access data.

Some researchers argued that one of the key components of this optimisation, the finding and accessing of open science knowledge and data, is to enhance the knowledge and data's metadata. Generally, metadata-quality features and retrieval rates are closely linked, and there is evidence that both highly influence findability and accessibility of knowledge, in turn affecting knowledge retrieval tendencies and frequencies (Curty et al. 2017; Gamble & Goble 2011; Neumaier et al. 2016; Tenopir et al. 2011; Wallis et al. 2013). For instance, after a study that compared three forms of metadata structures, including socially-generated metadata, professional metadata and automatically-generated metadata, the researchers found all forms were roughly equally effective to increase findability and accessibility of useful content and facilitate the knowledge content retrieval process (Melenhorst et al., 2008). Groff and Jones (2012) argued that clear metadata or classification rules can lead to an easy content retrieval relevant to users' needs.

However, the extant knowledge management literature and literature review offers few insights into how organisations that run those large open science knowledge portals can optimize the usage of metadata to increase the findability and accessibility of knowledge optimally. Hence, organisations may underinvest in knowledge-sharing practices and not provide appropriate incentives for individual knowledge suppliers. Gregory et al. (2018) emphasised the importance of *meta-data completeness*, as it positively relates with data findability. Especially as users need to first discover and find a data collection before accessing and retrieving it. Simmhan et al. (2005) stressed the importance of the *data-provenance factor*, i.e., data lineage and pedigree. A dataset with good lineage information should have a comprehensive track of its historical information, such as sources, authors, creation, and alterations. In this regard, Lee et al. (2002) proposed to include an information quality assessment instrument, to determine the organisation's data-quality management level at a given time: an information quality benchmark gaps analysis, could for example be used to assess the benchmark with another organisation. As Gregory et al.'s (2018) interview-based research demonstrated, the *reputation and the network* of the data providers can also factor into data users' retrieval and reuse decisions, but this factor's effect may not be deterministic. *Age of data* is another important predictor that is known to influence download number. Long-standing data collections have usually accumulated higher numbers of downloads than newer collections. To conclude, these components are necessary for effective platform management, essential to ensure data quality measurements and ultimately are enablers for user value of open science knowledge exchange.

Further, contextual differences that influence findability and accessibility of information for users of open science knowledge exchange need to be considered, as data, data platforms and accessibility vary with research groups and academic disciplines (Wallis et al., 2013). One contextual difference is the volume of data in research domains. For example, data sets in 'big-science' areas—i.e., disciplines that tend to have large research teams, long-term projects, and significant instrumentation, such as astronomy and high energy physics—tend to have high retrieval rates

(Birney, 2012). In contrast, ‘small-science’ areas, that is, the long tail of science, have lower retrieval rates, since individual researchers and small research groups typically generate datasets from data collection for specific projects (Birney, 2012; Heidorn, 2008). Data collections that are highly automatic, well-curated, and standardised tend to be highly visible to scientists worldwide; yet, as most research data collections exist in the long tail, and users rarely reuse them, a huge amount of hidden value from these data remains unshared (Heidorn, 2008).

Gregory et al. (2019) showed that *another contextual difference* in open science knowledge exchange is related to the dataset-retrieval process and the dataset's field of research. They found that, for astronomy datasets, users tended to rely more on authors' reputation and contextual information. e.g., documentation, data descriptions, and collection methods. For earth and environmental sciences, researchers preferred data collections with richer contextual information about the data provenance and with more comprehensive metadata. For bio-medicine data collections, users tended to place importance on relevancy and, in order to determine it, tended to use textual background information, visual inspection, and mental comparison to imagined ideals. As Markonis et al. (2012) suggested, believable supporting documentation such as attached good-quality exams or biopsies help people trust datasets. For data collections in the social sciences, users, especially novice researchers, value contextual information the most, and they also rank metadata completeness high in terms of importance. In this research area, repository reputation plays a more important role in signalling data trustworthiness than author/journal reputation does (Curty, 2016; Faniel et al., 2013).

These contextual differences highlight the need to consider diverse factors, including data volume, contextual information, and reputation signals, when addressing the findability and accessibility challenges in open science knowledge exchange.

Users' behaviours in market-based knowledge exchange platforms

In the previous section, an analysis was conducted on the trends observed in modern knowledge exchange platforms. This analysis revealed that the traditional centralized, top-down approach to managing knowledge resources and eliciting knowledge from experts in these platforms has become less effective. To adapt to the new features and trends of knowledge exchange platforms and address the emerging challenges, a small yet growing body of literature emphasizes the value of openness for innovation and problem-solving.

One avenue through which firms can embrace the benefits of open innovation is by utilizing market mechanisms. As explained by Benbya (2015), a market-based knowledge exchange platform facilitates connections between knowledge seekers and experts within specific communities. This approach offers several advantages, including matching knowledge seekers with relevant sources, enabling efficient interactions with diverse knowledge, promoting the reuse of existing knowledge, and assisting in finding solutions to previously unsolved problems.

The subsequent sections of this paper will delve into the theories, progress, and applications within the realm of knowledge markets. Firstly, the characteristics of market-based knowledge exchange platforms will be discussed. Following that, the focus will shift towards the economics of knowledge exchange and the unique characteristics of knowledge as the underlying assets traded within these market-based platforms. Lastly, the knowledge market design theory will be presented, alongside recent applications of knowledge markets.

Overall, this section aims to provide an in-depth exploration of market-based knowledge exchange platforms, shedding light on their distinctive features, economic aspects, and the theoretical frameworks guiding their design. Additionally, notable real-world applications of knowledge markets will be showcased, highlighting their potential impact and relevance in various domains.

Market-based knowledge exchange platforms

A knowledge market brings together a collection of knowledge suppliers and consumers who, via interactions, collectively determine a price of the commercialised knowledge. In different forms of knowledge markets, the names and the natures of the participants can be different. For instance, MOOC (Massive Open Online Course) sites and MOOC-related software also create a knowledge market where people can trade knowledge production—some people term it “k-mall” (Skyrme, 2012). In such a market, the major market participants are the students, as the buyers, and the institutions, as the suppliers. A knowledge market public question answering site can also be in form of a public question-and-answer site, such as Google Answer and Stack Exchange where the questioners, answerers, viewers, commenters and tip providers constitute the major user groups of these markets (Chen et al., 2010). In companies such as AECOM and SAP, the market is the internal knowledge management platform aiming to increase the match between the consumers and producers. The experts and novices of the valuable knowledge resources that are in a decentralised manner facilitate knowledge exchange across a distributed organization, and generate faster responses inside their knowledge management systems (Van Alstyne, 2013).

Conceptually, Benbya (2015) named four types of knowledge markets: normal knowledge markets (for peer-to-peer assistance), prediction markets (for event forecasting), idea markets (for idea genesis and evaluation), and innovation markets (for problem solving). Specifically, normal knowledge markets are mainly used for peer-to-peer assistance by matching up knowledge seekers and experts and broadcasting both news and also questions in need of answers. This type of knowledge market can usually facilitate the sharing across a distributed organization and community and optimise the best practice capturing procedures by speeding up the generation of good responses. The main purpose of prediction markets is to connect a group of participants and let them forecast uncertain events. Shares of virtual stocks were traded and these shares represent a bet on the outcome of future events. Hanson (2003) has mentioned that, since the 1980s, prediction markets have been successfully used for many different forecasting purposes (e.g., help businesses improve investment decisions and help governments make better fiscal policy portfolios) and have proven to be more reliable than alternatives, such as polls, surveys or econometric models. Ideas markets are usually in the form of a forum whose main function is to generate, combine, and rank ideas based on open contributions and collectively sorted values. As Benbya (2015) described, although traditional knowledge management approaches can also be used for idea generation and selection, an idea market can allow more participation from a diverse group of users which reassures transparency, promotes mutual understanding, and increases the probability of idea acceptance and transfer. Innovation markets are markets for R&D problem solving that act as “brokers” for matching a problem solution seeker with a network of problem solvers. Ideally, an innovation market can offer companies a cost-effective way to let the companies' research and development problems be exposed to researchers and problem solvers around the world. Terwiesch and Xu's (2008) preliminary study pointed out that external innovation markets such as InnoCentive and TopCoder, missed the opportunity to bring these benefits to firms. They are all geared to unsticking external knowledge but leave these principles outside the company wall. Some follow-up studies investigated the conditions and contexts of innovation markets and attempted to understand under what conditions these markets can be functional. For instance, Agrawal et al. (2016) found that innovation markets appear to be more functional when the innovation is incremental, compared to the situations when innovation is moderate or radical.

Several empirical studies report positive results from having an intra-organizational market for knowledge. Based on an experiment, Lukashov (2011) showed that a knowledge market with a price structure performs significantly more efficiently than a market without it (i.e., trading knowledge for free), and market participants, both buyers and sellers, can use information in the knowledge market to identify, optimize, and sustain their long-term positive returns. Jeong et al. (2013) found that knowledge technology (KMS) and reward positively affect the trade in a knowledge market. Dev et al. (2017) argued for the importance of a market's size (i.e., different knowledge markets have different return-to-scale patterns, and normally an increase in user participation and content dependency leads to a constant percentage increase in the output but may negatively affect market health). Zhang et al. (2017) and Burtch et al., (2018) focused on online knowledge trading and sharing and both argued that a knowledge market can offer financial incentives to knowledge suppliers so that suppliers should often boost their intention to share and contribute for-fee content, although Jeon et al. (2010) found the marginal benefits that such monetary benefits create diminish quickly. Similarly, Benbya (2015) noted that excessive rewards may not benefit an internal knowledge market. Some research focused on the technical side of the story. For instance, to enable better and faster seller-buyer matching, firms can use expert-based recommendation systems to reduce transactional costs if a knowledge market grows extremely large, and to mitigate the excessive price problem, which often reduces both knowledge transactions and market interactions (Zheng et al., 2018). Sundaresan & Zhang, (2020) recommended that firms should analyse the knowledge category, the network structure, and the dominant type of learners before deciding whether to increase or reduce the amount of financial incentive.

Market inefficiencies and market failures may occur. First, some of the early adopters refined their firms' centralized knowledge management systems by adding market-based components, but their markets still reserve a centrally planned legacy (i.e., there is a central authority having a strong market-manipulating power that can prioritize development to address knowledge-management-related problems). However, nowadays, as the knowledge recipients' demands for knowledge becoming increasingly diverse and unpredictable, the centrally planned systems often result in a large community base with unsolved knowledge problems. For instance, Benbya (2015) mentioned a case where a consulting firm hired experts who spent more than two years codifying best practices and storing them in the firm's centrally-managed system; however only 130 out of 1,500 workers in the firm reported that they were able to find useful content in that system. Second, market competition may cause perverse effects on sharing culture and team collaboration. A market-based approach entails financial incentives, but previous research gives inconsistent conclusions regarding using financial incentives to maintain sustainable level of knowledge transfer and sharing. Goh (2002) found that, if a knowledge platform purely relies on providing financial incentives for motivating knowledge suppliers, fierce competition will be triggered and therefore an overall negative impact will be exerted upon knowledge sharing as well as team cooperation. Benbya and Van Alstyne (2010) also used InnoCentive's initially failed market, which included only competition without supporting collaboration, as a bad example to argue that a well-designed market needs to properly balance competition and collaboration. In the same vein, Di Vincenzo et al. (2021) found, in a market for crowdsourcing ideas (a common knowledge product that participants in internal knowledge markets commonly exchange),that competition for attention negatively moderates the relationship between idea attention and comments, which can eventually harm the survival of ideas. Also, introducing a knowledge market may increase the competition between the paid knowledge products and the free ones, and people generally do not choose to pay for knowledge products when there is a wide range of free choices, which is especially a problem considering it is difficult to judge a knowledge product's quality before acquiring it (Berger et al., 2015; Zhang et al., 2020). Third, some firms used fixed rewards to avoid competition, but this fixed rewarding system introduced new inefficiencies. According to Van Alstyne (2013), Siemens AG used a "fixed shares-based" system in which they rewarded each knowledge contribution 20 "shares" and each market bid 10 "shares". "Shares" could be redeemed for prizes. However, the company found fixed incentives can significantly increase the number of knowledge contributions but not the quality of those contributions. For another example, the Hewlett-Packard company established a fixed incentive program rewarding each useful knowledge contribution 2,000 frequent flyer miles and each question 1,000 miles; however it was unable to draw sufficient participation (Benbya, 2015). Hui et al. (2020) found targeted financial incentives (i.e., incentives that are only available for a subset of sellers) can be more effective than universal incentives only after the target size reaches a certain threshold.

Overall, the participants of these markets bargain with each other based on their preferences in this marketplace, attempting to approach an optimised allocation of knowledge resources. In this vein, Rustam and van der Weide (2016) offered an architecture to analyse such knowledge marketplaces and argued that "market information", such as price and reputation, is fundamentally important in the bargaining process and, therefore, vital for achieving a successful and smooth matching process between demand and supply. The ultimate goal of this matching is to approach an optimal level of knowledge exchange.

Besides the market participants, a knowledge market typically consists of two other core components: a) Rules and institutions for governing the market; b) Spaces allowing transactions to match suppliers and consumers (Desouza et al., 2005).

The rules used in a knowledge market are also comparable with the rules that govern other types of markets. For instance, as Van Alstyne (2013) commented on early knowledge market implementations, C-Suite executives can be dangerous to a knowledge market because they tend to flood the market by injecting incentives over a short time, which leads to internal market inflation, rapid devaluation of the designated incentives, and market instability. Rules to prevent this market from being abused are needed in advance, and contractionary policies are expected to curb such “inflation” after such a market abuse happens.

Running a knowledge market also requires a space for consumers and suppliers to meet and interact. Traditionally, most of the previous research in this field focused on paid Question-Answering platforms (Lueg, 2003), but there are also many other forms of space, such as knowledge exchange forums, discussion forums, source code management platform, and online consulting and crowdsourcing platforms, where a knowledge market can reside (Cai et al., 2019; P. Huang et al., 2018; Kinsman et al., 2021; Li et al., 2019).

There are three problems commonly encountered by knowledge market researchers and practitioners, as discussed in the literature. The first problem arises from the perception of online information and knowledge as zero-price goods due to their historical exchange without charges (Rifkin, 2014). Shampanier et al. (2007) highlight the difficulty in reintroducing a price tag to goods that were previously provided for free, as consumers tend to associate them with intrinsic value. The success of free knowledge markets, such as Open Science and Wikipedia, seems to support the notion that designing a knowledge market on the internet should be entirely free to achieve maximum efficiency (Gans & Stern, 2010). However, Shampanier et al. (2007) found that introducing a price tag results in a significant change in individuals' perceptions, affecting their affections and attitudes towards the products. This shift from social contract norms to market exchange norms makes individuals more cautious about the additional utilities gained from the goods. Although paying for knowledge has existed in certain business models (Qi et al., 2019; Rafaeli & Raban, 2003), the majority of transactions on knowledge exchange platforms still involve sharing rather than trading. Lamb (2004) refers to this phenomenon as the "Intellectual Property Impossibility Theorem," explaining that copyright policies and the controlling nature of intellectual property rights lead community-based virtual knowledge platforms to remain open-access and free for end users. However, with the emergence of the "knowledge-sharing economy" (Zhang et al., 2018), attitudes towards paying for knowledge are changing, particularly in China. A growing number of people are willing to pay for quality knowledge, driven by factors such as the increasing time cost for knowledge receivers to generate premium content (X. Zhang et al., 2018).

The second problem lies in the development and deployment of business models that support paying for knowledge (Jan et al., 2018; Shi et al., 2018; Y. Zhao et al., 2020). While these models are not yet considered mature, they have facilitated micro-payments and enabled knowledge suppliers to provide richer media in response to knowledge recipients, differentiating their paid services from free ones that typically involve only text and images.

The third problem is the rise of paying behaviors as a form of escapism, where individuals pay a small amount of money to content creators (e.g., videos) as a means to escape from reality (L. Liu et al., 2021). This trend reflects the increasing number of people seeking ways to disconnect from everyday life. As discussed so far, these developments indicate a shift towards accepting the idea of paying for knowledge, driven by various factors including changing perceptions, the evolution of business models, and the desire for escapism.

Second, building a knowledge market can sometimes raise ethical issues. For instance, MOOCs were widely free, whilst now they are usually subject to a fee. All participants, especially those who are financially limited, under-educated learners from developing countries, do not welcome pricing MOOCs. Although MOOC platforms offer tuition waivers and tuition discounts to financially challenged students, access to these types of discounts is still limited. Imposing a price tag may exacerbate the uneven distribution of the benefits that knowledge products (for instance, the MOOCs) can bring. Baker and Passmore's (2016) work expresses frustration of the fact that MOOCs are becoming “less open” and have abandoned one of their original promises: that is “incurring zero costs to students”. That said, in the long run, it is not surprising that MOOC providers and agencies try to charge a price, because the development and the maintenance of MOOCs, as well as the platforms they run on, requires a lot of financial resources, which are currently still unsustainably subsidized by venture capitalists and by universities (Cusumano, 2013; Gaebel, 2014).

Third, knowledge markets, regardless of their types, provide environments where users trade their knowledge via explicit price mechanisms and, to ensure the overall efficiency of the market, the prices need to be set as accurately as possible (Benbya, 2015). This explicit and accurate price mechanism can serve as an incentive for sustaining knowledge exchange (Ba et al., 2001). However, such explicitness and accuracy may adversely affect people's motivations for sharing knowledge. For instance, a knowledge of explicitly high (perceived) value correlates with high emotional ownership (Ipe, 2003; Tian et al., 2021). Further, high emotional ownership affects knowledge suppliers' behaviour. According to Empson (2001), highly valued knowledge tends to be guarded by the knowledge owner, especially in companies in which employee knowledge is the key source of revenue to the firm. Further, establishing an accurate knowledge pricing system in knowledge markets needs functional competition among knowledge suppliers. Nevertheless, highly competitive environments also introduce contradictory incentives to supply knowledge (Ipe, 2003). As a result, a precise knowledge pricing schema and a perfect knowledge market may ironically lead to a dilemma where people become reluctant to trade their knowledge when the knowledge is of high commercial value and where the knowledge market offers an accurate and explicit pricing system (Ipe, 2003; Jo & Jeon, 2010; Weiss, 1999).

Also, putting the accuracy and explicitness of pricing aside, the price effect itself does not linearly correlate with better knowledge exchanges. Some observations and results of experiments and field studies on paid knowledge platforms have reported this phenomenon. For instance, Sun et al.'s (2017) research on user-generated content communities found that the price effect is negative in particular for those who are highly connected in the community. Table 2 summarises some of the conclusions that I found in the literature regarding this issue.

Author(s)	**The effect of explicit monetary reward scheme**	**Type of research**
Bock and Kim (2001)	Positive in short run, but the effect of money diminishes quickly	Exploratory study
Jeon et al. (2010)	Financial rewards increase the likelihood of a knowledge seeker receiving an answer but generally do not assure high answer quality	Empirical research
Jan et al. (2017)	Financial incentives motivate knowledge sharers' intentions and their response speed but have no significant impact on users' knowledge-seeking behaviour	Quasi-natural experiment

Yan et al. (2017)	Financial incentives can increase users' participatory behaviours significantly due to indebtedness, and there is no substitution effect among the paid-for and free knowledge	Empirical research (Crawled data)
Khern-am-nuai et al. (2017)	Monetary incentives cause inflated star ratings and lower-quality reviews but the level of participation of the old reviewers degrades	Natural experiment on a review platform
Li and Hu (2017)	Generally positive, but high rewards also cause high competition intensity which moderates the relationship between rewards and knowledge trading propensity	Empirical research (Crawled data)
Yan et al. (2018)	Monetary incentives did foster both negative behaviours (e.g., Bounty hunters or collaborative users working hard to solve questions) and positive behaviours (e.g., Game the system behaviours, spamming, and collusive/collaborative behaviours)	Empirical research (Crawled data)
Zhang and Liu (2021)	For UGC contributors, if monetary incentives are used as a proportional mechanism (i.e., the monetary rewards for each contributor are proportional to the audience attracted), the incentives' impact are generally positive, but if monetary incentives are used as a quality control mechanism (i.e., only if a contributor can attract an audience larger than a threshold, the contributor can get monetary rewards), the impact will be negative.	Empirical research
Burtch et al. (2021)	Peer awards, which are considered as a type of extrinsic motivator are more likely to foster and maintain recipients' intrinsic motivations when sharing knowledge online.	Empirical research
Qiao et al., (2021)	Monetary incentive may negatively affect voluntary knowledge sharing, but by integrating goal-setting and challenge-seeking intervention strategies, practitioners can use small incentives to encourage voluntary contributions	Empirical research

Table 2. A Summary of the Effect of Explicit Monetary Reward Scheme in the Literature

The economics of knowledge exchanges

As suggested by Davenport and Prusak (1998), the existence of a genuine market for knowledge allows for the application of economic analysis models, rules, and laws to observe, explain, and predict this market. This subsection will delve into the economics of knowledge exchanges, examining two key aspects: demand and supply analysis for knowledge markets in general, as well as pricing knowledge. By exploring these subsubsections, I can gain a deeper understanding of the economic dynamics at play in knowledge exchange platforms.

Demand and supply analysis for knowledge markets in general

This subsubsection will focus on the analysis of demand and supply within knowledge markets, providing insights into the motivations of knowledge seekers and the factors impacting knowledge providers. By examining the factors that influence the demand for knowledge, such as the perceived value of specific expertise or insights, I can gain a better understanding of the dynamics driving knowledge seekers. Additionally, an exploration of the supply side will shed light on the factors impacting knowledge providers and their willingness to share their expertise within the market.

In line with investigating the economics of knowledge being exchanged on virtual knowledge marketplaces, this thesis utilizes a traditional economic analysis model known as demand and supply analysis (DSA). The aim is to apply the DSA framework to examine the dynamics of knowledge markets. It is noteworthy that while Matson et al. (2003) have previously utilized the DSA approach in their research on knowledge markets, there are certain essential factors, such as elasticity, that were not fully considered in their analysis. Therefore, this thesis seeks to address this gap by incorporating these vital factors into the analysis. By doing so, a more comprehensive understanding of the economics underlying knowledge exchange in virtual knowledge marketplaces can be achieved. Although Weaver's (1949) book, "The Mathematics of Communication", had excited economists by giving a method to quantitatively measure information using the notion "information entropy", some scholars still reject the idea of applying information theories onto information or knowledge valuation fields (Belkin, 1978; Machlup, 1962). As Raban (2007) indicated, although there may be an objective intrinsic value for each information/knowledge, the acquisition decision of it depends largely on knowledge takers' personal perceptions, expected value in use and prior knowledge accumulated. The perceived value is based on a rather subjective user-centred process, so it causes the price of the knowledge products to be exceedingly dynamic. For a knowledge product, I denote such perceived price as the willingness to pay (WTP) of a knowledge buyer. It is worthy of mentioning that the number of WTP can be determined by collecting data from surveys, field works and experimental studies. Most of those studies are based on contingent valuation methods (CVM) (Venkatachalam, 2004). For example, Klain et al. (2014) measured how much more money people were willing to pay, if there existed a “made in America” label, a small knowledge piece. The result showed that the WTP for that knowledge per transaction (choice) was worthy of 0.016 – 1.08 USD, on average, and varied greatly between individuals. However, some may argue that the purchasers were not paying for a premium price brought by the knowledge piece exactly but for a feeling (e.g., patriotism-driven gratifications or a trust in the perception of the good quality of local products) that was triggered by the knowledge piece they received.

Reasonably, as Raban and Mazor (2013) argued, there are more people willing to pay less for knowledge than the number of people willing to pay more. Assuming that people always “purchase” a knowledge product when the price of the product equals or is smaller than his or her WTP, a demand curve can therefore be drawn where, for a given period of time, as the price of a given knowledge products increases, the quantity demanded decreases. Henceforth, a demand curve of knowledge products can be drawn as in Figure 2. It is speculated that the curve shall have high convexity: most of the knowledge products, as mentioned, are currently traded without any charges. Therefore, it is expected to show a very large quantity when the price is zero. However, researchers mainly focused on the knowledge goods that have a price, so a hollow circle is used to denote this fact. The demand curve shall become very elastic particularly when the price rises from zero to a positive number— this is called the repugnance effect—and implies that there exists an observable social norm preventing knowledge to be traded for a positive price. As indicated by Shampanier et al. (2007) and Anderson (2008), there is a barrier caused by transactional cost and also a significant psychological gap between cheap and free, and it is this gap that makes many micropayment designs fail. Moreover, only a very small fraction of knowledge takers are willing to pay a high price, so the quantity of demand should be extremely small and the slope should be larger when the price is higher (Gans & Stern, 2010).

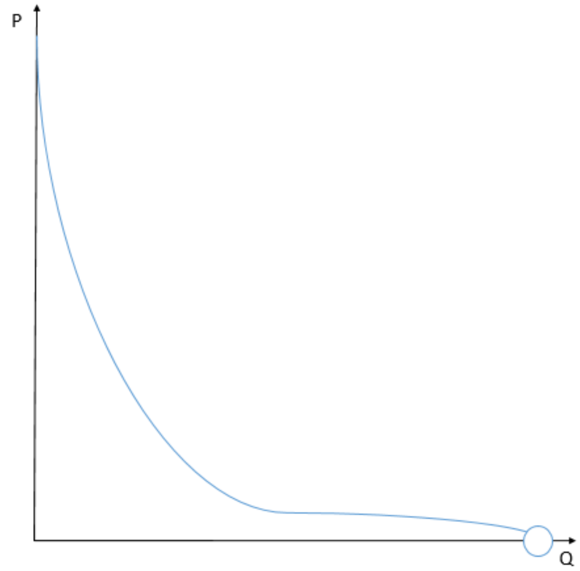


Figure 2. An Indicative Demand Curve for a Hypothetical Knowledge Product

The price to be accepted by a seller is denoted as willingness to accept (WTA). The supply curve based on WTA shall have a higher inelasticity than the demand curve based on WTP. Based on a series of experiments, Rafaeli and Raban observed that people value knowledge they own significantly more than when they do not own it, probably as a result of "the endowment effect" and "the loss aversion effect" (Raban & Rafaeli, 2006, 2007; Rafaeli & Raban, 2003), and they conclude that people have a preference for purchasing knowledge but they can be relatively reluctant to sell it. When the selling does occur, people become more sensitive about the price, compared to the time of purchasing. Furthermore, supplying knowledge needs the supplier to do some preparation work, such as accumulating a certain level of prior knowledge. For institutional suppliers, supplying knowledge typically accumulates significant quasi-fixed costs and sunk costs such as producing costs, delivering costs, and disseminating costs (Sanderson et al., 2017). For individual suppliers, the burden of some of the fixed cost may be transferred to the knowledge brokers' side, but they still encounter costs such as codification costs, searching costs, and opportunity costs (Zhang & Jasimuddin, 2008). Since a person will only supply his or her knowledge when his or her total payoff is positive, the supply of a priced knowledge product will only ensue after a threshold level is reached. Such a supply curve is depicted in Figure 3—the red circle denotes the hypothetical threshold level.

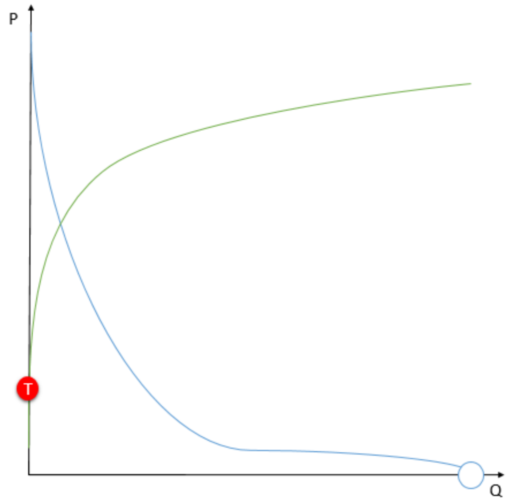


Figure 3. An Indicative Supply Curve for a Hypothetical Knowledge Product

As shown in Figure 4, when the market is not well-functioning and when the price is mal-established, deadweight loss (the grey area) may occur. Particularly, when the price is overcharged, minimal-salary-like problems may arise, where, in this paper's context, knowledge suppliers asking for a selling price higher than the equilibrium level prevents knowledge takers from purchasing the knowledge products, eventually resulting in a loss in total revenue for the suppliers. When the price is undercharged, rent-ceiling-like problems arise. In this context, knowledge seekers become even more reluctant to supply knowledge on the market, so knowledge buyers must spend more time, even fees, on searching useful information and/or knowledge. Non-optimal price settings are quite common (Chen & Wang, 2008; Graham & Wright, 2010; Nimark, 2008).

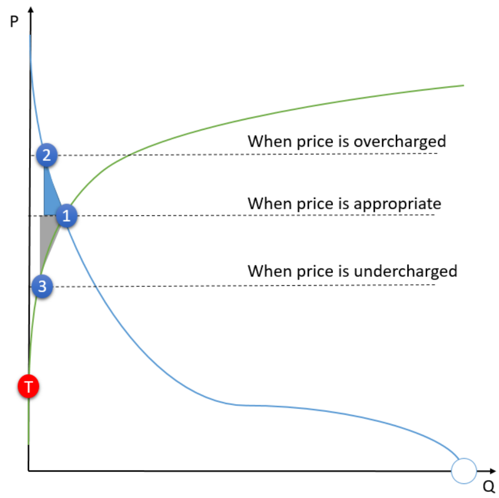


Figure 4. An Indicative Deadweight Loss in Hypothetical Knowledge Product

Pricing knowledge

This subsubsection focuses on the intricate mechanisms involved in pricing knowledge within the knowledge exchange landscape. By examining various pricing strategies, models, and factors that influence pricing decisions, insights can be gained into how knowledge is valued and exchanged within the market. Understanding the dynamics of pricing knowledge is crucial for both knowledge seekers and providers as they navigate the economic aspects of knowledge exchange platforms.

When considering the value of a knowledge product, it is important to note that it often differs significantly from its price. The value of a knowledge product is determined by multiplying its "price" by the "quantity sold." Consequently, it is possible for the value of a knowledge product to increase even when the price of information drops within a certain range. In this range, a higher number of individuals can benefit from the utility provided by the knowledge products. On the other hand, sellers may also seek to maximize their profits by limiting access to knowledge, creating a sense of scarcity and a potential monopoly (Melody, 1985, 1987). By understanding these dynamics, knowledge providers can make informed decisions about pricing strategies, balancing accessibility and profitability, while knowledge seekers can assess the value, they derive from knowledge products and make informed choices based on their needs and preferences. Unlike normal products whose ownership is transferred when the transaction is done, information products are transferred only as a copy (or multiple copies) to the buyer(s) after a transaction. This implies that the sunk cost and the fixed cost of manufacturing and disseminating knowledge products is high, but the variant costs are relatively low, sometimes even effectively zero, which posits the possibility of the supply-side economics of scale but also complicates the products' pricing (Sutton, 1991).

When pricing knowledge, it is also worth noting that knowledge has significant positive externalities, which means that acquiring knowledge (via a knowledge transaction) not only delivers utility to the knowledge receivers but generates a network effect that positively influences a considerably large group of market participants around that transaction, including the knowledge depositors, knowledge brokers, and second-order knowledge users (Davenport & Prusak, 1998). The externality of knowledge is enlarged by the proliferation of the internet (Jing, 2000). According to

Bansler and Havn (2004), such externality tends to start slowly and either has an explosive expansion after the number of its user base reaches a “critical mass” level or goes extinct if the user's participation rate remains stagnant.

A cost-based pricing system—a fixed sum or a percentage of the total cost of creating a product is added to its selling price (Courcoubetis & Weber, 2003)—may not be functional for knowledge products and services. From a cost perspective, as aforementioned, the cost of a knowledge product rests not only on the cost of search, which incurs on the buyer side, but also on other economic factors such as the costs of creation and reproduction, cost of bundling knowledge service, cost of storing and distributing, cost of reviewing and revision, all of which incurs mainly on the seller side (Argote, 2012; Ba et al., 2001; Bhatt, 2000).

Knowledge’s market prices are influenced by economic factors such as the timing of availability, the age of knowledge, the number of people the knowledge is known to, the capability to protect against uncertainty and contextual factors such as market supply, demand curves, information propagating costs, etc. (Ahituv, 1989; Machlup, 1962, 2014; Varian, 1995).

A series of experiments and field studies have been conducted regarding pricing knowledge on virtual knowledge marketplaces. In terms of the timing of the payment, in the current priced-based knowledge marketplace, normally money is either paid before acquiring the information (i.e., bidding) or after the acquisition (i.e. tipping). Direct observations of those online knowledge marketplaces offer several interesting findings. First, based on data from 2002 to 2004, Rafaeli et al. (2005) crawled more than 70,000 questions from Google Answer, and they found that roughly 30% were paid with real money and 10% were tipped, and the average payment was around 20 dollars (Yang et al., 2008). Second, higher bidding prices (i.e., pre-defined prices) correlated with high-quality answers, but tips had no clear effect (Chen et al., 2010). Brabham (2012) indicated that price is a significant factor for participation in crowdsourcing project. Zhao et al. (2018) and Hsieh and Counts (2009) reported that pricing greatly influences answerers engagement levels, which affects their content quality and quantity, which eventually affects user payment decisions in paid knowledge exchange platforms. Jan et al. (2018) also reported that answerers contributed more to the paid question answering service than the free one. Zheng et al. (2011), however, argued that price does not play a significant role in increasing participation for a crowdsourcing market. Jeon et al. (2010) offered an intriguing finding that, in a Korean Question-Answering platform, higher level payments significantly raised the possibility of receiving a better-quality answer but after the question received an answer, the effect of the price level quickly diminished. Furthermore, in terms of payment mechanisms, popular options included fixed price, direct negotiation, auction, and reverse auction (Kafentzis et al., 2004). The results from the paying-for-knowledge experiments and field studies generally implied that proper pricing strategies will optimise the utilities for both the knowledge suppliers and the knowledge takers on virtual marketplaces. Pricing strategies can exert a significant impact on users' engagement, loyalty, satisfaction and adoption behaviours. With the booming of the platform and gig economy (Vallas & Schor, 2020), more and more paying-for-knowledge platforms have emerged which provides a rich research background to analyse the impact of knowledge product pricing strategies (Qi et al., 2019). Table 3 below summarises the findings in this area.

Category	**Author(s)**	**Platform, project, or experimental settings**	**Findings**
Payment level and options	Rafaeli, Raban et al. (2005)	Google Answer	Average payment is around 20 dollars
	Kafentzis, Mentzas et al. (2004)	Generic	Popular options include fixed price, direct negotiation, auction, and reverse auction
Price and knowledge quality and participation	Chen, Ho et al. (2010)	Google Answer	Higher biddings attract high-quality knowledge, but tips have no clear effect
	Brabham (2012)	Next Stop Design (a crowdsourcing project)	Extrinsic factors such as to make money and to advance career is a significant factor for participation
	Zheng, Li et al. (2011)	Taskcn.com	Money is not significantly associated with participation intention

	Hsieh, Kraut et al. (2010)	Mahalo Answers	Paid questions generally had more participation than free questions, and quality positively correlated with the payment level
	Jeon, Kim et al. (2010)	Naver.com	A higher-level payment significantly raises the possibility of receiving a better-quality answer but after the question receives an answer, the effect of price level diminished
	Edelman (2004)	Google Answers	Specialised answerers tend to earn less money
Practical works	Ahn and Chang (2004)	KP3	Developed a measurement model to assess the contribution of knowledge to business performance
	Wang and Li (2014)	Three types of network structures of agile supply chain	Examined the effect of improving information quality on the performance of e-Government
	Hu (2015)	A large R&D organization with a background in the aerospace industry	Attempt to measure, unlock, and visualise the value of knowledge embedded in an organisation
	Dev et al. (2017)	Stack Exchange	Different knowledge markets have different return to scale patterns. An increase in user participation and in content dependency leads to a constant percentage increase in the output but may negatively affect market health (questions to get an accepted answer)
	J. Liu and Ye (2016)	The largest online healthcare consulting platform	Providing healthcare knowledge online by professional medical staff use price as a quality cue. Price not only has a direct positive effect, but also indirect

		effect mediated by perceived quality on purchase behaviour.
Wu and Lu (2018)	Haodf.com	The researchers found there is an inverted U-shaped correlation between service price and satisfaction: if knowledge suppliers set the price at a low level, price led to an increase in knowledge seekers' satisfaction, whereas the high price level (over 330 CNY/US$49) could have just the opposite effect. Additionally, price dispersion among knowledge suppliers can significantly reduce knowledge demanders' satisfaction.

Table 3. A Summary of Recent Empirical Research on Knowledge Prices' Impacts on Knowledge Markets

The ultimate goal of setting pricing strategies is, via proper strategies, that all market participants, including buyers, sellers, and other members such as brokers, market makers, and market rulers and designers, shall have their opportunities to maximise their economic returns on the knowledge marketplace, approaching a Pareto-efficiency or a Pareto-optimality (Duffie, 2010). In fact, it may cause formidable market distortion due to lack of such pricing strategies and due to lack of appropriate mechanisms to ensure functional strategies, considering the fact that pricing knowledge entails high subjectiveness (Raban, 2007), meaning that market participants' behaviours on such markets are much more "irrational" as the decisions are vastly based on 'rule of thumb' and on personal instinct (Raban et al., 2014).

In addition to ensuring the maximisation of the operational efficiency of the knowledge market, pricing strategies also help to increase market participation, accelerate market responsiveness, reduce the level of information asymmetricity, and alleviate market barriers (Ba et al., 2001; Raban et al., 2014; Varian, 1995; Z. Zhang & Jasimuddin, 2008).

There hardly exists an “all-fitting” pricing strategy. Hence, before discussing the pricing strategies in detail, the rest of this section presents a basic framework that I developed from summarizing the extant literature about the existing virtual knowledge marketplaces. I categorised these marketplaces into three groups based on the source of income the supplier acquired. After that, I introduced the befitting price strategies for each category. For simplicity, I assumed there were only three types of market participants in the market, as discussed in the previous paragraph, including the buyers, the suppliers, and the brokers (who play the roles of all other market participants).

In the first category, the market brokers only provide a virtual place for people to meet and to trade, and the suppliers’ income comes directly from the knowledge buyers. For example, most of the online knowledge exchange platforms and the crowdsourcing sites belong to this group, and they use different forms of “direct payment” methods to reimburse knowledge service providers.

The second category contains those knowledge markets where an indirect payment method is often used. Such methods are commonly used by digital database providers, such as JSTOR, whose end-users are often not the direct payers for the knowledge. If considering music as a commercialised knowledge product, then Spotify could also be a good example of this category. It is the broker who manages the money flow by collecting it from the buyers and paying it to the sellers.

The third group involves a number of internal marketplaces running inside firms where the broker, the firm, pays money to the knowledge suppliers, and the money is often expensed under the name of IT investment and comes from the benefits added via a higher level of knowledge transfers resulting from such investment.

For the knowledge marketplaces in the fourth category, they do not have a broker, or they say that the broker is the entire Internet, and all the knowledge transactions are handled directly and freely between the buyers and the sellers. It can also be claimed that, in such cases, the data/knowledge providers are also the brokers. Examples of knowledge providers of this type range from journal article publishers providing paid online access services to research data disseminators such as

CSIRO's Data Access Portal[2]. A summary of the categories introduced in this paragraph can be seen in Table 4.

Category	Existence of brokerage	Payment Method
I	Yes	From the buyer directly
II	Yes	From the buyer indirectly
III	Yes	From the broker
IV	No	From the buyer directly

Table 4. Categories of KMs

One of the most appropriate pricing strategies for the knowledge market under the first category is price discrimination, which, if used effectively, can prevent consumers with high willingness to pay to pay less and let the seller(s) turn almost all the "consumer surplus" into revenue (Varian, 1995). A typical discrimination strategy used by KP suppliers is to charge a higher amount of price from the person who demands the KP more immediately than the person who is willing to wait for the price to drop down. Another common strategy is to discriminate the quality of a KP, which is of particular interest for the sellers of online content (e.g., CQA sites) and online services (e.g., crowdsourcing) since there exists a large difference in the tastes for quality among KP purchasers on those platforms (Varian, 1997; Wei & Nault, 2014). Common practices utilising this strategy include adopting a freemium model where the users of knowledge products are able to choose the basic functions (i.e., inferior quality services) for free but need to make an extra payment for enjoying additional premium functions (i.e., high-quality services). Another example that is common on online knowledge-sharing sites such as Quora is for answerers to provide a brief article on the knowledge market for free with a

[2] CSIRO's Data Access Portal (DAP) is a service provided by Commonwealth Scientific and Industrial Research Organisation (CSIRO), offering research data products to public. As of October 2016, the DAP has 1,928 published data collections, with a total of just over 70,000 downloads since November 2012. Sanderson, T., Reeson, A., & Box, P. (2017). *Understanding and unlocking the value of public research data*. https://publications.csiro.au/rpr/download?pid=csiro:EP168075&dsid=DS2

link inside the article, redirecting readers to a place where the knowledge supplier provides a premium level service. The modern freemium model is not only useful in gaining profitability and in reducing customers' pre-procurement uncertainty but also in anti-piracy, because the existence of pirated goods enlarges the user base, and the supplier will eventually gain benefits from the network effect brought by the increase in user base and from the high ratio of turning a pirate user into a lawful user (Nan et al., 2016; Waters, 2014). Furthermore, versioning, also called vertical differentiation, is another popular option under the vein of price discrimination (Wei & Nault, 2014). A simple example would be a knowledge provider that offers an in-depth article in its comprehensive version for a higher price and at the same time gives a streamlined version for a lower price (Shapiro & Varian, 1998).

Product bundling befits the second category well. Product bundling is a profit-maximising practice where a seller, instead of selling one item, offers a package of items at one time, which greatly decreasing the heterogeneous "Willingness to Pay" of the potential purchasers (Bakos & Brynjolfsson, 1999; Varian, 1995). Following this fashion, JSTOR maximises its profits by selling a bunch of journals at one time rather than vending them, item by item. Sundararajan (2004) argued that, under the condition that the market has only incomplete information, a knowledge provider will earn the highest revenue when they adopt both a fixed-fee pricing model and a non-linear pay per use model together, though there may exist a scenario where a stand-alone fixed fee model is always superior over the others. Shivendu and Zhang's (2016) research discussed the bundling strategies between the physical medium and the digital medium. Bockstedt and Goh (2014) illustrated the key elements of designing a useful customized bundling via analysing the "design-cost effects" and the "compromise effects". Adomavicius et al.'s (2015) experiment suggested that for digital goods, such as music, people tend not to show a variety-seeking behaviour as they often show such preferences towards consumable goods, indicating that, when designing bundling options, KP suppliers do not need to consider whether the consumer will purchase the KPs in group in one session, add it to a wish list and then buy them at a future date, or purchase each KP singly over time. In Z. Zhang et al.'s (2016) study, the authors claimed that there exist some conditions where an entirely free software offering (a free trial model either with time limitation or with limited functions) outperforms the ones using a bundling strategy. Azadeh et al. (2014) applied mathematical methods to investigate a bundling problem regarding how to approach the optimal bundling mixes and to set optimal bundle prices for two hypothetical products with limited stock in a monopoly environment.

The third category concerns those internal knowledge markets where incentives are used to encourage knowledge codification, knowledge transfer, knowledge reuse, and urgent response line (Desouza & Awazu, 2003). For example, Siemens' ShareNet is such a platform where knowledge suppliers contribute to the ShareNet for a Bonus-on-top or ShareNet Shares, offered by the company (Voelpel et al., 2005). In ShareNet-alike cases, the company is the establisher, the maintainer, and the broker of this knowledge market and is responsible for recompensing the suppliers of the knowledge (Zhang & Jasimuddin, 2008). The money, or other types of resources, used for reimbursement is either from the company's existing income or from the future income added that would be able to track back to the enhancement of knowledge transfer. In either case, the remuneration will eventually reduce the amount of money that originally would be used for a human resource purpose. Therefore, it is safe to say that the supplier and the buyers ultimately share the expense of the knowledge transactions. The firm decides the allocation of the money, and intuitively the higher the allocation to the knowledge suppliers, the higher the participation (Zhang & Jasimuddin, 2012). Hence, the specific number of the allocation ratio, a critical part of the incentivisation schemes for knowledge management, needs to be fine-tuned based on several firm-specific factors, such as organisation culture and employees' interpersonal relationships and on individual-level factors such as personality and existing incomes (Kankanhalli et al., 2005). Some of the abovementioned factors, nonetheless, are difficult to quantify.

In real life, the boundaries between categories may blur. For instance, Google Answer was a mixed version of Category I, II, and III: it had a public-accessible knowledge market with a broker, and it is the broker who collected the money from the knowledge buyers and relocated a fraction of the money to the knowledge suppliers (Google Answer Researchers) based on a pre-set ratio (Edelman, 2004). In fact, a knowledge market without brokerage, the Category IV, which will be discussed in the next paragraph, can be treated as a market with a pre-set ratio equal to one, indicating that all the income goes into the pockets of the suppliers.

To maximise the value of the data and the knowledge provided, knowledge providers in Category IV can achieve the value maximisation via a "data plus service" model (Sanderson et al., 2017). Raw data is of low use value but has high flexibility. Research services add-ons, such as providing clear documentation and packaging data into contextualised knowledge, will add value on top of the data and will be able to deliver the data/knowledge service to a larger range of users. However, doing so also hurts the flexibility and, therefore, reduces the option value of the raw data. Welle Donker et al. (2016) suggested that it is wise to satisfy different groups of users who have different demands by providing different products in terms of the differentiated "flexibility" and the "rawness" of the data/knowledge. The best strategy is to make the data product available at all stages of the "knowledge development process", resulting in a place where all the potential sources of value are maximised. In addition, providers in Category IV can also adopt a price strategy similar to the Bundling method, which has been discussed previously.

Several price strategies can be used in different categories. Shiller (2014) discussed the possibility and profitability of Netflix using Big Data technologies to achieve first order price discrimination, a person-specific level discrimination, which is ideally the most profit-maximising model. Big crowdsourcers should implement such a model to maximise their profit on crowdsourcing sites. Moreover, large-scale research data providers, such as DAP, should also attempt to apply this strategy to its users. That said, as Jeong and Kim (2014) mentioned, a price discrimination mechanism may annoy consumers because they will feel unfairly treated particularly when they find out they have to pay a higher price for a homogeneous product without any reasonable explanation—such annoyance has a potentially large negative network effect.

Pricing strategies can also be used for reducing, if not eliminating, low-quality participation. According to Zhang and Jasimuddin (2008), the market contains two groups of users, the spin-off users and the mainstream users. The former group merely use the knowledge market as an alternative way of finding useful information but seek no additional utility, while the latter group properly utilise the market to acquire additional utilities. The spin-off users exert a negative effect on the knowledge market because they do not provide accurate price information. Sometimes they even give distorted information via asking less responsible questions, giving random answers and displaying inconsistent voting behaviours. For example, according to West (2002), some users asked impromptu questions offering money for someone to tell a joke. Toba et al. (2014) mentioned a case where an answer with apparently low-quality won high votes. On the other hand, allowing spin-off users joining the market increases the number of market participants, and therefore, enhances the market thickness and the overall operational efficiency. Hence, it is essential to adjust the number of "spin-off" users to an optimal level. Zhang and Jasimuddin (2008) argued that, by adjusting the minimal posting price level, the market regulators are able to moderate the structure of the knowledge market.

An accurate pricing strategy and method can ensure efficient knowledge exchange because the underlying assumption of knowledge markets is to make all market signals (e.g., prices) of the knowledge more explicit and more transparent. Thereby, the market mechanisms will contribute the optimisation of distribution by offering accurate and informative market signals and by allowing benchmarking of the transactions across time (Gans & Stern, 2010). However, there is little evidence that shows a perfect pricing strategy is approachable. Also, it seems that the effect of pricing strategies is not deterministic (Raban, 2007). Henceforth I argue there is a need to investigate and understand the complex relationship between pricing and incentivisation in knowledge exchange initiatives.

Sources of values of knowledge exchanged in knowledge markets

Although the pricing of knowledge resources involves many difficulties, knowledge resources can undeniably bring long-standing values to their users. To understand the value of knowledge, as Sanderson et al. (2017) suggested, it is essential to analyse the sources of such values in an "as comprehensive as possible" manner. The following paragraphs will provide a comprehensive review of the progress and the thoughts from the current literature.

Historically, valuation methods include statistical decision theory-based approaches, multidimensional value approaches, psychological cognitive theory-based approaches, and equilibrium approaches (Repo, 1989). The statistical decision theory-based approaches attempt to solve the price of information/knowledge based on statistical tools such as Bayesian approach and decision trees (Carter, 1981; Cook et al., 2010). Such methods are particularly popular in experimental settings and in accounting practices (Feltham, 1968; Lawrence, 1979). The multidimensional value approach determines value by looking at the economic significance and attributes (Hirshleifer, 1973). The psychological cognitive method digs deeply into the root of the knowledge and emphasises the non-economic value part of the knowledge, examining the value of knowledge but not from a product view. For example, McCain (2006) studied the non-economic value of cultural and the artistic goods, stating that such value only overlaps with the Intellectual Property by a small fraction. The equilibrium approaches, based on formal economic theories, focus on finding a market price for information via collecting empirical market data (Galatin & Leiter, 2012). According to Sanderson et al. (2017), the Total Economic Value (TEV) model, which is widely used for Cost-Benefit Analysis, is particularly suitable in this situation. TEV was initiated by Randall and Stoll (1983). Although the method is criticised for "its non-additivity of the elements" and for "the difficulties in quantification of the components" (Adger et al., 1995), it is particularly useful in providing an all-encompassing framework for identifying sources of values of the information/knowledge from its acquisition to processing and from dissemination to final use (Machlup, 2014).

TEV assumes that an economic resource's value has two major components, namely its Use Value and its Non-use Value. The Use Value part can be further categorised into "value for direct use", "value for indirect use", and "value for future use (a.k.a. option value)". Non-use Value includes Bequest value and Existence Value.

It seems that the primary part of a knowledge's value originates from its direct use value. For example, saving in time is a key benefit from direct use. As in Stigler's (1961) paper, the author deems that a piece of information (knowledge) has its value because, in an information-asymmetric market, people have to devote their time and effort to searching so as to gain utility. In an ideal world where everyone's utility is maximised, the marginal value of information (knowledge) equals the marginal cost of the searching and of the efforts devoted, and, if the searching costs were prohibitively high, people would stop such searching. As the marginal cost is reckonable, the value of the knowledge becomes determinable. For example, for a customer who wants to purchase an ice-cream, assuming that all the ice-creams that being sold in store A and store B are homogeneous, if he or she knows ice-cream sold in store A is 10 dollars more expensive than that sold in store B, then he or she will purchase the ice-cream only at store A, thus saving 10 dollars. The maximum marginal value of this knowledge piece is henceforth 10 dollars, and if there is a knowledge seller selling such knowledge, for a knowledge buyer, as a rational person, he or she will be better-off as long as the knowledge's price is less than 10 dollars. In terms of the source of value, this knowledge can be acquired either by searching (by the person) or by purchasing from another person who did the search whose time cost of such search, reasonably, is worth less than 10 dollars. The cost of this (the substitute) is a key part of the value of such knowledge. Further, from the knowledge sellers' perspective, the value of a piece of information/knowledge, as Stigler expounded, is generated from the ability to gain profits by taking the advantage of price dispersion and by eliminating such dispersion under the context of information asymmetry. Also, it is reasonable to conjecture that the more challenging the searching process, the higher the price of that knowledge piece.

Direct Economic value of knowledge also can be gained from countering uncertainty. That is to say, purchasing knowledge is similar to buying insurance because it reduces the level of a potential loss from future risk (Hansen, 2017; Lawson, 1985). People often make decisions within an uncertain environment, limited by incomplete knowledge, and based on subjective probability, resulting in problems such as risk aversion bias, less confident investment, hampered forward-looking decisions (Beckert, 2009; Latsis et al., 2010; Lawson, 1985; Weber, 1987). Therefore, knowledge is similar to an insurance policy or a future contract, and the value of it comes from reducing uncertainties and, therefore, from securing a future gain.

Because the direct use value of knowledge can be traced from the value of time, the question of valuing knowledge is transformed into a question of measuring time's value. An effective way of calculating the value of time is mentioned in Sanderson et al.'s (2017) paper in which the value of time can be calculated based on publicly available data of average hourly salaries at different clusters and different employment levels, though the value perhaps varies greatly among different countries, age groups, and professions. Although in some countries such data may not be available from the government and not from the public database, which implies the necessity of pre-sampling. Fortunately, in Australia, such data are available and are stored in and disseminated via the Commonwealth Public Service. Note that, as the authors also mentioned, this calculation method automatically ignores people's leisure time because the subjects in that study were mainly using scientific data for work.

Values originating from "indirect use" are obtained by those people who enjoy the utility of the goods and services that are provided by the group of people who obtained the value of direct use. For example, comparing a knowledge piece to an orange: the person who directly eats the orange will be the one who enjoys the value from direct use. If the person instead turns the orange into juice, then the person who purchases and drinks the orange juice would enjoy the indirect use value of the orange, while the producers of the juice would still be the ones who enjoy the value from direct use. It can be posited that knowledge has a large externality effect. For instance, in the case of online education platforms, the students obtained college-level knowledge and skills, which will generate positive externalities. The benefits of spillovers from knowledge acquisition are received by people around the student, rather than the students themselves. Therefore, such economic benefits can be identified as an indirect use value of the knowledge, and sometimes the beneficiary party is so large that the value would be added to the entire society (Moretti, 2004). The exact number of the value comes from indirect use; however, is relatively harder to estimate than the value from direct use. That said, there are econometrics methods, such as the Mincerian approach and Barro's economic growth model (Cohen & Soto, 2007), which can be used to quantitatively examine the effect of knowledge's externalities. Estimations of the returns range from 30% to 10% and are highly dependent on the methods adopted and samples used (Ashenfelter et al., 1999; Barro, 1991; Carneiro & Heckman, 2003; Klenow & Rodriguez-Clare, 1997, 2005). In terms of knowledge services, Sanderson et al. (2017) conjectured that externality calculation will follow Metcalfe's law and/or Reed's law. The former law suggests that the value's increment is proportional to a number of users (N) in a square basis (i.e., N^2). The latter law implies that the increment follows an exponential increase (i.e., 2^N).

Option value exists when the knowledge piece has a known future use or sometimes even if the usage is still uncovered. It draws an analogue between the "knowledge" in knowledge markets and the "options" in financial markets which offers the owner a right to gain an uncertain amount of money at a future date. Sanderson et al. (2017) argued that, with the rapid advancements in technologies and the advent of the new knowledge economy, option value will occupy a dominant proportion in knowledge's value. Caution needs to be exercised, as the future values of knowledge are much based on visionary predictions, if not merely guessed; consequently, the value tends to be highly uncertain. That said, relevant measurements have been studied for decades, attempting to achieve accurate valuations. (Housel & Nelson, 2005; Lombardi et al., 2016; Sudarsanam et al., 2003; Sudarsanam et al., 2006) For instance, based on Black–Scholes Model for pricing call options, Chen and Chen (2005) suggested that option valuation models can be used on knowledge valuation, as a measurement framework to enable knowledge assets to be leveraged effectively and efficiently.

Non-use Values include Existence values and Bequest values. The former refers to the money paid to secure the existence of a resource even though no use of it is expected (Walsh et al., 1984). Some knowledge pieces that are never used after their storage will fall into these categories, as long as they are not deleted entirely from the database. The latter suggests some knowledge products have a potential level of economic importance that needs to be passed to future generations (Diafas et al., 2017). Non-use Values are of less importance, as they are highly abstract, hard to estimate, and difficult to identify. Table 5 summarises the values.

Class	Types	Author(s)	Main Argument
Use Value	Value for direct use	Stigler (1961)	The marginal value of information (knowledge) equals to the marginal cost of the searching.

		Lawson (1985), Hansen (2017)	Value comes from countering uncertainty
		Sanderson et al. (2017)	Price of the knowledge equals the value of time saved by knowing the knowledge
	Value for indirect use	Moretti (2004)	Online education is becoming increasingly popular and convenient; the students obtaining college-level knowledge and skills will generate positive externalities to the entire society
	Value for future use	Sanderson et al. (2017)	The future values of knowledge are much based on visionary predictions, if not merely guessed; the value tends to be highly uncertain.
		Chen and Chen (2005)	Option’s valuation models can be used for knowledge valuation
Non-use Value	Bequest value & Existence value	Diafas et al. (2017)	Knowledge products have a potential level of economic importance that needs to be passed to future generations

Table 5. Knowledge Value's Sources (Total Economic Value Perspective)

Knowledge evaluation

The studies mentioned in the previous sub-section discuss the value of knowledge from a theoretical perspective. There is, however, a need to have a closer look at the market in a more practical and pragmatic way. Findings from experiments and field studies (mostly based on crawled data from real-world online knowledge platforms) shed some lights.

Furthermore, intuitively, it can be conjectured that there should be a strong correlation between a KP's quality and its value; that is, a KP of better quality comes with a higher level of utility, henceforth resulting in a higher price. Also, high quality attracts a higher quantity of consumers. Because "quality" contributes to both the "price" and the "quantity" of KP and because the "value" of KP equals the "quantity" multiplied by the "price", it can be concluded that quality has a positive relationship with value. Fen et al. (2015) used a Multi-Stage Game that proved this speculation. Therefore, the task of "knowledge valuation" can be partially analogous to "knowledge quality assessment". There are many papers discussing the quality-assessing methods for knowledge sharing and trading on the virtual knowledge exchange platforms. For example, Anderson et al. (2012) assessed StackOverflow and found that knowledge pieces' long-lasting value can be quantitatively determined by factors such as questioner features, activity, and Q/A quality measures, community process features, and temporal process features. They found that there is no significant correlation between the reputation of answerers and the quality of the questions, nor between the questioners' and the answerers' reputations. However, high reputation users indeed tend to gather together with only a small group of questions rather than be uniformly distributed among all questions. In Jeon et al.'s (2006) research, based on Q&A pairs collected from Naver, a Korean CQA site, the authors proposed a quality-assessment model comprising non-textual features, such as click counts. Those features are handled by kernel density estimation and maximum entropy approaches. Toba et al. (2014) also examined the intrinsic criteria for high-quality QA pairs on CQA sites but they argued that different QA pairs have different characters and therefore need a different quality assessment model to evaluate its quality. However, it would be prohibitively costly for researchers to build an individual assessment model for each question. Therefore, this study proposes a trained-two-layers model for assessing knowledge quality. The first layer is a classification layer where knowledge pieces are classified into different categories, and in this paper, there are six categories: definition, factoid, opinion, procedure, reason, and Yes&No. The second layer is for quality evaluation in which each category embeds a slightly different quality-assessment machine measuring the quality of the knowledge according to its category based on its lexical and syntactic and semantic features, such as statistical features, answer-question ratio (e.g., ratio of question length to answer length), density, readability, monolingual word translation, number of links/URL and sentiment polarity. Also, as most of the knowledge shared on virtual marketplaces is text-based, it would be useful to look at those business-level artificial-intelligence-based automatic essay graders (a.k.a. Automated essay scoring systems), such as eRater (developed by Educational Testing Service, US), Intellimetric (developed by Vantage Learning) and Intelligent Essay Assessor (developed by Pearson Knowledge Technologies3), which are commonly used in international-wide language tests or graduate entrance examinations, such as TOEFL, PTE, and GRE, and GMAT (Balfour, 2013). Features of high-quality texts include high lexical complexity, low proportion of grammar errors, diversified styles, smooth organisations, rewarding idiomatic phraseology, and affluent supporting evidence (Attali & Burstein, 2004).

Inside organisations, Otto et al. (2009) developed data quality metrics to measure the value of internal data from a business process perspective. Ahn and Chang (2004) attempted to build a model to connect business performance directly to knowledge. Wang and Li (2014) conducted a case study to investigate the knowledge price in an agile supply chain based on factors including the stickiness of knowledge, the distance of knowledge, and the degree of reliable relationship between trading parties. Hu (2015) conducted a case study on a Chinese R&D company that sufferedhindrances including a lack of innovation competence and a limited capacity in knowledge resources management. Under a "value" perspective, they implemented and tested a knowledge performance evaluation model and integrated an Analytic Network Process (ANP) with a Balanced Scorecard (BSC) to measure, unlock, and visualise the value of knowledge embedded inside the organisation.

Knowledge's characteristics

As previously discussed, a knowledge market shall allow knowledge, which assumedly has its inherent value, to be evaluated and priced. The process of valuing knowledge products is termed "knowledge valuation" (Menon & Blount, 2003). However, practitioners who want to conduct knowledge valuation in a market-oriented knowledge exchange platform are facing a number of difficulties due to the nature of knowledge and knowledge products. Unlike valuing a typical tangible product whose real price is relatively easier to estimate by its "appearance", "material", "cost of production", "future income generate-ability", and other straightforward factors, evaluating a product on a knowledge market tends to be more peculiar. Hereafter, I have listed five atypical characteristics that exist in the literature.

Experience goods

Information and knowledge have been long and widely recognised as experience goods. This implies that the real worthiness of an information piece will only reveal itself after its consumption (Shapiro et al., 1999). Some call this phenomenon the Inspection Paradox, asserting that, to evaluate a knowledge product, people have to access the knowledge first. However, once accessed, the knowledge evaluation is no longer needed (Van Alstyne, 1999). The direct empirical implication of this feature is that the market participants (especially the knowledge receivers) cannot accurately evaluate the possible gains from participating in knowledge exchanges but deciding to engage or not takes time and energy, which involves uncertainty and perceived burden of costs. People generally prefer avoiding uncertainties and weigh the costs as being higher than the uncertain gains and consequently they decide against the time-consuming engagement in network activities, which results in difficulties for knowledge management officials to motivate companies to participate in network activities (Feser & Proeger, 2017).

Insufficient information about the quality of knowledge products and misunderstandings among the market participants cause market frictions, which eventually translate to high inefficiencies in knowledge transferring and in market loss. For example, misestimation of WTP of the knowledge seekers, either by the knowledge sellers or the knowledge buyers themselves, would cause economic deadweight loss (Auerbach et al., 2013).

Cost structure

The nature of knowledge means that almost all of the costs are incurred to produce the first item (i.e., high initial investment), while subsequent items have very low (or zero) marginal costs (i.e., high scalability). The marginal cost of producing an additional knowledge product on the Web is, in some cases, close to zero, even when time cost and other opportunity cost are put into consideration. Therefore, there is also no clear market stop point. As indicated by Lemley and Myhrvold (2007) and Gans and Stern (2010), like other scenarios, intellectual property protections on the Web can help to protect creations and also to build an effective knowledge market by turning intangible ideas into tradeable assets so that they can be safely exchanged without permitting unlimited reproduction and expropriation. However, sometimes patents also result in a negative effect on the market by biasing the market signals and by violating the principle of free trading which is one of the key underlying assumptions of establishing this market. It also hampers the creation of new knowledge, as knowledge, in nature, is not only an output but also an input of its own production. Therefore, the "walls" built by the above-discussed protection mechanisms, used for keeping the benefits of the knowledge producers, would inevitably distort the market, especially in a short run. Langinier and Moschini (2002) argued that this distortion would hurt the benefits of all the parties participating in the market. Traditional theories of economics argue that, in a perfect market, products are optimally transacted when the marginal cost equals the sale price. This economic law suggests two tricky facts: First, when the markets are far from perfect, as they are in most cases now, traditional economics analysing tools have difficulties in analysing issues such as the logic of price, because most of the tools are built upon assumptions of the perfect market or relaxed version of assumptions. Second, even though the knowledge market is now imperfect, the ultimate aim of practitioners and researchers is to design a well-functioning marketplace allowing conditions such as nearly perfect competition to occur. However, if an optimal market were to be approached, the price would be equal or close to zero. Regardless of whether the transactions are illegal or not, the valuation of those knowledge pieces would, unfortunately, become meaningless.

Intangible assets

Knowledge is an intangible asset whose value is comparatively uncertain and unreliable compared to tangible ones. Valuing intangible assets often encounters problems of misidentification, of mismeasurements, and of high uncertainty (Cohen, 2011; Ortiz, 2011). Misidentification means that there exists a disagreement about what can be counted as an asset. Mismeasurements suggests that, for some assets of this type, different measurement tools may generate very different valuation results. Uncertainty mainly comes from an asset's option value which is defined as the ability to use the asset and/or generate economic benefits in the future—these details will be further explained in the following paragraphs. Most knowledge products can easily have all three features, so in practice, prudent considerations and strict auditing are needed when selecting the correct methods and strategies to assess the knowledge assets' value, and researchers should also note during the investigation that because knowledge is largely a type of intangible product, the effects of influential factors on askers' switching behaviour vary significantly before and after a switch (Z. Liu et al., 2021).

Heterogeneity of knowledge

Knowledge is highly heterogeneous in nature, so finding a "comparable" on market is often challenging. Knowledge heterogeneity refers to different knowledge products being very different in terms of their structures, types, contents, levels and characteristics of audience (Rodan & Galunic, 2004). Tong and Mitra (2008) divided knowledge heterogeneity into three types: information, social attribute, and value heterogeneity. Huosong et al. (2019) argued that knowledge heterogeneity arises from cumulative learning processes, and during these processes, different people embrained, embodied, encultured, embeded, and encoded knowledge differently because they receive different information, have different social attributes and have different views of value. As such, a piece of knowledge can have different manifestations in different situations. The implication of this heterogeneity is that, for a knowledge product, typically, it is hard to find substitutes. Difficulties in finding a comparable knowledge product seems to indicate that market-based methods would fail in tasks of valuing knowledge when a purely free market exists (Chen et al., 2010).

Subjectiveness of evaluating knowledge

The heterogeneity feature also correlates with another important feature—the high subjectiveness of valuing knowledge pieces. Knowledge's price entails high subjectiveness, and the value of "this knowledge" also changes with "other knowledge" that a person has accumulated (Raban, 2007). It does not eliminate the possibility that people, functional algorithms and big data analysis, derive a reliable price range for online knowledge markets. An efficient market can hardly be built where its clients' bids and tips are merely hinging on the rule of thumb; that is, based on their subjective feelings, past-knowledge and personal instinct. However, it is admitted that the intrinsic and objective fair value carried by knowledge goods, at most of the modern knowledge market, is still not accessible when the knowledge consumers making purchasing decisions (Abhinav & Dubey, 2017), though those knowledge goods are largely based on their perceived value rather than the fair value of the goods, and the perception may be affected by changing market and social influences. There exist only very limited methods to ensure the accuracy and appropriateness of the price-setting of the knowledge products and service exchanging on such platforms. Prices are often set in an arbitrary manner by merely following some community or industry norms (Oh et al., 2016; Regner, 2004) and guidelines provided by the platform (Zhang & Jasimuddin, 2008), leading to a variety of market inefficiencies. Also, there are platforms where knowledge demanders are price makers, but the market information in these knowledge markets are generally asymmetric, so knowledge suppliers have more information and thus stronger bargaining power to get a price premium (Pan, 2018), which causes a disadvantage towards the buyers of knowledge goods and wide price dispersion of these goods (Qi et al., 2019).

Knowledge market theory & designs

Modern market designs theories are useful for directing knowledge exchange platforms' planning, maintenance, and administration, and decreasing the possibility of knowledge market failures, which is the primitive motive for implementing market designs (Roth, 2007). Much literature also discussed modern market design theories being useful for directing virtual knowledge markets planning, maintenance, and administration, decreasing the possibility of knowledge market failures. Via providing float and valid market signals (e.g., price, quantity sold, quality cues, etc.), optimal matchings, and simplification of participants' messages (therefore reducing transaction cost), a well-designed virtual knowledge market can facilitate and support the mobilisation, sharing, and exchange of information and knowledge for dedicated parties.

Further, according to Hirshleifer et al. (2005), if a fixed price system was used to regulate and to stimulate the market, inefficiencies would occur. That is, setting a fixed price is a method commonly used in a controlled economy, and in a planned economy, the price is easily set too high or too low, causing a distortion in the market (knowledge oversupply or undersupply). Current IT-supported knowledge marketplaces offer a seemingly viable way to approach a real-time floating price system, which tends to gain higher efficiencies. Some virtual knowledge markets inside an organisation can be utilised as a hub to dynamically interweave with other knowledge channels and to integrate knowledge resources on those channels (Lichtenstein et al. 2007). Lukashov's (2011) experiment showed that a knowledge market with a price structure is significantly more efficient than a market without it (i.e., trading knowledge for free), and market participants, both the buyers and sellers, are able to utilise information in the knowledge market to identify, optimise, and sustain their long-term positive returns. Therefore, the question now becomes: "How to build an effective knowledge market?"

Abundant literature in market design shows that one of the motives for designing a market is to ensure an efficient operation by reducing the possibility of market failures (Teece, 2008). Also, via multilateral market exchange, a functional knowledge market allows its members to find the existence of those "close and available substitutes" (Gans & Stern, 2010). That is to say, the market makes it easier to find "the next best available knowledge product", reducing the possibility of market inefficiencies and bargaining breakdowns. The "market value" of a knowledge product, therefore, becomes publicly accessible, largely stabilising the market price and therefore making contributions towards an efficient allocation of knowledge resources (Issing, 2002; Sim, 2021).

Three features are particularly important for a well-functioning market: market thickness, market safeness, and the market's ability to overcome congestions (Agrawal et al., 2015; Roth, 2007).

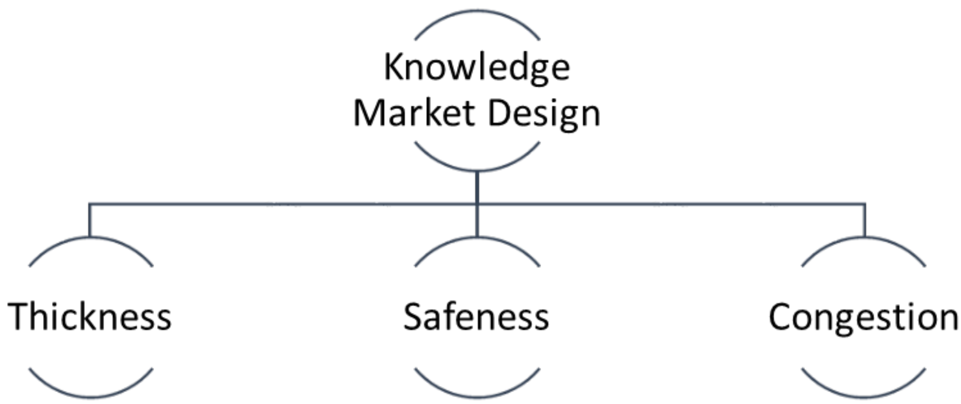


Figure 5. Three Pillars of a Good Knowledge Market Design

Market thickness, critical mass and knowledge seeding

Market thickness means the knowledge marketplace's capacity to attract a large number of market participants trading a wide range of knowledge products. The online market for knowledge, including data, information goods, contents, and digital products, is majorly a "long tail" market (Bimba et al., 2016; Enders et al., 2008; Lang et al., 2009; Seely Brown & Adler, 2008; Wallis et al., 2013), which suggests that 20% of the knowledge suppliers create 80% of the knowledge, while each knowledge product may only have a very limited number of buyers in the market. Market safeness means that the market designers need to set up rules to prevent some parties committing or becoming involve in misconducts and misrepresentations which would undermine other parties' interest in participating in the market, resulting in difficulties in the evaluation of potential trades. Effective IP protection may reduce the likelihood of market failures (Agrawal et al., 2015). Nonetheless, such effect seems only to be significant for higher income countries (Bascavusoglu & Zuniga, 2002). However, a rigid patent and licensing system may also deter the exchanging of knowledge products: As mentioned by Murray and Stern (2007), in this regard, IP protection plays a negative role over scientific knowledge and researchers are more likely to avoid citing papers with an associated patent. Nuvolari (2004) recorded that the exchanging of technical know-how, a vital prerequisite for incremental innovation, was blocked by the release of a stronger patent law. Market congestion occurs when the speed of transactions is too slow to ensure the market clearance, the point where all the consumers match with their corresponding suppliers at a correct price (Roth, 2008). For example, suppose there is a market selling the knowledge embedded in journal articles, provided that most of the journal articles are dreadfully lengthy, and suppose a person, who is under huge time-pressure, needs to make a purchasing decision between two papers. Both of them are more than 50,000 words, but only one of them is of good quality. The buyer cannot reach a sound decision by reading them all, so there is a high chance (in this case, 50%) to cause market inefficiency as long as the person purchases the inferior one. A simple feature, such as adding an abstract section, can be utilised to achieve a less congested market (Gans & Stern, 2010). In addition, Agrawal et al. (2015) studied the market for ideas (licenses, i.e., a knowledge product). They found that such a market is prone to fail and market thickness plays a salient role at the very beginning of the licensing process, that is, the identification of the potential buyers and sellers. Once one trading party initiates negotiation, the importance of the market thickness becomes less important, but market safety becomes more vital to reaching an agreement between the trading parties.

As Van Alstyne (2013) stated, like a normal market, the matching and pairing between knowledge recipients and sources would become prohibitively hard if a knowledge market cannot reach a critical mass fast enough, and the market would fail. Also, they argued that market participants need to know how to take part in a market—participating for the first time may require considerable knowledge, which can present a barrier to some potential participants. Henceforth, initial seeding and subsidizing the market is important. Prior research suggests participants in knowledge markets need an initial portfolio to start trading (Benbya, 2015), and this initial portfolio shall be sponsored by knowledge market owners (i.e., the firm who runs the market). As P. Huang et al. (2018) argued, owners shall seed the market with critical knowledge and subsidize key knowledge producers because this can be conducive to building trust between market participants and the owner of the knowledge management system, which leads to a greater propensity and capability of the participants to contribute. Once the owner shows a genuine care about the well-being of the knowledge market participants (rather than showing a pure profit-seeking motivation), the participants' beliefs in the platform owners' benevolence can be reinforced, which leads to members' increased willingness to supply more to the knowledge market (Guo et al., 2017; Porter, 2015).

Market currencies

To enable market participants to exchange knowledge, a medium of exchange is needed (Serrat, 2017). Though Benbya and Van Alstyne (2010) argued that a knowledge market should accept both material (e.g., fiat money) and social currencies (e.g., social recognition, peer rankings) and offer private and anonymous channels or transaction spaces to let shy, self-conscious people voice questions and seek knowledge, they also argued that using absolute rewards (e.g., real currencies) is better than using relative rewards (e.g., ranking). To individual knowledge owners inside a company, the value of knowledge typically comes from what the knowledge normally brings, such as status, career prospects, and individual reputations (Andrews & Delahaye, 2000), which coincides with Benbya and Van Alstyne's (2010) ideas that even though monetary rewards ultimately can be an important factor in a knowledge market, social currencies are still an indispensable component in such an internal market, though sometimes hybrid with real money, such as company-issued spendable currency (e.g., prize-redeemable coupons or tickets to conference), recognition of expertise, and an opportunity to gain a status impact are effective. For example, Garud and Kumaraswamy (2005) denoted that Infosys, a globalised consultancy, implemented "knowledge currency units" (KCU) in its internal "knowledge shop". Other companies also used a point-based system to denominate knowledge, which, as indicated by Servan-Schreiber et al. (2004), is as good as using real money.

Dynamic pricing

Via providing float and valid market signals (e.g., price, quantity sold, quality cues, etc.), optimal matchings between knowledge suppliers and receivers, and simplified participant messages (which reduces transaction costs), a well-designed virtual knowledge market can help participants mobilize, share, and exchange information and knowledge (Sanderson et al., 2017; Zhang & Sundaresan, 2010). Also, as aforesaid, fixed prices, whether in currency, points, or reputation benefits tend to create an oversupply of low-quality content and undersupply of high-quality content (Benbya, 2015).

Budget constraint

Theoretically speaking, a budget constraint is the boundary of the opportunity set (Gode & Sunder, 1993), and having a constrained budget for spending on the knowledge products and services in the market can increase the overall exchange efficiency of a market (Zhao et al., 2014). Empirically, according to Benbya, (2015), working within a limited budget, market participants are forced them to make choices about what is less important and what is more important. These decisions then can be transformed into market signals, and the market can gather dispersed and private information about knowledge consumers' preference, as a competitive market would. Yichen told employees that they could only spend money from the account in the knowledge market. They could not reinvest the money they earned from the market back into the market during the field study period. The company also told them that it would replenish their account by the end of each month.

Use market to heal itself

Prior research found that phenomena in financial markets will be resembled in knowledge markets. For instance, Benbya (2015) warned that people in charge of coordinating the knowledge market tend to intervene in the market and practise insider trading, so rules should be set to prevent these people manipulating the market signals with market forces.

Communal motivation preservation

As Kafentzis et al. (2004) argued, altruism is one of the keys ensuring the success of a market-based internal knowledge transfer platform, and after launching the platform, knowledge suppliers can still be motivated by not only the market rewards (mostly offering extrinsic motivations) but also can be driven by intrinsic motivators such as desire to pass their knowledge to others and love of their subjects. Market incentives and communal motivation can co-exist and in some cases, prior studies also showed that the market incentive can have a spill-over impact on non-marketised (i.e., free knowledge sharing) activities (Kuang et al., 2019). Benbya and Van Alstyne (2010) also used InnoCentive's initially failed market which included only competition without supporting collaboration as a bad example to argue that a well-designed market needs to properly balance competition and collaboration. This is supported by Di Vincenzo et al. (2021) whose study found that, in a market for crowdsourcing ideas (also a type of the common knowledge products exchanging on internal knowledge markets), competition for attention negatively moderated the relationship between idea attention and comments, which can eventually hurt idea survival. Zhang and Sundaresan (2010) theoretically argued that a company running an internal knowledge market needs to promote trust, and therefore, the firm needs to fine-tune market structures and find the best signalling strategies for knowledge suppliers. The authors also argued the importance of studying the company's primary type of knowledge recipients (knowledge connoisseur, knowledge public, or knowledge dilettante) and the nature of knowledge (implicit and explicit) that needs to be exchanged. They argued that a firm should invest more in IT when knowledge dilettante is the primary group of knowledge recipients in the company and when mainly explicit knowledge is exchanged, whilst if the primary group is the knowledge connoisseur and the primary knowledge exchanged is implicit in nature, rewarding the learnings becomes more important. This theoretical view is partially tested by Villasalero's (2013) empirical study, though the latter study is not conducted within a knowledge market context.

Also, some researchers speculated that, via applying gamification philosophies, knowledge market designers would maximise the positive motivational effects by realising a mechanism featured by individualised integration of both intrinsic and extrinsic incentives (Auerbach et al., 2013; Carrillo et al., 2019; Li et al., 2012; Qi & Wang, 2019; Zhao et al., 2018). The designs of gamification and serious games have been widely used to increase motivation in areas ranging from knowledge sharing to scientific explorations (Richter et al., 2015). Gamification is a stream of methods aiming at applying game elements into a non-gaming environment, resulting in users' engagement, loyalty, and experience improvement (Seaborn & Fels, 2015). For example, gamification elements have been used in a QA system to determine the effectiveness of the knowledge shared (Shah et al., 2014). Based on a review of 143 papers, Boyle et al. (2016) argued that the most frequently occurring outcome for gamification is knowledge acquisition. Based on real-world market research, Cechanowicz et al. (2013) found that gamification can motivate people's participation rate and increase the data quality in a short run. Vasilescu et al. (2014) analysed Gamification used on Stack Overflow, and Nguyen

(2015) also envisaged the possibility of online knowledge providers utilising gamification tools to enhance the overall result for learners. The gamified design methods may offer extra help in designing an advanced interactive knowledge market from a user's view, especially its capability of combining a spectrum of incentive mechanisms to satisfy and to motivate people having different needs and preferences (Vassileva, 2012). Complex and fine-tuned gamification is able to provide different incentive mechanisms to different "players" in keeping with personalised goals and rules (Nardi, 2006).

"Two-sided market" and "Multi-sided market"

In terms of the forms of the market designs, Rochet and Tirole (2006) endorsed the idea of building a two-sided market or a multi-sided market for knowledge exchange. A "two-sided market" is a market aiming at enabling interactions between at least two groups (sides) of its end-users. A "Multi-sided market" additionally allows intermediaries to facilitate exchange of knowledge (Song, 2019; Zingal & Becker, 2013). For example, typical two-sided markets are Steam and Airbnb with "two groups of users", the goods and service consumers and the sellers (suppliers) (Rochet & Tirole, 2003; Song, 2019). An asymmetric pricing structure is often suitable for this type of market; that is, a pricing strategy aimed at charging a lower price to the group that has the strongest positive cross-side effect on the other side in order to enlarge the participants' base and to start a positive feedback loop (Belleflamme & Jacqmin, 2016). I believe that all above-mentioned technologies can bring benefits to facilitate the functional running of a knowledge market, but their exact effect needs to be tested, validated and evaluated in real-world market settings. I henceforth argue that observing and designing real knowledge markets are critical.

Summary

Drawing upon a multidisciplinary approach, this chapter provides a comprehensive analysis of current and emerging research issues in online knowledge exchange platforms. The literature review encompasses various subheadings, including an overview of the field, exploration of time and sources, keyword frameworks, forward and backward research, and definitions. The chapter also focuses on promoting online knowledge contribution behaviors, motivating knowledge and data retrieval from open science knowledge portals and leveraging market-based mechanisms to enhance the effectiveness of knowledge exchange platforms.

Specifically, the chapter summarizes the existing literature on motivating online knowledge contributions, examining theories and mechanisms for engaging knowledge contributors in online platforms. It also explores the state-of-the-art applications and approaches aimed at mitigating problems associated with modern knowledge exchanges.

Additionally, the chapter discusses the dynamics of market-based knowledge exchange platforms, investigating the economics of knowledge exchanges. It explores the sources of value in knowledge markets and presents theories and designs for effective knowledge market implementation. The budget constraint is also examined in relation to knowledge exchange platforms.

So far, this chapter provides a comprehensive review of the literature and research in the field, shedding light on the complexities of knowledge exchange and offering insights into promoting engagement, enhancing open science knowledge distribution, and leveraging market-based mechanisms.

Chapter 3: Overarching research approach

Besides a throughout literature review, this thesis is also based on a rigorous process of research approach selection. Based on the philosophical worldviews and research assumptions, the research methodology chosen adopts a quantitative design. This paradigm is meticulously selected to uncover true statements and causal relationships, primarily to understand the myriad of factors driving users to exchange knowledge online. This rigorous review, coupled with a discerning selection of research approaches, shapes the bases upon which this research is constructed.

Specifically, this chapter overviews the key components as well as the justifications of the overarching research approach that this thesis utilised to achieve the desired research purpose and objectives and presents descriptive portraits of the five studies that were conducted in this thesis.

An overview of research approach selection

According to Creswell and Creswell (2017), a research approach contains plans and procedures for research to follow. These plans and procedures typically start by making broad assumptions, and then the researchers need to select detailed methods of data collection and analysis, until the final interpretation. When planning the procedures, researchers need to make several decisions about the philosophical assumptions and philosophical worldviews the researcher brings to the study, procedures of inquiry (formally called research designs), and specific methods of data collection, analysis, and interpretation (i.e., the research methods).

Researchers shall make explicit philosophical assumptions. Previous research philosophers have proposed several categorisation schemes for philosophical assumptions. In my thesis, I adopted Saunders et al.'s (2009) view which argues that science is about building a system of beliefs that develop knowledge and that these beliefs are shaped by three philosophical assumptions: ontology (the nature of the world or reality, i.e., what exists), epistemology (the nature of knowledge and truth and is concerned with what researchers accept as valid knowledge, i.e., how things really work) and axiology (how and the extent to which personal values influence the research process).

Making different philosophical assumptions leads to different philosophical worldviews (Denzin & Lincoln, 2011). A philosophy worldview is a basic set of beliefs that guide research actions (Guba, 1990). Some researchers refer to them as research paradigms (Lincoln et al., 2011) or research methodologies (Neuman, 2007). According to Creswell and Creswell (2017), there are four types of research philosophy worldviews: The Post-positivist Worldview, The Constructivist Worldview, The Transformative Worldview, and The Pragmatic Worldview.

The Post-positivist Worldview (also called positivist/post-positivist research, empirical science, and Post-positivism) states that there is a singular objective reality, and human knowledge is based not on a priori assessments from an objective individual but from human conjectures (Creswell & Creswell, 2017; Lee, 1991). According to Smith (1983), the tradition of post-positivist came from 18^{th} ~ 20^{th} century philosophers, such as Comte de Saint Germain, Émile Durkheim, and Karl Popper. People who believe in this worldview hold a deterministic philosophy in which causes (probably) determine effects or outcomes. Therefore, the best form of resolving research problems is to identify and assess the causes that influence outcomes, and this identification and assessment process shall adopt a reductionist's perspective (i.e., researchers shall decompose research problems into small, discrete sets to test, such as the variables that comprise hypotheses and research questions).

The Constructivist Worldview upholds that people seek understanding of the world in which they live and work. Since these understandings are subjective, varied and multiple, researchers need to look for the complexity of perspectives rather than taking a pure reductionist's view by reducing the dimension of complexity. Many constructivists use qualitative studies in which researchers typically ask broad and general open-ended questions to their participants, so the participants can construct the meaning of a situation, typically forged in discussions and conversations with other participants (Creswell & Creswell, 2017). As Crotty (1998) identified, constructivists use inductive reasoning to interpret what they find and generate meanings from the findings socially, arising in and out of interaction with communities, and this process is inevitably affected by their own experiences and backgrounds.

There is another group of researchers who uphold the Transformative Worldview. Many researchers in the 1980s and 1990s started to find that theories and laws that were established by post-positivists did not fit marginalized individuals. Also, they also argued that post-positivists' research cannot mitigate issues such as power and social injustice, discrimination, and social oppression. Transformative Worldview researchers often draw on the works of Karl Marx, Theodor W. Adorno, Herbert Marcuse, Jürgen Habermas, and Paulo Freire (Mertens, 2008; Neuman & McCormick, 1995). Mertens (2019) also summarised that there are four prominent features that transformative researches share: a) the researchers have a special interest in groups whose lives have been constrained by oppressors and the strategies that these groups use to resist, challenge, and subvert these constraints; b) the researchers focus on understanding how inequities (gender, race, ethnicity, disability, sexual orientation, and socioeconomic class) cause asymmetric power relationships; c) researchers have obligations to exert political and social actions to tackle these inequities; d) researchers also need to understand why problems of oppression, domination, and power relationships exist.

Another world view, the Pragmatic Worldview, is derived from the work of Charles Sanders Peirce, William James, George Herbert Mead, and John Dewey (Zalta et al., 1995). As Picardi (2011) explained, pragmatists are anti-representationalism: that is, they argue that the function of research is not to represent reality but to enable people to act more effectively. Pragmatists are concerned more with applications—what works—and solutions to problems (Patton, 1990). In this worldview, truth is whatever works at the time. The truth is not based on a duality between reality and representation, which means it is independent of the mind. Many investigators who adopt mixed methods applied this view: they use both quantitative and qualitative data because they work to provide the best understanding of a research problem (Creswell & Creswell, 2017).

Philosophical assumptions and worldviews can help researchers explain why certain research designs were adopted for conducting the underlying research (Creswell & Creswell, 2017). There are three types of research methods: quantitative, qualitative, and mixed designs.

Quantitative designs originated mainly in Psychology and are invoked mainly by the post-positivist worldview (Campbell & Riecken, 1968). Some quantitative research methods often employ longitudinal data collection over time to examine the development of ideas and trends, and some structural equation models, hierarchical linear modelling, and logistic regressions to determine causal paths and identify the relative strengths of different variables. Common quantitative research methods include experiments, quasi-experiments, causal-comparative research, correlational research, and applied behavioural analysis (Creswell & Creswell, 2017).

Qualitative research designs originated from anthropology, sociology, and humanity studies (Creswell & Poth, 2016) and are often used to understand people's beliefs, experiences, attitudes, behaviours, and interactions (Pathak et al., 2013). Qualitative research designs are more reliable than quantitative designs when the research interest involves non-numeric data that need subjective interpretation (Gibson et al., 2004). With the development of new technologies and new research toolkits, quantitative studies are becoming more and more confronted with experimental research, and consequently, there is an increasing number of researchers that now use qualitative research designs to add a new dimension to interventional studies that cannot be obtained through the measurement of variables alone (Gibson et al., 2004). According to Creswell and Creswell (2017), there are five types of popular qualitative research designs; namely, narrative research, phenomenological research, grounded theory research, ethnography and qualitative case studies.

Mixed methods design sits in between quantitative designs and qualitative research designs. Researchers who use mixed designs usually combine and integrate qualitative and quantitative methods, as well as the data that are collected by both methods (Creswell & Creswell, 2017). Mixed method designs began in the 1980s or 1950s, depending on the definition of mixed methods designs followed. Teddlie and Tashakkori (2010) provided an extensive discussion on the development of mixed methods research, and they argued that mixed methods research should achieve four tasks: a) to find ways to integrate quantitative and qualitative data; b) researchers should be able to use one database to explain another database with different types of data; c) to build better research instruments based on multiple databases than having only one database; d) to ensure one database can build on other databases, and that one database could be compatible with other databases in a longitudinal study.

After deciding the choice of research designs, researchers then need to decide what specific research methods are needed to conduct a series of research tasks. There are many methods available for collecting data, tools for analysis, and interpretation that researchers propose for their studies, and none is substantially superior to another (Williams, 2007). As Hancock et al. (2001) suggested, choosing a correct research method is dependent on the research questions, the research phenomenon explored, and the data availability, interpretivity, and type. Creswell and Creswell (2017) summarised the distinctions in features among the methods that are commonly used in different research designs:

Research designs	**Quantitative designs**	**Qualitative designs**	**Mixed-method designs**
Method maturity	*Emerging methods*	*Pre-determined methods*	*Both*
Question type	*Open-ended questions*	*Instrument-based questions*	*Both*
Statistical method type	*Text and image analysis*	*Statistical analysis*	*Multiple forms of statistical methods, such as statistical and text analysis*
Data type	*Performance data* *Attitude data* *Observational data* *Census data*	*Interview data* *Observation data* *Document data* *Image data*	*Multiple forms of data*
Desired outcome	*Statistical interpretations*	*Themes, patterns, interpretations*	*Across databases interpretations*

Table 6. Features distinction between research methods of quantitative designs and qualitative designs

Also, according to Creswell and Creswell (2017), after making decisions on the above assumptions, world views, designs and methods, researchers arrive at an overall **research approach**. This decision and selection process is based on the nature of the research problems being addressed, the researchers' personal experiences, and the audiences for the study.

As previously discussed, this thesis mainly focuses on addressing three research problems, including how to motivate knowledge contributors to write better quality knowledge, how to motivate people to retrieve more data and knowledge from an open knowledge portal, and how to motivate users to exchange more knowledge on market-based knowledge exchange platforms.

According to Creswell and Creswell (2017), the researchers' own personal training and experiences also influence their choice of approach. I have received multi-disciplinary training ranging from *Economics, Finance, Computer Sciences,* and *Information Systems* and have mature programming and quantitative research skills. I also have more than seven years of experience in teaching and working in a wide range of industries such as telecommunication, NGO, banking and medical equipment manufacturing. This education and working background has helped me not only to better comprehend the research problems more incisively but also has enabled me to liaise with people in industries when required.

Each thesis shall have a targeted audience. In this thesis, I expect my future audience will be those who want to design tools to tackle practical knowledge exchange problems with valid theoretical underpinnings.

Based on the above information, I selected the Post-positivist Worldview with quantitative research designs in developing my research methods as the overarching research approach to guide the five studies of this thesis. The reasons are as follows: First, as Phillips et al. (2000) contended, the Post-positivist Worldview enables a researcher to develop relevant, true statements, ones that can serve to explain the situation of concern or that describe the causal relationships of interest. Through this process of finding causal relationships, I can advance the knowledge about the relationship among potentially useful factors that can motivate users to exchange more knowledge pieces online, answer relevant research questions and test my hypotheses.

Also, my research aims at resolving a series of inconsistent findings on the effects that are provided by the traditional motivational factors on users' online knowledge exchange behaviours. As Creswell (2014) contended, post-positivists aim to find more deterministic relations through research in which causes probably determine effects or outcomes.

Specifically, in the Information System research field, according to Gregg et al. (2001), the essence of the post-positivist epistemology is “confirmation”: As aforementioned, researchers upholding this view need to prove or falsify a series of hypotheses by manipulating experiment conditions and by observing different factors’ effects objectively. I also set up confirmation-oriented and falsification-oriented propositions, and by testing these propositions, I undertake a step-by-step investigation of the three overarching research questions around online knowledge exchange platforms. Additionally, the investigation results can be later used as grounds for further researches that adopt other interpretivism-oriented research paradigms.

Justification of selecting experimental research method in Study 1 and 2

In Study 1 and Study 2, I attempted to conduct random-assignment experiments to explore the impact of the motivational factors (e.g., extrinsic motivators), trying to prove or falsify their proposed effectiveness.

My study is practised in a manner of reductionism, trying to build a knowledge base of how to design a functional nudge for motivating knowledge contribution behaviours in online knowledge exchange platforms, step-by-step. According to Tharenou et al.(2007) a true experiment has five prominent features: it has an experimental condition or group derived by a stimulus; it has at least one control group; it shall be conducted in a controlled experiment; the allocation of participants shall be random; and it measures the dependent variables after the introduction of the treatment (stimulus). By doing so, researchers can reject alternative explanations, thereby allowing them to draw strong causal inferences (Graziano & Raulin, 1993). This is also supported by Creswell and Creswell (2017) who argued that experiments are suitable for examining causal relationship between and among variables. My first and second studies focus on finding a potential causal relationship between a motivational factor (i.e., the proposed nudge design and its variations) and desired knowledge exchange behaviours (especially the knowledge contribution behaviours). To this end, using an experiment research method can help me control other variables and ensure the high internal validity of the causal inferences of the usefulness of the extrinsic motivation designs that I have proposed in this thesis. Also, as I mentioned in the previous section, because there have been many inconsistent findings about extrinsic motivations noted in previous online knowledge exchange literature, it is preferable to use an experimental research method to isolate possible confounding factors when attempting to draw causal inferences.

Both Study 1 and Study 2 utilised a Posttest-Only Control-Group Design, which, as Creswell and Creswell (2017) defined, is an experiment where participants are randomly assigned to groups, a treatment is given only to the experimental group, and both groups are measured on the posttest. As Cooper et al. (2006) suggested, this research method uses random assignment to avoid risks that threaten internal validity. This method provides time for the participants to finish but also reduces the errors that potentially can be caused by repeated testing and instrumentation. Cooper et al. (2006) also suggested a double-blind research strategy (i.e., a design in which neither the researcher nor the participant knows when a subject is being exposed to the experimental treatment) for this type of experiment because it is necessary to control the pressure that is potentially applied by the researchers (the designers of the proposed nudge solutions) as well as unwanted complications such as subjects' willingness to achieve some desired outcomes influenced by experimenters.

As Cooper et al. (2006) pointed out, a Posttest-Only Control-Group Design can do little in terms of increasing the external validity of a study. Also, as Steckler & McLeroy, (2008) defined, external validity is the generalisability of a study's conclusion across different times, different settings, or different persons. Therefore, after conducting Study 1, I added a validation study (i.e., Study 2) to boost the external validity. In the follow-up study, I changed the overall settings of the experiment and also I hired a new group of participants, aiming for an increment in the consistency of conclusions that I drew from these studies.

Justification of selecting field study research method in Study 3 and 4

By cooperating with CSIRO's open science portal management team, I conducted Study 3 to assess the relative effects of several metadata quality factors on motivating people to retrieve more knowledge pieces from open knowledge exchange portals. In regard to this study, I needed to test hypotheses and find out answers to the root research question (i.e., what is a valid cost-efficient way to increase open knowledge's visibility and to better unlock its value?) of this study by assessing real-life settings and examining the extent to which the dependent variable and each independent variable are correlated. According to Tharenou et al. (2007), field studies are suitable for serving this type of research purpose. Similarly, Study 4 also focuses on collecting data in a natural setting rather than a highly controlled setting (i.e., a laboratory) and the purpose of the research in this study is to examine the current price structure of edX.org, formulate a model to examine what factors can usefully explain the differences in course prices, and investigate the "usefulness" of the price data, that is, what conclusions can be made from a given price information (e.g., checking if there is a salient effect caused by the price factor).

As with other field studies, my studies also used multivariate analysis toolkits to examine the correlations between the independent and dependent variables. This study followed Sekaran & Bougie's (2016) guidance that, in a field study, all variables shall exist in the field and be measured *in situ,* as they exist with minimal human interference.

I also followed Mitchell's (1985) guidance in my research method designs for Study 3. As this author also argued, when collecting data, researchers shall use a non-contrived design (i.e., researchers shall give as small a scale of contamination and manipulations to the research environment as possible). The research shall proceed in a naturalistic manner. The conclusion of the study, as I summarised in the corresponding chapter, largely makes associational (correlational) inferences rather than causal inferences.

Mitchell (1985) also argued that having a field study may commonly incur some problems, such as: a) the measurements may be not reliable; b) the statistical model for analysis may have low explanatory power; c) the planned sampling may be inadequate and unrepresentative; and d) it may lack of generalizable conclusions.

In my pursuit to enhance both the interpretability and validity of the study, I employed a systematic approach while designing Study 3. This method, detailed in the following paragraphs, was designed to provide a robust, transparent and replicable framework.

The first step in this process involved selecting a suitable sample pool for data collection. To achieve this, I turned to one of the world's largest open science knowledge portals. The selection of such a comprehensive and diverse sample source aimed to ensure the collected data is as representative as possible, covering a broad range of variables and interactions.

Next, I drew upon existing, mature models of research to ascertain the independent variables for the study. By aligning my study with established methodologies, I aimed to increase the credibility and comparability of my findings while also providing a solid basis for further scholarly investigation.

Thirdly, I conducted three rounds of investigation to deductively test the hypotheses and verify the conclusions. This iterative process was designed to add a layer of rigour to my research, ensuring that the results were not merely a one-time occurrence, but rather a consistent pattern that could stand up to repeated scrutiny.

The fourth aspect involved using an established procedure to determine the right statistical model for running the multivariate analysis. This allowed me to sift through the complex, multidimensional data, and draw meaningful conclusions that take into account the interplay between different variables.

For Study 4, I applied a similarly thorough approach to address potential insufficiencies common in field studies. Initially, I developed a crawler to extract the population of data from one of the world's largest MOOC platforms, edX.org. Additionally, all data fields that edX.org provided at the time of the research were retrieved. The intention was to ensure that the study had access to the most comprehensive dataset possible, thereby enhancing the reliability of the findings.

As with Study 3, I adhered to established procedures for modelling and statistical analysis. By doing so, I ensured the methodological rigour of the study and maximised the interpretability of the data.

By implementing these methods, I believe that the common insufficiencies typically associated with field studies can be substantially mitigated. This meticulous approach lends further credibility to the findings and offers a firm foundation upon which future studies can build.

Justification of selecting quasi-experiment research method in Study 5

When researchers cannot control enough of the extraneous variables nor the experimental treatments to use a true experimental design, a quasi-experiment approach shall be used to infer casual relationships (Cooper et al., 2006). In Study 5, I attempted to test the usefulness of adopting a market-based approach on motivating users to exchange more and match more useful knowledge pieces on knowledge exchange platforms. To validate that users will react positively when a market-based knowledge platform is introduced and to identify what factors may affect people's economic behaviours when they are involved in this market, I introduced a time series design in which repeated observations (before and after the implementation of the market-based approach) were made, and by doing so, I was able to turn the subjects to act as their own controls. Cooper et al. (2006) contended that this type of research method is preferable where regularly kept records are a natural part of the environment and are unlikely to be reactive. My Study's context, a knowledge exchange platform, fits this description well.

As Cooper et al. (2006) alerted, researchers who practise this type of research method may inevitably encounter a number of internal validity problems. To mitigate this problem, one of the most useful ways is to identify potential extraneous factors during the experiment and attempt to adjust the quasi-experiment results to reflect their influence. Following this recommendation, in my study, I also controlled four control variables (sex, income, department, and seniority).

Ethical considerations applied within the studies

Throughout the study, I abided by the ethical principles outlined by Israel & Hay (2006) and Hox & Boeije (2005) as well as the protocol requirements, policies and guidelines set up by the Research Ethics Office of the Australian National University (ANU). The key ethical considerations are seven-fold:

(1) Informed consent from participants and authorities

(2) Caring for the confidentiality and privacy of participant information

(3) Minimising risks of harm

(4) Using proper, small incentives to encourage people to consider participation

(5) Providing sufficient feedback

(6) Setting up proper research participant recruiting plans

(7) Developing a Data Management Plan (DMP) before beginning the research

As Rallis & Rossman (2009) suggested, reasonable adherence to ethical principles can promote the trustworthiness of the research process, establish a long-standing relationship between researchers and the participants, and provide an unwavering guide for the researcher's efforts throughout every aspect of the study.

Moreover, this thesis was granted the following research ethics clearance from ANU: 2017/807, 2018/215, 2018/820, and 2022/025.

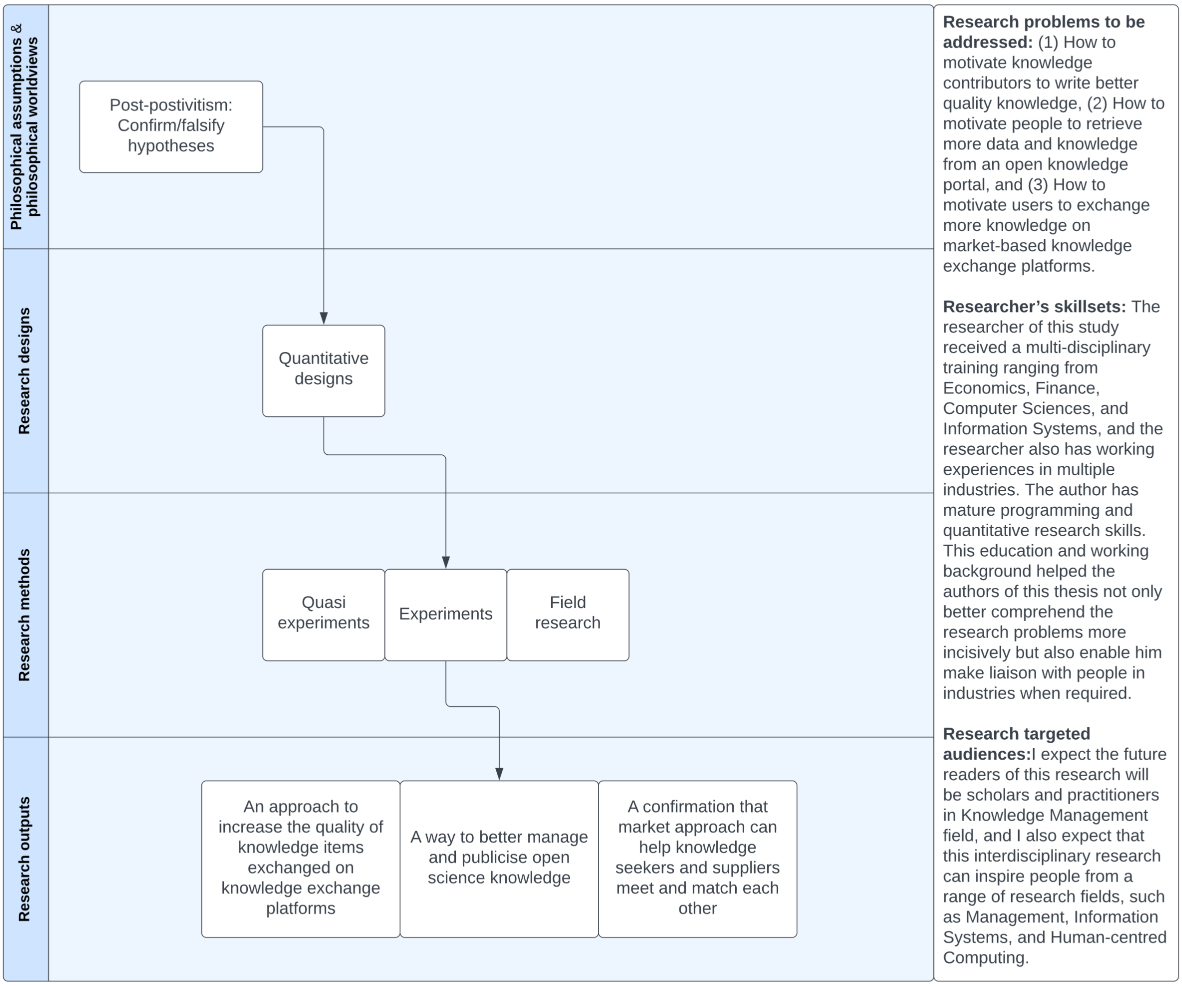


Figure 6. A review of the research approach selection adopted for this thesis

Chapter Summary

This chapter provides a summary of the overarching research approach that guides this thesis. As the picture shows, the research approach selection process commences with determining the overall philosophical assumptions and philosophical worldviews, followed by a selection of the corresponding research design. I mainly used three types of quantitative research methods to solve the research problems that I identified in the previous chapters, and the overall research approach is expected to resolve three research outputs which are also summarised in previous chapters.

To this point, the foundation of this thesis has been established through an exhaustive literature review and the meticulous selection of research methodologies. As I transition into the subsequent chapter, I will venture into the empirical realm of online knowledge exchange platforms.

Therein, I will elucidate the observations, processes, and outcomes of my research, all aimed at enhancing and elevating the quality of knowledge exchanges.

Starting from the next chapter, this thesis delves into the empirical realm. The initial study presented in Chapter 4 examines whether and how the nudge mechanism influences user behaviour within online knowledge-sharing communities. Specifically, the study aims to determine if immediate feedback can truly enhance the quality of knowledge contributions. Consequently, this thesis aspires not only to establish a theoretical framework but also to provide actionable insights for those seeking to refine these platforms. The overarching goal remains steadfast: to enhance and elevate the quality of knowledge exchanges, delivering a more effective and enriching user experience.

Chapter 4: Study 1 - Increasing the quality of knowledge exchanged on knowledge exchange platforms

Online knowledge exchange platforms have proliferated, each differing in form and function. From community-driven question-answering platforms like Stack Overflow and Zhihu to specialized forums in MOOCs and open knowledge data portals, the landscape is vast and varied. While they each serve the broader purpose of knowledge dissemination, their underlying mechanics, challenges, and incentives vary greatly. The journey of this thesis begins with the most ubiquitous form - social/community-based question-answering platforms. These platforms, rich in interaction and community spirit, have tried myriad incentivisation methods, from direct monetary benefits to subtler, reputation-based rewards. While the allure of monetary and social incentives is undeniable, many platforms still find themselves gasping for active, quality contributors, leading to their eventual decline. To revitalize these platforms, the thesis introduces a digital 'nudge'— Real-Time Quality Analyzer (RTQA)—a software solution aimed at bolstering knowledge contributors' enthusiasm and ensuring their contributions are of high calibre.

To achieve this objective, the study draws on Gratification and Nudge theory, to conceive and develop an immediate feedback nudge, the RTQA. The RTQA, a software prototype developed using JavaScript, resembles a plug-in that provides dynamic, real-time analysis of a user's textual contributions. Functioning via a JavaScript-based listener on the webpage, it estimates and reports the quality of textual contributions as they are being made, leveraging an algorithm grounded in natural language processing (NLP). The RTQA focuses on textual features due to their predominant role in online communication of general knowledge and their mature, computationally efficient characteristics. Its effectiveness and accuracy in estimating quality were confirmed through a pilot test involving 25 diverse knowledge contributions, which allowed for meticulous tuning of the nudge, reinforcing the reliability of the algorithm in use. This tool provides an innovative avenue for influencing user behaviour by targeting the immediate gratification component of decision-making. This nudge was rigorously tested by several approaches and then I used an experimental design to explore the effect of an immediate feedback functionality on knowledge quality and user engagement. The results of this chapter show that: 1) immediate feedback is an important motivator and positively affects users' online knowledge exchange behaviour; 2) the quality of users' contributions increase—without the need for users to spend more time editing their answers. This chapter offers an important contribution to the information management literature by demonstrating how users can be motivated to engage in higher quality online knowledge exchange behaviours.

Context

Some prior research suggested that exchange knowledge contributors consciously consider factors such as the size of the rewards, social networks improvements, trust in the community, types of content to be shared, and the perceived value of their contribution (Li & Du, 2011). Yet, recent research also shows that, largely, human behaviours are guided by non-conscious cognition and can be influenced by seemingly irrational elements in the environment (Khansa et al., 2015).

Nudge theory argues that these non-conscious heuristics and irrational elements can be exploited to nudge desired behavioural outcomes. That means that in the online context, purposeful interface designs can enable a system to influence users' behaviours by applying well known biases in human decision making in predictable ways (Acquisti et al., 2017; Schneider et al., 2018). For example, in a field experiment of a leading online education and career knowledge-exchange community in China, N. Huang et al. (2018) demonstrated that nudge messages that have a monetary incentive and relational and cognitive capital framing have a significant positive effect on users' knowledge exchange behaviours. However, the authors also reported that a nudge message with only a simple request for contributing something could reduce contributing-related behaviours, indicating that suboptimal design of digital nudges may decrease, rather than increase, desired behavioural outcomes.

To find an applicable bias, I must first understand why people make positive high-quality knowledge contributions in this specific context.

Generally speaking, Uses and gratification theory suggests that the key to promoting positive behaviours is to offer some form of external gratification. For example, Dolan et al. (2016) confirm that users' high gratification levels stimulate effective engagement and positive contributions, whereas low gratification levels lead to user detachment and negative contributions. Online community providers generally want users to engage actively to create value through positive interactions and contributions and do not want their users only to consume content passively (Dolan et al., 2019; Silic & Lowry, 2020; Yan et al., 2018). Uses and gratification theory, which originated in the communication field, elucidates why community members actively seek out and use specific media to fulfil needs, explains users' motivations, and predicts users' engagement behaviours (e.g., continuous content-contributing behaviours) on their knowledge-sharing community platforms (X. Liu et al., 2020; Muntinga et al., 2011; Shah, 2006).

Particularly, in the online context, gratification refers to the satisfaction perceived by users when they purposefully access certain media. Different levels of gratification lead to different levels of engagement behaviours (Chua et al., 2012). For example, as Dolan et al. (2016) summarised, high gratification can lead to positive-valanced engagement behaviours such as value co-creation and positive contributions, while low gratification provokes negative contributions and co-destruction.

Motivation as a gratification indicator has a strong influence on users' online behaviours. Users who actively engage in online knowledge-sharing communities are either intrinsically motivated (e.g., by the desire for self-expression) or extrinsically motivated (e.g., by anticipated extrinsic rewards such as points and badges), or are both intrinsically and extrinsically motivated (Ghasemkhani et al., 2016). Prior studies argued that a well-designed extrinsic motivation mechanism should curb individuals' intrinsic motivation by enhancing their perceived competence, which increases users' propensity and their capacity to make knowledge contributions (Catersteel et al., 2017; Priharsari et al., 2020; Yu et al., 2018). In some scenarios, even weak forms of extrinsic motivation can be useful in generating gratification for users and promoting their online knowledge-sharing behaviours (Zhao et al., 2016). Thus, there are many practitioners using tools and mechanisms that provide extrinsic motivation and recognition to increase user engagement levels, encourage desirable behaviours (i.e., high-quality knowledge-sharing behaviours) and discourage undesirable behaviours (e.g., writing low quality contributions, vandalisms, destructions, etc.) (Guo et al., 2020; H. Liu & Li, 2017; P. K. Roy, Ahmad, Singh, Alryalat, Rana & Dwivedi, 2018). However, it remains unclear what types of gratification-conferring mechanisms are most effective, particularly because some of the mechanisms that have been designed to reinforce positive user behaviours have been shown to produce no or even a negative effect on people's attitude and intention to contribute knowledge (Bock et al., 2005; Fischer, 2021; Jung et al., 2021; H. Liu, Zhang, Liu & Li, 2014; Zhao et al., 2016). As Yan et al. (2018) found, knowledge contributors commonly have a threshold for their motivation to trigger contributing behaviours, and the external intervention will have a positive effect on contributing behaviours only when the level of motivation exceeds the threshold value. Given that the amount of knowledge that a user is willing to contribute is a function of the user's perceived gratification brought by motivators, there is a need to maximise the effect that a motivator can exert.

Moreover, as Yan et al. (2018) argued, knowledge contributors generally have a threshold for their motivation, and only an incentive that brings external gratification that exceeds their motivation threshold value can have a positive effect on their contribution behaviour, meaning that an incentive that is below this threshold will not have a positive effect and might even have a negative effect. However, an online knowledge-exchange environment usually involves a significant time lag between a user supplying knowledge and receiving gratification, feedback and motivational recognition. When writing their knowledge contributions, contributors often do not know whether they are doing well, feel unsure of the value and use of their contribution, and do not receive a sufficient level of guidance (Ma & Agarwal, 2007). This lack of synchronicity further attenuates the positive effect that gratification can have on the motivation threshold.

To increase a knowledge sharer's willingness to contribute high-quality knowledge and to maximise the effect of a motivational tool's ability to confer external gratification, after reviewing literature, I theorise that one bias that can be utilised for knowledge-content creation is present-time bias (i.e., people prefer immediate gratification over delayed gratification (Adusumalli et al., 2020)). To test the effect of present-time bias on knowledge-content creation, I designed a nudge that provides instant feedback to the content creator; if the design is successful, I expect to see improvement in the quality of the knowledge content being contributed.

I argue that designing this nudge is important in managing online knowledge exchange and knowledge-exchange communities because it can address two prominent user-management problems that have been identified in the literature: 1) decreasing user engagement; and 2) low-quality contributions. First, decreasing user engagement is a problem that often manifests in unison with the growth of the number of users in a community (Butler, 2001; Tausczik et al., 2017). Low user engagement then leads to issues such as 'knowledge starvation' and a degradation of the community's overall effectiveness and usability (Cheng et al., 2017; Shtok et al., 2012). Second, low-quality contributions are often a consequence of the loss of user engagement. A knowledge-exchange community platform typically receives excessive poorly written, low-quality or even irrelevant contributions that can overwhelm other users, who need to filter out redundant information (N. Huang et al., 2017). This is a major problem for knowledge-exchange communities because it leads to users adopting increasingly passive behaviours, such as detaching from the community. Ultimately, a knowledge-exchange community then risks users disengaging, which can even lead to a community losing its purpose and value proposition for users (Guo et al., 2020; P. K. Roy, Ahmad, Singh, Alryalat, Rana & Dwivedi, 2018).

Specifically, this study is guided by one overarching research question: *How does a nudge (i.e., a real-time feedback mechanism) influence users' online knowledge-exchange behaviours, enabling them to write new high-quality contributions when they contribute new knowledge pieces?*

To answer this question, I hold that there is a need to reference prior research on designing and implementing digital nudges for promoting knowledge exchange behaviours. Also, these designs need to be not only empirically tested but also theoretically sound.

Prior research on digital nudges' designs with valid theoretical underpinning

The literature review of thesis reported that a key issue is that knowledge contributors do not receive direct and immediate rewards from their contributions, which hurts contributors' engagement and, therefore, their willingness to contribute. Many previous studies have attempted to resolve this issue based on a variety of theoretical backgrounds such as social cognitive theory, social capital theory, social exchange theory, and self-determination theory, etc. (Kang, 2022). The main findings of these studies are in Table 7.

Author(s)	**Theoretical framework**	**Design/motivator**	**Result/target**	**Timing**
Lou et al. (2013)	Self-determination theory	Reward in reputation systems	People's expectation of receiving a reward or recognition boosts their knowledge contribution behaviours. Reputational reward boosts contribution quantity than quality	*ex-post*
Tang (2012)	Empirical study	Revenue-sharing scheme, reputation scores	Revenue-sharing scheme and reputation scores can both be used to motivate content contribution	*ex-post*
Hamari (2017)	Gamification theory	Badges	By using badges, which function as social markers, users' contribution behaviours can be encouraged by recognising the	*ex-post*

			value of contributions after the sharing occurs	
X Wei (2015)	Motivation theory & online community commitment theory	Badges & rankings	Various badges/reputation-displaying tools can simultaneously play different, potentially contradictory roles	*ex-post*
Lee et al. (2010)	Uses and gratification theory	A content-sharing and retrieval tool	Gamified rewards can generate perceived gratification, which has a significant positive effect on users' intention to generate content	*ex-post*
Chua et al. (2012)	Empirical study	MobiTOP, a mobile content-sharing application,	Users' mobile content-contribution intentions were positively associated with two gratification factors: easy access and entertainment.	*ex-ante*
Sutanto and Jiang (2013)	Empirical study	Semantic score	The effect of a 'semantic score' (i.e., a rate calculated by a 'sophisticated' knowledge-management system to evaluate shared online knowledge) on knowledge contributors' frequency and tendency to share knowledge on electronic	*ex-post*

			knowledge repositories. All the knowledge items contributed to the knowledge base were transferred to a third-party organisation to calculate the semantic score, and the researchers found that this explicit rating had a positive effect on knowledge suppliers' contribution quality but not frequency.	
Huang et al. (2019)	Framing theory	Immediate framing-based performance feedback messages	Framing message can increase content quality significantly	*ad-hoc*
Li et al. (2017)	The affective response model	Information cue, ambient cue, social cue	Information cue, ambient cue, and social cue can be used to create an urge triggers users' immediate information-sharing behaviour	*ex-ante*
Moon and Sproull (2008)	Empirical study	An ad hoc feedback mechanism	A manually operated ad hoc mechanism that provides feedback (e.g., praise or critical messages) right after a contributor finished contributing, users' answer rate, return rate,	Nearly *ad-hoc*

			volunteer retention time and average answer quality increased.	
Jabr et al. (2013)	Empirical study	A feedback-based and a quantity-based recognition mechanism	Both types of mechanisms may improve the overall quality and efficiency of such forums	*ex-post*
L. Chen et al. (2019)	Affordance theory & self-determination theory	Upvoting, downvoting, and commenting mechanism	As predicted, traditional popularity-based voting system (i.e., upvotes and downvotes system) can significantly influence contributors' engagement, and negative votes significantly decrease their knowledge contributions	*ex-post*
Yoo et al. (2021)	Principle of Least Effort (PLE) and Fear of Negative Evaluation (FNE) model	Positive and negative feedback	Overall, removing the downvote option may positively influence the discussion culture on the platform	*ex-post*
Goes et al. (2016)	Goal-setting theory; status hierarchy theory	Rank	Glory-based incentives may motivate users to contribute more before the goals are reached, user contribution levels drop significantly after that	*ex-post*

Table 7. Prior Designs on Digital Nudges with Relevant Theoretical Underpinning

As indicated in the above studies, people's expectation of receiving a reward or recognition boosts their knowledge contribution behaviours (Lou et al., 2013; Okoli & Oh, 2007; Tang et al., 2012). It is also acknowledged that contribution behaviours can be encouraged by recognising the value of contributions after the sharing occurs. Further, considering the best form for a nudge, Luo et al. (2021) suggest graphic intervention targeting perception seems have a satisfactory effect on reducing friction in providing informational feedback to promote desirable behaviours. While these prior studies indeed offer a treasure trove of insights and valuable lessons, my examination of the existing literature identified two major issues that persist in the context of nudge creation. These issues, detailed below, represent substantial challenges that must be effectively addressed to enhance the efficacy and applicability of nudges.

First, it is notable that most of the motivators reported in the literature reviewed in this chapter do not provide immediate feedback. Further, evidence of the effect of the immediacy factor on changing user behaviours is not sufficiently conclusive. For example, in Huang et al. (2019)'s study, they found that by providing immediate framing-based performance feedback messages (e.g. 'you are in the top 5%' and 'your contribution helped 2,000 people'), contributors' content quality increased significantly, and that gender moderated this motivational effect—specifically, female users were more motivated by pro-social feedback, while male users were more motivated by messages that aroused competition. However, these normative feedback messages were purposefully fake and did not really evaluate the quality of the knowledge content. In addition, other research such as Li et al. (2017) examines the antecedents and mechanisms of users' immediate information-sharing behaviours on microblogs, but not the motivational effects of immediate feedback on users' information-sharing behaviours.

In relation to assessing the quality of the knowledge shared on sharing community platforms, for at least two decades, previous researchers have found assessors of textual features to be the most mature (Fu et al., 2015). Such assessors are readily implementable and are pivotal in judging quality, and a wide range of methods and features have been introduced to assess textual quality (Anderson et al., 2012). In addition, in relation to computational costs, it is usually less costly to monitor textual features than non-textual features such as network features. This is particularly important for a nudge that utilises present-time bias, which emphasises the importance of immediacy, meaning that it is necessary to select textual features that can enable the nudge to balance the trade-off between estimation accuracy and timeliness. I reviewed methods existing in prior literature and find that most studies that used textual factors to assess knowledge quality commonly used three readily implementable textual factors: length, readability and style. Length is the most straightforward of the three. Edelman (2004) found an answer's length to be a critical predictor for the quality of the knowledge it contains. Adamic et al. (2008) found that if they used content length to predict a contribution's quality, they could achieve a 62% prediction accuracy, indicating most knowledge receivers prefer to receive informative answers, which indicates the longer answers were of higher quality. The empirical research of Jeon et al. (2006) indicates that, within a certain range, an answer's length positively correlates with the answer's quality, but the relationship is not monotonic. P. K. Roy, Singh, Baabdullah, Kizgin and Rana (2018) also successfully used length, as well as the number of nouns, verbs and adjectives, to identify the most promising answers in question-answering platforms. Research shows that the probability of creating a good answer increases with the length of the answer initially, but eventually declines. For example, Fink et al. (2018) suggest that a contribution's length has a parabolic (inverted-U-shaped) relationship with its quality. Sufficiently long articles can contain more diversified styles, more supporting evidence, and better organisation (Attali & Burstein, 2004). Therefore, even when conciseness is considered, within a certain range, 'good-length knowledge' and 'high-quality knowledge' do not conflict with each other. In the nudge proposed in this study, an article's length was used to calculate the length score which follows a parabolic curve for length, with the highest value reached when the length of the contribution is approximately 500 words. This means that an increase in length score is positively correlated with a contribution's quality when it has fewer than 500 words and negatively correlated with quality when the contribution has more than 500 words. In the pilot test stage of this study, 91 answers were randomly retrieved to fine-tune the analyser that was developed for this study. Those answers attracted millions of views and thousands of comments from Quora and established approximately 500 words as the desired length for a high-quality answer.

Readability is also highly relevant to determining an answer's quality, particularly for texts in virtual spaces (Laplante-Lévesque & Thorén, 2015). Researchers have created various methods to measure readability, such as the Flesch–Kincaid readability test, the Gunning fog index and the SMOG index (Fu et al., 2015). This research adopted the Flesch–Kincaid readability test. This test determines readability based on average sentence length and the average number of syllables per word—shorter words and sentences score higher for readability—and this method has been used in previous studies that predict high-quality answers (P. K. Roy, Singh, Baabdullah, Kizgin & Rana, 2018). This study also recognise readability as an important adjusting factor for evaluating textual-based knowledge (and particularly for evaluating online knowledge). That, users may not accept a high-quality essay (based only on its grammar and content) as a 'good' answer for knowledge-sharing purposes on question-answering platforms. Rather, they may read and prefer answers that they can more easily understand (Jeon et al., 2010). In fact, during the pilot test stage, I confirmed this pattern on Quora: I found that high-quality answers had a better readability score (~83.52/100 on average) than 52 selected pieces of exemplary high-quality English essays (~52.06/100 on average).

Style refers to writing style. Although such style is highly personal, some English writing styles perform significantly better in relation to how well they express and convey information in an online context (Krashen, 2003). A high verb-to-noun ratio represents a good writing style because it produces writing with vigour, persuasiveness and a dynamic voice (Moxley, 2015). While individual sentences vary, the average of this ratio across a written text is informative (Polinsky, 2012). Overly large or excessively small verb-to-noun ratios can often indicate that text contains many grammatical mistakes (Zingeser & Berndt, 1990). A sentence without a verb usually signals an incomplete sentence or a sentence fragment, and a sentence without a noun may be grammatically complete but is usually not suitable for formal writing. Both cases can serve as useful indicators for low-quality writing.

Hypotheses development

As the literature review section mentions, the quality of the knowledge content is important for open innovation, knowledge accumulation and diffusion, customer collaboration and co-creation, and crowdsourcing. Thus, there is a need to develop a motivational nudge that can utilise present-time bias to provide immediate gratification to user to promote their engagement when contributing knowledge. When engaged, as Hafeez et al. (2019) argue, contributors tend to spend more time writing and editing and write longer contributions.

Thus, if the design of the nudge is successful, it is expected that the nudge will successfully motivate knowledge contributors to write longer contributions and will increase their editing time.

H1 The implementation of a nudge that utilises present-time bias to provide immediate gratification to knowledge contributors can increase the length of contributors' written contribution, compared with having no such nudge.

H2 The implementation of a nudge that utilises present-time bias to provide immediate gratification to knowledge contributors can increase the length of time users spend editing their contribution, compared with having no such nudge.

Furthermore, it is anticipated that the nudge will enhance the motivation and engagement of knowledge sharers during the contribution process, thereby improving the overall quality of their knowledge contributions. This presents an opportunity to reconcile the inconsistencies highlighted in existing literature and addresses the gaps discussed in the preceding sections of this chapter.

H3a The implementation of a nudge that utilises present-time bias to provide immediate gratification to knowledge contributors can enhance the overall quality of the contribution, compared with having no such nudge.

Finally, as previously discussed, if a knowledge-sharing community's platform contains too much poorly written information that can overwhelm users, users need to spend considerable time searching for what they want and filtering out what they do not. This has led to many knowledge-sharing sites, both private and public, losing a significant number of users, and therefore knowledge suppliers (Campanelli, 2006; Fang et al., 2018). If the nudge developed for this study is effective, the proportion of non-inferior answers to all answers that the person contributes will be higher, which means lower searching costs for community members. Therefore, the following hypothesis is also formulated:

H3b The implementation of a nudge that utilises present-time bias to provide immediate gratification to knowledge contributors leads to an increase in the proportion of non-inferior-quality contributions, compared with having no such nudge.

Method

Materials

This chapter presents an experimental study, and the first step of it was to develop a working nudge. It was a software prototype and the name of it is Real-Time Quality Analyzer (RTQA). The RTQA was a plug-in like ‘displayer’ (see Appendix 1). It has an algorithm based on natural-language processing (NLP) embedded in it. The software was developed as a JavaScript and is able to monitor and estimate the quality of a single piece of a user’s textual contribution. The software can evaluate textual features in real time and report the evaluation result back to the user dynamically (i.e., through a JavaScript-based listener on the webpage used to capture the user contribution). This software focuses on textual features for three important reasons. First, general knowledge, rather than on domain-specific knowledge, was used and this type of knowledge communicated online is mainly text based (Fu et al., 2015). Second, as stated, these features are relatively mature and consume few computational resources. In the pilot test, the nudge was well-tuned using 25 knowledge contributions of different levels of quality (the criteria for assessing quality are listed in *Procedures: After the experiment, page 151*). Based on the pilot test and the post-hoc test on the nudge, it can be confidently concluded that the algorithm adopted in this study was sufficiently effective and accurate in estimating quality.

The experiment settings

To analyse the effectiveness of the nudge proposed in this study, a randomly assigned double-blind experiment was conducted. In this experiment, a mock generic question-and-answer knowledge-sharing platform was built on which participants could select and answer questions. Notably, the question bank that was used in this study contained questions extracted from the test bank of the Graduate Management Admission Test's (GMAT's) Analytical Writing Assessment section. One of the merits of having these questions was because they were in a standardised form (i.e., they all have a similar level of difficulty) (GMAC, 2018). Also, the questions are designed to be uniformly of low interest and are not expected to generate a great deal of intrinsic motivation and gratification in users. Therefore, in the treatment group in this study, the source of motivation and gratification, if any, is expected to be from the nudge. I transformed the presentation of the selected questions into a form that seemed more like questions that require general knowledge on question-answering platforms, such as Quora, a typical platform for such communities.

Participants

The participants for this study were called through advertisements in a participant-pool system that a public university in Australia owns and sponsors. Table 8 describes the participants. Notably, there are several variables were used a filter in this experiment, including academic capability (i.e., participants must have had a cumulative grade point average (cGPA) higher than 5/7[3]);

[3] Note that in the context in which the researcher of this thesis conducted this experiment, the cGPA is calculated on a seven-point scale (7 = high distinction ≈ A; 6 = distinction ≈ B, 5 = credit ≈ C, 4 = pass ≈ D, and 0 = fail = N).

professional English ability (i.e., participants needed to be native speakers or to have an International English Language Testing System score or its equivalent of 7 or higher in writing[4]).

I also expect the participants have prior experiences in participating in online knowledge-sharing communities. If they do not have that experience, a special education session was presented to them.

The researchers also tested participants' attitude to money via a personality test whose questions were extracted and adapted from the International Personality Item Pool (Furnham, 1984; Goldberg et al., 2006; Khare, 2014). This test was conducted because it could be argued that the nudge tested in this study merely serves as a moderating variable that enhances the relationship between monetary reward and knowledge sharing. If that was the case, users with different money attitudes could be expected to have different levels of outputs (i.e., users who are more eager to earn money would contribute more). This study showed attitude towards money had no significant effect on the results.

During the experiment, the researchers did not know who belonged to the control group and who belonged to the treatment group. All the participants sat in a lab using identical computers with physical barriers installed to prevent them from communicating with each another.

Conditions	Treatment group	Control group	Total
Number	35	36	71
Gender	Female: 21 Male: 14	Female: 19 Male: 17	Female: 40 Male: 31
GMAT-test experience	No: 29 Yes: 6	No: 30 Yes: 6	No: 59 Yes: 12

[4] These control variables were used to ensure the experiment's internal validity, but these controls inevitably limited the external validity of the research (i.e., this step might automatically exclude less academically successful users who had low grade point average and low GMAT scores).

Have used question-answering-based knowledge-sharing communities in the past 12 weeks or engaged in any question-answering-related knowledge-sharing, -seeking and -viewing behaviours	No: 4 Yes: 31	No: 6 Yes: 30	No: 10 Yes: 61

Table 8. Participant Demographics

Procedures

The experiment had the following five sections: 1) acknowledging and signing the information sheet and consent form; 2) introduction to community-based question answering sites; 3) familiarity exercises (to help participants learn to interact with the experimental environment); 4) experimental tests; and 5) demographic questions.

Before the experiment

Before conducting the experiment, the participants were provided with an electronic information sheet and a consent form that explained the payment details. The participants were paid in both the treatment and the control groups using the same payment schedule. The payment consists of two parts: a fixed pay (AU$10—approximately US$7.40 at 3 September 2021) and a small variable pay (depending on the quality and quantity of their contribution). The participants were given an information sheet which explained what a question-answering platform is and what the background story of this study is. The information sheet also illustrated some exemplar knowledge-sharing communities and told the participants that people who provided good answers on some of those websites had the potential to receive a series of rewards and recognitions. The sheet also told the participants that, as on Yahoo!Answers and several other sponsored question-answering platforms, users who contributed good answers could even receive extra money. The sheet also notified them that the experiment would gather information around users' knowledge-sharing behaviours.

To avoid the Hawthorne effect, the researchers did not mention the existence of the nudge at this stage. In addition, this study controlled the participants' money attitude and random assignment method to cancel out any potential confounding effect generated by attitude towards money.

After reading the sheet and signing the form, participants went to a participant education session that has the following three steps: 1) two questions that asked participants about their prior experience with online knowledge-sharing communities; 2) an introduction to knowledge sharing on those communities; and 3) an experiment qualification test. Through these steps, the participants can get familiar to become familiar with the experiment environment and showed them how to interact with it.

During the experiment

Both the treatment and the control groups received the same questions in the same environment (i.e., the user interface had the same features such as layout, design, font and size), but the treatment group saw the questions along with the 'displayer' that showed the sentence: 'An AI [Artificial Intelligence] program estimates your answer's value and rates it: *x*', where *x* reflected the algorithm's assessment of each participant's contribution. High-quality inputs caused the indicator to move from the red area to the green area (See Appendix 1). Each participant received at least one and at most, three rounds of questions. They were required to complete only the first round.

The participants were provided with a question menu comprising seven questions. Out of these seven questions, participants could choose at the most two questions in each round. The participants in both the treatment and the control groups received the same questions, and they selected one or multiple questions to answer. After answering all the questions that they chose in the first round, the researchers asked participants if they wanted to participate in an extra round. Each participant could do two extra rounds at the most.

After the experiment, all the participants received a block of demographic questions. In addition, in the wrap-up section of the experiment, the participants were informed about how to obtain reimbursement, the quality-assessment criteria for their knowledge contributions, and how to access the results of the study. For each session, when a participant chose more than one question, the participant could go back and forth between questions by pressing the '<<' and 'next' buttons, respectively. The system they used automatically recorded and saved the text they input. However, participants could not go back to a previous session (e.g., from the second round to the first round) if, for example, they wanted to edit an answer they had previously submitted. In addition, all participants could stop the experiment at any time, which was reiterated verbally as they began the experiment.

After the experiment

Trained research assistants, who were paid AU$20 (US$14.81) per hour) judged the quality of the answers that the participants provided. These research assistants were referred to as graders. To do so, a custom-built designated PHP-based website was used, and this website was built for this study. Each grader was assigned a password-protected account, so that they could not see or change each other's decisions, and the graders could not interact with each another when grading. The graders assessed two responses to the same question at a time (see Appendix 2) and were required to judge which one had better quality based on the following four factors:

- Accuracy: An answer is convincing, that is, it contains valid and reliable factual information and credible sources for references (Jeon et al., 2010). It is relevant, that is, it pertains to the question (Jeon et al., 2010), and is complete and objective (Shah & Pomerantz, 2010).
- Readability and interestingness: An answer should not be boring (Chen & Sin, 2013). The answer should be understandable, clear, and the logic of the contribution should be coherent and easy to follow (Ghose & Ipeirotis, 2011).
- Richness and informativeness: An answer should provide many details and should be presented in a diversified manner and reflect diverse perspectives (Jeon et al., 2006).
- Usefulness: An answer should have value in use and be perceived as helpful, that is, it can address the problems mentioned in a question (Shah & Pomerantz, 2010).

Based on the above criteria, the graders awarded one 'point' to the answer with better quality. For every grader, each answer reappeared four times, so each answer had a maximum score of four points and a minimum of zero. After the grading process, I automatically categorised all answers into five quality classes based on their score: 'excellent' (four points), 'above average' (three points), 'moderate' (two points), 'below average' (one point), and 'inferior' (zero points). In addition, the grading system was designed in such a way that each answer had an equal chance of appearing before the graders assessing it. The final results show that this type of quality estimation mechanism was effective, and it shows that a substantial level of agreement among the graders was obtained.

	ICC	95% Confidence interval		F-test with true value 0			
		Lower bound	Upper bound	Value	df1	df2	Sig
Average measures	0.871	0.839	0.897	7.755	232	464	.000

Table 8. Intra-Class Correlation Coefficient for Graders

Results

This section focuses on examining the outcomes of several key variables including knowledge-quality score, time, proportion of non-inferior answers, and length, which were treated as dependent variables. In this study, the presence of the nudge was examined as an independent variable. I also took into consideration other potentially influential factors such as the total time spent by a participant in editing answers. The goal was to determine whether these factors could shed light on the effect and impact of the nudge.

Concept name	Definition	Measure	Range [0, 4]
RTQA score	'AI' score generated by the system	Automatically calculated by system	0 = Pointer at red area 1 = Pointer at dark yellow area 2 = Pointer at light yellow area 3 = Pointer at light green area 4 = Pointer at dark green area
Knowledge-quality score (experts' score)	Score given by a group of human experts	Expert rating	[0, 4]
Time	Time the participant spent on completing the experiment (seconds)	Automatically recorded by system	[193, 7293]

Proportion of non-inferior answers (expert scores)	Number of non-inferior answers participant contributed / Total number of answers that participant contributed	Expert rating	[0,1]
Length	Length of answer (characters)	Automatically calculated by system	[247, 10327]
Treatment condition	Participants were randomly assigned into an experimental group—either the treatment or the control group	N/A	Treatment/Control

Table 9. Measurement Definitions

		Time (seconds)	Proportion of non-inferior answers (experts)	Length (characters)	Knowledge-quality Score (experts)
Treatment	M	3325.91	0.78	4328.71	2.35
	SD	(237.01)	(0.43)	(414.53)	(0.12)
Control	M	2989.00	0.59	3109.43	1.69
	SD	(255.76)	(0.36)	(305.41)	(0.11)

Table 10. Descriptive Statistics, Means (standard deviations) for Treatment and Control Groups

Subsequently, a one-way analysis of variance (ANOVA) was conducted to test the effect of the treatment. Note that the measurements were standardised using z-scores. Then, a homogeneity of variance was performed based on Levene's test ($p > 0.01$) and found no major concerns. As Table 11 demonstrates, the immediate feedback mechanism had a significant positive effect on answer length and the knowledge-quality experts' scores ($F(1,69) = 4.803$, $p < .032$ and $F(1,231) = 17.130$, $p < .001$, respectively). Therefore, this study's result demonstrated that participants reacted positively to the nudge. That is, the knowledge contributors who experienced the nudge while creating a response wrote longer and higher-quality contributions than those who did not experience the nudge.

		SS	**df**	**Mean square**	**F**	**Sig.**
Time	Between groups	0.931	1	0.931	0.930	0.338
	Within groups	67.069	67	1.001		
	Total	68.000	68			

Proportion of non-inferior answers (expert scores)	Between groups	0.623	1	0.623	3.993*	0.049
	Within groups	10.772	69	0.156		
	Total	11.396	70			
Length	Between groups	4.556	1	4.556	4.803*	0.032
	Within groups	65.444	69	0.948		
	Total	70.000	70			
Knowledge-quality score (expert scores)	Between groups	16.017	1	16.017	17.130***	<0.0001
	Within groups	215.983	231	0.935		
	Total	232.000	232			
Note: *p < .05. **p < .01, ***p < 0.005						

Table 11. ANOVA Table (One-way) for Time, Proportion, Length and Knowledge-Quality Scores

It is also found that the nudge had a slightly positive effect on the time users spent writing their contributions. Participants who experienced the nudge spent averagely 10.12% more time on editing. However, the effect did not reach statistical significance.

From the result, it can be observed that some participants preferred to refine their answers after finishing their first draft. These participants were found in both groups and used more time to compose their contributions. It is possible that, although users in the treatment group wrote longer answers, users in the control group with this preference might have taken more time refining their answers because they had no present-time information about their answer quality. However, the participants in the treatment group might have taken less time to refine their answers because they were interacting with the nudge proposed in this study, which gave explicit feedback, consequently saving them some time. This may be reflected by the fact that users in the treatment group contributed significantly fewer answers of inferior quality than users in the control group. Participants in the treatment group also contributed a higher number of standard-quality (non-inferior) level answers, but this difference only marginal reached statistical significance. Table 12 summarises the support for the hypotheses.

No	Hypothesis	Support
H1	The implementation of a nudge that utilises present-time bias to provide immediate gratification to knowledge contributors can increase the length of contributors' written contribution, compared with having no such nudge.	Yes
H2	The implementation of a nudge that utilises present-time bias to provide immediate gratification to knowledge contributors can increase the length of time users spend editing their contribution, compared with having no such nudge.	No
H3a	The implementation of a nudge that utilises present-time bias to provide immediate gratification to knowledge contributors can enhance the overall quality of the contribution, compared with having no such nudge.	Yes
H3b	The implementation of a nudge that utilises present-time bias to provide immediate gratification to knowledge contributors leads to an increase in the proportion of non-inferior-quality contributions, compared with having no such nudge.	Yes

Table 12. Summary of Support for Hypotheses

Discussion

In an online knowledge-sharing community, poorly written, low-quality contributions may be worse than no contributions at all, but willing contributors are rare, so a knowledge-management system needs to find mechanisms to nudge users to make useful contributions. To promote user positive engagement, increase high-quality contributions and reduce poor quality contributions, a nudge was designed, and it can assess users' knowledge contributions and provide motivational feedback in real time. The feedback mechanism is designed as a nudge in such a way that it can promote gratification and, therefore, hedonic motivations in users, thereby influencing users' online knowledge-sharing behaviours. The proposed nudge also highlights the notion of immediacy and by doing so, the tool can maximise the power that a motivational mechanism has in encouraging desired actions, making the mechanism create sufficient user gratification to exceed the motivation threshold value for contribution, thus motivating users to engage in pro–knowledge-sharing behaviours.

As previously discussed, the nudge was created based on existing literature on knowledge management, uses and gratification theory, nudge theory and text-assessment techniques. This study uses a double-blind experiment to confirm that the nudge boosted users' gratification and encouraged more and better knowledge sharing. Specifically, users' contributions were more accurate, relevant, interesting, readable, informative and useful. According to Y. Zhang et al. (2019), these are the most common factors for determining knowledge quality in an online knowledge-sharing environment. This study's experiment generated robust results and one of the reasons is a range of variables were well-controlled, such as user's writing capability, prior experience and familiarity participating in online knowledge-sharing communities, academic ability, writing environment, input equipment, attitudes towards money, income level, gender and educational attainment.

Limitations and future research

The study presented in this chapter has some limitations. Cultural factors were not consider in this study, but this study did acknowledge that different cultures have different knowledge-sharing behaviours and preferences (Ford & Chan, 2003). For example, in firms with a Confucian culture, users with a strong perceived ability to share knowledge have a weak intention to do so in public because others can perceive such behaviours as 'showing off', which can lead to negative consequences for the individuals who display them (Kuo & Young, 2008). Other personal and cultural factors (e.g. face saving and face gaining) may reduce or negate the effectiveness of the extrinsic motivators that were described in this study (Ding et al., 2017; Huang et al., 2008). Further, the quality estimator proposed in this study can deal only with English answers mostly because NLP techniques have a higher maturity for English than for other languages (Hirschberg & Manning, 2015). Ideally, one could mitigate if not eliminate this inclusiveness problem by further developing NLP technologies. Further, as one of the graders argued: 'Different people may have different tastes and opinions on what should be counted as a high-quality answer'. Moreover, there is a need to collect longitudinal data to verify whether the mechanism has long-term usefulness for contributors, because a previous study suggests that the motivational effect on contribution effort and quantity of extrinsic recognition tends to be very high for first-time recognised contributors, but is followed by a declining trend in both effort and quantity when the extrinsic recognition is received in subsequent years (Bhattacharyya et al., 2020). Thus, it could be beneficial to combine the proposed mechanism with other types of proven motivators. However, it can be believed that the mechanism proposed in this study would play a critical role in any such combination because the effect of automated, objective motivators—such as the nudge that was proposed in this study—for recognising members is usually higher than that of non-automated, subjective recognition because the former may avoid the case of unwanted demotivation and reduce the chance of non-recognition of deserving members (Bhattacharyya et al., 2020).

Therefore, it seems reasonable that, when evaluating the quality of knowledge contributions, future research should consider factors such as knowledge type, user subjective preference and user cultural background. Although, in this study, fixed factors were used to evaluate the quality of a knowledge contribution, in the real world, this evaluation process may be less useful because one cannot force everyone to accept a pre-defined set of high-quality criteria (i.e., assessing knowledge quality involves a great deal of subjectivity). Hence, there may exist a need to have a better-quality estimator to ensure the nudge can provide accurate feedback to motivate the desired behaviour, and future practitioners should use the proposed estimator as 'a' tool, rather than 'the' tool. Future research could adopt other research designs to verify the conclusions drawn in this research. The nudge was observed effective in motivating users to share better-quality contributions to avoid receiving a low score, which, in an experimental scenario with undergraduate students, is more likely to become a factor that motivates users to provide a better-quality contribution. However, in a non-experimental setting, users may become annoyed over time, particularly when the score does not meet their personal expectations, and, consequently, decide not to share at all. Despite this possible effect on the results, Compeau et al. (2012) argue that student samples are appropriate for testing theories about phenomena that are expected to hold true across the general population, and there is evidence that students contribute knowledge to and participate in online knowledge-sharing communities (Kim et al., 2015). Nonetheless, a field study of a real-life online knowledge-sharing community would be useful for future research.

Implications

Despite the limitations of this research, this study has three important implications. First, the study extends previous research using two established theories (i.e., uses and gratification theory and nudge theory) to build and evaluate a nudge (as an extrinsic motivator) that provides immediate motivational feedback to promote knowledge-sharing behaviours. Although previous studies acknowledge the usefulness of offering gratification to users when they share knowledge and the importance of the immediacy factor on information sharing and contributing, as C. Wang et al. (2015) suggest, empirical evidence, is still lacking, and this study fills in this gap by experimentally testing the ability of a nudge to increase users' engagement level and motivate them to contribute high-quality knowledge in online knowledge-sharing communities. This study demonstrated that the nudge proposed in this study could increase contributors' knowledge-sharing behaviours and cause positive engagement behaviours and reduces negative engagement behaviours.

Because the result of this study has shown a new form of extrinsic motivator that provides immediate feedback, I believe the conclusion from this study also adds to theoretical knowledge of extrinsic motivation mechanisms in an online knowledge-sharing context and help reconcile the inconsistent findings about extrinsic motivations from previous online knowledge-sharing and knowledge-management research by highlighting the importance of the immediacy factor. It is argued that this factor can amplify the motivational power of extrinsic motivators, provide sufficient positive gratification, motivate people to react to the external motivator, and eventually, make the extrinsic motivator more likely to translate into real-life knowledge-sharing behaviours.

The results of this study provide a potential technological solution to a real-world problem with measurable improvements. As Pan and Pee (2020) argue, an information systems research output should be able to translate research findings for users in a practically applicable form, have both depth and breadth of use, and provide efficiency and effectiveness improvements for users. The results can also be used by community managers, particularly those who run an online platform, forum, or other form of online communities that requires detailed answers or knowledge contributions to seed further knowledge-sharing behaviours in a low-cost manner. As Bhattacharyya et al. (2020) and Gneezy et al. (2011) state, such a cost-effective tool can be a preferred way of implementing external interventions because it imposes less financial cost. The finding shows that an immediate feedback system can improve overall contribution outcomes of an entire online knowledge community by increasing the proportion of better-quality contributions and thereby reducing the search costs of all users. This can further increase the vibrancy of online knowledge communities and increase the level of user engagement. The results of this study also provide evidence for the visualisation of such an analyser and suggest how it can be used in real-world settings. In addition, the results can be generalisable to communities that do not have payments for promoting good knowledge contributions and to non–question-and-answer websites, such as general electronic networks of practices, a superclass of question-answering platform, and other user-generated content scenarios, although this needs further research to confirm this generability. As S. Lee et al. (2018) note, readers tend to perceive and prefer user-generated reviews with detailed descriptions and many nouns, verbs, adjectives and adverbs. With a well-designed real-time feedback nudge, such as the one proposed in this study, future researchers may be able to directionally motivate contributors in knowledge exchange communities to author more and better-quality articles. Ultimately, the nudge that was proposed in this research can help mitigate the online knowledge-sharing problems identified at the beginning of this paper.

Summary

Historically, most studies probing into the motivators for enhancing user engagement in online knowledge sharing have hinged on ex-ante or ex-post motivators, overlooking the potential of real-time mechanisms. This research underscores the efficacy of immediate motivational feedback in fostering knowledge-sharing behaviors. Specifically, the study reveals how such feedback can sculpt user behaviors within an online knowledge-sharing community, prompting them to proffer superior quality answers. Drawing from a comprehensive review of prior research on knowledge contribution behaviors, and by weaving in the uses and gratification theory and nudge theory, I devised a novel nudge—RTQA—to test the hypotheses posited at the chapter's outset. In doing so, this chapter not only contributes to current understanding but also paves the way for future exploration. In continuation of this thread, the subsequent chapter will introduce another context wherein the proposed digital nudging mechanism may find applicability. The decision to segue into another context in the ensuing chapter is deliberate. Firstly, it provides a rich and varied environment in which to validate and broaden the applicability of the digital nudge, thereby enhancing its external validity. Secondly, the intricate nature of these forums, woven with student interactions and academic discourses, introduces a unique set of challenges and opportunities. This makes them an ideal backdrop for both the application of the digital nudge and the evaluation of the design paradigms discussed in the current chapter.

Chapter 5: Study 2 - To Promote Pro-Knowledge-Exchange Behaviours on MOOC forums via a Participatory Action Research

Venturing further, the spotlight shifts to MOOC forums, a specialized subcategory within the knowledge exchange sphere. Unlike broader platforms such as Yahoo! Answers, these forums cater to the educationally-inclined, fostering discussions anchored to course material. I expect the mechanism that I developed can also be used in these forums. Thus, this deep dive also aids in assessing the broader applicability and robustness of the aforementioned digital 'nudge' beyond general platforms.

MOOCs (Massive Open Online Courses) are a promising form of knowledge sharing and are considered by many as a disruptive teaching and learning approach which can supply knowledge resources on a massive scale (Aparicio et al., 2014; Kaplan & Haenlein, 2016; Ryan & Williams, 2014). A MOOC usually involves a very large number of students from different backgrounds, learning capabilities, and motivations, and it needs to provide its students with a flexible learning pace and allow an on-demand certification (García-Molina et al., 2021; Kim, 2014). Most MOOCs have a strong focus on collaboration and cooperation among learners, so the traditional way of classroom education, which emphasises a teacher-centric way of sharing knowledge, becomes less effective in MOOCs (Li & Xing, 2021). Due to these characteristics, most MOOCs (especially cMOOCs, featured by their "connectivism" nature and having been launched on mainstream MOOC platforms, such as edX, FutureLearn, and Coursera) emphasize the importance of social-networked learning and knowledge-sharing behaviours among their participants (Beaven et al., 2014; Kaplan & Haenlein, 2016; Mackness et al., 2010). To enable social-networked learning, many MOOCs providers and instructors use discussion forums as their primary tool, and they also expect the forums to enable knowledge exchange among peer students, monitor how learning proceeds in the course, and enhance students' overall learning experiences and learning outcomes. The positive effect of running a healthy discussion MOOC forum has been adopted by many prior researchers and practitioners (Engle et al., 2015; Gillani & Eynon, 2014; He et al., 2018; Kizilcec et al., 2013). As indicated by Daradoumis et al. (2013) and Mackness et al. (2010), a MOOC's success is largely determined by its effectiveness in knowledge sharing.

Clearly, knowledge exchanging in forums is an important part of MOOC. However, many researchers have found forums usages are inactive and inadequate for many MOOCs. The low level of lack of exchange among MOOC learners can yield negative effects on students' learning and create high dropout rates (Li & Xing, 2021; Mackness et al., 2010). As stated by Yousef et al. (2014), it is common to see MOOC forums having insufficient participation rates and knowledge with inferior levels of quality being shared, resulting in high-quality knowledge pieces crowded out by the low-quality ones. A low level of knowledge exchange and interaction on MOOC forums also leads to knowledge suppliers feeling they are isolated, which further suppresses the desire to share knowledge and ideas (Almatrafi et al., 2018). Consequently, useful content becomes hard to find, which increases potential knowledge sharers' frustration and further degrades the participation rate (Graham & Wright, 2010). As a result, the problem of knowledge starvation also becomes common in MOOC forums, resulting in a decrease of their overall knowledge exchange effectiveness (D. Onah, Sinclair & Boyatt, 2014; Shtok et al., 2012).

MOOCs' discussion forums have their special characteristics: given the vast number of MOOCs' learners, a MOOC forum usually generates fairly large data which makes it difficult, if not impossible, for its instructors and learners to manually provide necessary interventions and support to all participants in need (Li & Xing, 2021). Henceforth, some researchers argued for using tools that can automatically analyse texts and conversations on MOOC forums and provide feedback about the productivity of the content exchanged in those forums (Lalingkar et al., 2022; Li & Xing, 2021).

Another stream of prior research also found such tools may also discourage MOOCs' learners from participating in these forums. First, the feeling of being monitored by an AI may reduce users' intention to use a system (in this case, the discussion forum) (Wang & Scheepers, 2012). Second, people are less likely to trust and react to computer-generated information. Based on a survey of 138 participants, Reeson et al. (2017) found that although robo-advisors have great potential to extend users' reach of advanced, objective, and professional advice and can easily serve large numbers of people, only a little over half of the sample indicated that they would trust robo-advice, and most still stated they preferred human advice. Also, considering the open and diverse nature of participants on these platforms, it would be difficult for some participants to meet standards (García-Molina et al., 2021), eventually discouraging them from using the forum and future participation in the course and resulting in an even higher dropout rate.

To mitigate this inadequacy and to validate the mechanism proposed previously, I modified the mechanism. The results of the study introduced in this chapter showed that the mechanism that follows the design paradigm introduced in the previous chapter was robust as it can successfully strengthen learners' intentions to contribute better knowledge pieces on MOOC forums, another common platform where people normally share and exchange their knowledge. To the best of my knowledge, researchers know little about how to design and implement a mechanism to regulate knowledge shared in MOOC forums. Henceforth, this study contributes to the development of intelligent computer-assisted learning environments which provide motivational interventions in the form of nudges to encourage knowledge-sharing-related forum participation and foster quality-knowledge writing behaviours. Second, by offering and comparing three different types of interface designs, this study provides evidence for the format of presenting nudges and suggests how they can be used in real-world settings. Third, because of the above-mentioned findings, it is argued that this study not only presents a new applicable, robust, and rigorous design paradigm but also adds to theoretical knowledge of extrinsic motivation mechanisms in an online knowledge-sharing context. In addition, the results also shows that the mechanism may negatively affect peoples' tendency to contribute knowledge when they have a strong aversion to being monitored and being forced to share or when users feel frustrated using the mechanism. Suggestions for alterations and refinements of the current designs are discussed in this regard.

Context

MOOCs (massive open online courses) have gained popularity in recent years. The three major MOOC platforms, Coursera, edX, and Udacity, have triggered a boom in MOOC education since

2011, and the CoVid-19 pandemic has triggered another boom in demand because MOOCs have been acknowledged as an important part of the educational response to the pandemic (Bylieva et al., 2020; Impey & Formanek, 2021). The forced transition to distance learning due to the CoVid-19 pandemic has triggered many researchers' passion and also provided new opportunities to study online education (Shah, 2020). Among these research endeavours, one of the more stable research focuses is on knowledge-sharing among teachers and students in MOOC forums (Bylieva et al., 2020).

Participating knowledge-sharing activities in MOOCs' forums are very important for MOOC learners to fulfill their learning objectives. Due to the large enrolment numbers and the highly diversified participants, traditional ways of teaching support with a teacher-centred learning moderation style, are no longer applicable in MOOCs, as it is the interactions among the peers that are endorsed (Churchill, 2017). Discussion forums, which are the interactive places where students, tutors, and teachers can share ideas, ask questions, offer peer-wise help, and make social interactions with each other, are the main arenas for knowledge-sharing behaviours on MOOCs platforms (D. Yang et al., 2014). However, prior research and practitioners found MOOC forums often encounter a serious low participation problem. For instance, Breslow et al. (2013) studied MOOCs offered through edX, and concluded that only 3% of students posted messages in the discussion forum. Similarly, Manning and Sanders (2013) found the participation rate was under 5% for 23 MOOCs offered by Stanford University. Moreover, Belanger and Thornton (2013) found only 7% of enrollees posted messages in the forum of a MOOC offered by Duke University. According to D. Onah, Sinclair, Boyatt & Foss (2014), the proportion of active forum participants is around 15%. In a more recent study, Poquet et al. (2018) found that students' participation rate in MOOC forums is still on a downward trend. Also, according to Kizilcec et al. (2014), most of the forums are largely underutilized, and only a small fraction of the learners report they are benefiting from participating in those forums.

These problems are partially because of the natural characteristics of MOOCs. According to Mackness et al. (2010), an ideal MOOC is expected to meet four standards: ***Autonomy*** (i.e., students of MOOC have high flexibility and control over their learning and other engagements); ***Diversity*** (i.e., learners are from very diversified backgrounds, and have different levels of expertise and prior knowledge); ***Openness*** (i.e., the course itself ensures the free-flow of information through the network and thus stimulates a culture of knowledge sharing and creation); and ***Connectedness*** (i.e., the technologies linking everyone together and making all the other three characteristics possible). These four characteristics are interlinked. For instance, Mackness et al. (2010) summarised, that the more autonomous, diverse, and open the course, the more connected the learners.

Although these characteristics are the basis for the success of MOOCs, they are also the reasons for the problems encountered by the MOOC forums. First, although autonomy has been widely accepted as an enabler for learners to master their pursuits and motivate their active participation in MOOC learning activities (Wu, 2021), prior research reported that many learners perceived low levels of autonomy and their autonomy needs were undermined during the course of learning (Cheng, 2019; Rad et al., 2021). Perception of autonomy is a motivational basis for MOOC learners to participate in discussion forums (Wu, 2021), and an increase in students' perception of autonomy enhances their interest in MOOCs (Sun et al., 2019). Also, high openness results in a large number of learners enrolled in MOOCs with diverse backgrounds and motivations, which poses difficulties when course designers develop courses that attempt to satisfy everyone's needs. Mackness et al.'s (2010) paper also argued that the four expected standards, to some extent, inhibit the sharing of knowledge in MOOC forums. For instance, as they argued, diversity in ages, in cultures, and in prior knowledge levels poses an extra burden on interpersonal communications (i.e., connectedness) and lowers a potential sharer's knowledge-sharing intention.

Therefore, I argue that it is still difficult to design and implement a mechanism to regulate knowledge sharing in MOOC forums, and the number of studies on using information system designs to help do so is limited. Henceforth, I wonder if the mechanism can provide extra help in this MOOC context.

Some researchers endorse using certain motivational tools to promote learners' knowledge-sharing behaviours and encourage active participation in MOOC forums. According to Ortega-Arranz et al. (2019), proper interventions and motivational mechanisms may increase students' knowledge-sharing and participation rate in MOOC forums. For instance, Brooker et al. (2018) mentioned MOOC instructors shall actively use live polls and specific prompts to encourage participation and shall not just expect learners to use the forum of their own volition. As their empirical study showed, in courses that lack such interventions, students were generally less active in their participation in discussion forums.

Nonetheless, there is another stream of research reporting that motivational tools' effect can be negligible and sometimes cause even negative side effects. For example, Vassileva's (2002) and Cheng and Vassileva's (2005) studies found that merely implementing rewards to motivate sharing behaviours in an online community may cause some users to try to game the system, resulting in a massive production of resources of medium or low quality, which makes it difficult for users to locate high-quality resources. Also, these excessive low-quality resources may result in an "information overloading" problem, causing users' satisfaction loss and people leaving the platform (Jones & Rafaeli, 1999). Therefore, the evaluation, the incentivization, and the controlling of the quality and the overall quantity of user contributions are essential (Vassileva, 2012). As implied by Boroujeni et al. (2017), it is hard to build a sustainable knowledge-sharing community as the fluctuation in users' forum participation (active users' activities, threads patterns) is quite large. A MOOC usually involves a large number of learners, so it is prohibitively costly to provide such interventions manually for all students (Li & Xing, 2021).

Recently, some researchers have argued the usefulness of utilising automatic text analysis tools to support MOOC learners and increase their engagement in discussion forums (Baker et al., 2016; García-Molina et al., 2021; Lalingkar et al., 2020; Li & Xing, 2021). For instance, Almatrafi et al. (2018) implemented a machine-learning-based text analysing tool that can automatically detect learners who need urgent attention and report the situation to instructors and teaching assistants, allowing them to offer timely assistance. They found a tool designed as such can increase learners' performance. Similarly, Cui and Wise (2015) and Wise et al. (2017) adopted machine-learning algorithms to automatically classify whether learners are posting meaningful content or merely irrelevant content. García-Molina et al. (2021) designed and implemented an Artificial-Intelligence-based automatic grading tool that looks not only at learners' interactions and contributions in the discussion forum but also at their summative assessment activities in a MOOC platform. In Ferschke et al.'s (2015) and Mittal et al.'s (2018) studies, researchers built a chatbot with NLG (Natural Language Generation) techniques for MOOC learners and found the artificially generated texts could offer informative answers to students' questions and therefore increase their engagement level such that and the students would be less likely to drop out as the course proceeded. Yang et al. (2016) built a monitor that can identify confused learners through their posts in discussion forums. Moreno-Marcos et al. (2018) examined the impact of an automatic analyser that was able to monitor the collective sentiment of learners in a MOOC based on linguistic features of forum posts and produce an alert if a certain sentiment was detected. Using latent semantic analysis (LSA) and machine learning approaches, Yang et al. (2022) designed a tool to automatically quantify meaningful forum participation, policing off-topic posts, and reduce chaos (i.e., an abrupt increase of number of posts) and information overload problems for learners.

However, as Mohammadhassan et al. (2022) pointed out, many existing motivational tools can be used to increase learning and engagement but they could be very time-consuming and demanding for teachers. Hence there is a need for having a tool that is more automatic and simpler.

There is a small but emerging stream of research attempting to increase learners' engagement to participate in knowledge-sharing behaviours by adding explicit interventions in the form of prompts (Mohammadhassan et al., 2022). Mitrovic et al.'s (2019) research argued that personalised prompts encourage students to promote engagement behaviours (e.g., write comments) and foster a learning atmosphere. Nudge theory provides theoretical underpinnings and guides me in designing these prompts (Baker et al., 2016). This theory argues that human behaviours are heavily guided by non-conscious cognition and can be influenced by seemingly subconscious elements in the environment (Khansa et al., 2015). As Peer et al. (2020) explained, these non-conscious heuristics and irrational elements can be used and exploited to "nudge" desired behavioural outcomes, motivating users to achieve more and to overcome challenges with more confidence.

Functional nudges can be designed effectively through the intentional manipulation of interfaces, harnessing well-established biases in human decision-making. Such purposeful interface designs act as pivotal tools for constructing impactful digital nudges. These designs leverage cognitive biases to predictably influence user behaviors, thereby fostering desirable outcomes within knowledge-sharing environments (Acquisti et al., 2017; Schneider et al., 2018).

The key to designing a well-functioning digital nudge that can facilitate the knowledge-sharing process in MOOC forums is to find an applicable bias. In this research, I still focus on the present-time bias. Note that the details of present time bias have been well documented in the literature review section.

Interface designing is also not a trivial endeavour. Researchers and practitioners can alter the effect of the applicable bias by changing the manner in which information is presented to the decision makers (Adomavicius et al., 2019). As Bettman and Kakkar (1977) explained the manner of presenting information significantly changes people's cognitive costs and the benefits of the tasks and, therefore, influences their decision-making processes. Specifically, Budescu et al. (2012) found a Star-Numeric dual display caters to people with different preferences for information presentation formats and can improve the quality of communication by helping people, regardless of their ideological and environmental views, to better understand human-induced climate change issues. There is also another stream of research arguing that adding a layer of numerical interface to an existing graphical interface may increase people's scale compatibility effects (i.e., a bias that people prefer scales which is superior to the objective measured with the same unit scale than with a different unit scale (Keren & Wu, 2015)), and therefore a Star-only display interface is favoured (Adomavicius et al., 2019). Some interface designs (e.g., a binary interface using a thumb up or down associated with the item) stress the importance of a layer of vagueness, and as Dieckmann et al. (2010) argued, this vagueness may not necessarily trigger people's "ambiguity averse" feelings but rather, gives them a higher level of source credibility. Also, as Dieckmann et al. (2010) introduced, personalized recommendations can introduce biases to users (e.g., when viewers re-rate a movie while being shown a "predicted" personalized rating that was artificially altered upward or downward from the original rating, they tended to give higher or lower ratings accordingly, when compared to a control group receiving accurate original ratings), and if a recommender gives a recommendation in numeric format, the increase can be significantly increased, compared to recommenders that give a recommendation in binary format or graphic format). Some studies focused on textual-based interface designs. For instance, Huang et al. (2019) proposed that motivating users to contribute knowledge content can be achieved by well-selected feedback messages that speak to different motives for contributing behaviours. However, prior research also showed that this process is nuanced and highly contextual. According to Reeson et al. (2017), people perceive messages sent out from robo-advisors to be less trustworthy, and most prefer messages sent from humans. Saposnik et al. (2016) reported that individual's sharing knowledge intention is influenced more by how the information is worded than by the information itself: a nudge that sends out a textual message in the form of only a simple request for sharing reduced individuals' level of knowledge sharing. All the above-mentioned findings indicate that there is a need for a systematic test of different interface design components and their impact on designing a nudge to promote knowledge sharing among learners in MOOC discussion forums.

Research methods

To investigate those MOOC-specific research questions, I conducted action research, a clinical method that can help researchers find a solution for a practical problem and, at the same time, extend the existing theoretical literature (Baskerville & Myers, 2004). Stringer (2013) defined action research as a participatory approach that typically collaborates with communities (who are as well the focus and eventual beneficiary of the research) and seeks to find a local solution for problems under certain circumstances. A good action research both satisfies the need for scientific rigor and the promotion of a sustainable social change. As implied by Baskerville and Myers (2004), action research provides a valid way to improve the practicality of information system studies in the human context.

Specifically, I performed my rigorous design research through an iterative two-stage process (i.e., a. diagnostic stage; b. therapeutic stage). It simultaneously helps the *praxis* (i.e., mitigation of problems in reality) and the *theoria* (i.e., advances in theory) (Mårtensson & Lee 2004).

According to Baskerville and Myers (2004), action research has many variations and forms. Susman and Evered's (1978) canonical action research methodology stated that the process of action research shall be both cyclical and iterative. Each research may contain several cycles and iterations, and, in each iteration, researchers need to go through five phases: problem diagnosing, action planning, action-taking, evaluating, and specifying learning. Applying Lawler's (1994) competency-cantered theory, the researchers argued that, for a knowledge-intensive company, it is essential to replace its legacy system which adopts a job-based paradigm by a system that embodies the skill-based paradigm. The evaluation strategies included one experiment and four workshops, where the experiment was used to give the end-users a hands-on experience while the workshops aimed to collect feedback and reactions to the prototypes. In another research, Mårtensson and Lee (2004) adopted a dialogical action research design to identify current information system flaws and to initiate possible mitigations. This method, as they argued, predominantly relied on interviews, whilst other types of methods, such as observations and documentation and archival records analysis, were complementary. Therefore, in their research, they mainly conducted two types of interviews: semi-structured interviews and unstructured ones. In the semi-structured interviews, they worked with the practitioners to identify and understand the inefficiencies in their daily operations. In the end, the authors argued that the successfulness of a dialogical action research is determined by the ability to facilitate reflective dialogue which gives the practitioners and the researchers an opportunity to enhance mutual understandings, to identify current business problems, and to develop research-based interventions. Via reviewing historical context and origins of action research and practices and synthesizing previous action research types, Hayes (2011) and Council (2005) produced a state of the art handbook that offered a guide for researchers who want to perform such research. This research also referenced the structures and processes introduced in their articles.

Specifically, this study applied Council's (2005) Double Diamond model, one of the most recent and appropriate models for designing in-system innovation. Compared to other popular design models such as, The Model of the Hasso-Plattner Institute, IDEO’s Human-centred Design Model, and Design Thinking 3 I’s (Inspiration, Ideation, Implementation) model, the Double Diamond model is more complete, detailed, and more business and management-oriented (Tschimmel, 2012). The study contained four cycles (see Figure 7), that is, Discover, Define, Develop, and Deliver, and at the end of each cycle, a reflection and evaluation session was executed to determine if there was a need to roll-back to the last stage or to proceed to the planning of the next stage.

Stage 1: (Discover) Content Analysis

The first stage aims to find common problems that are associated with knowledge exchanging and knowledge sharing on MOOC forums, as well as their possible root causes.

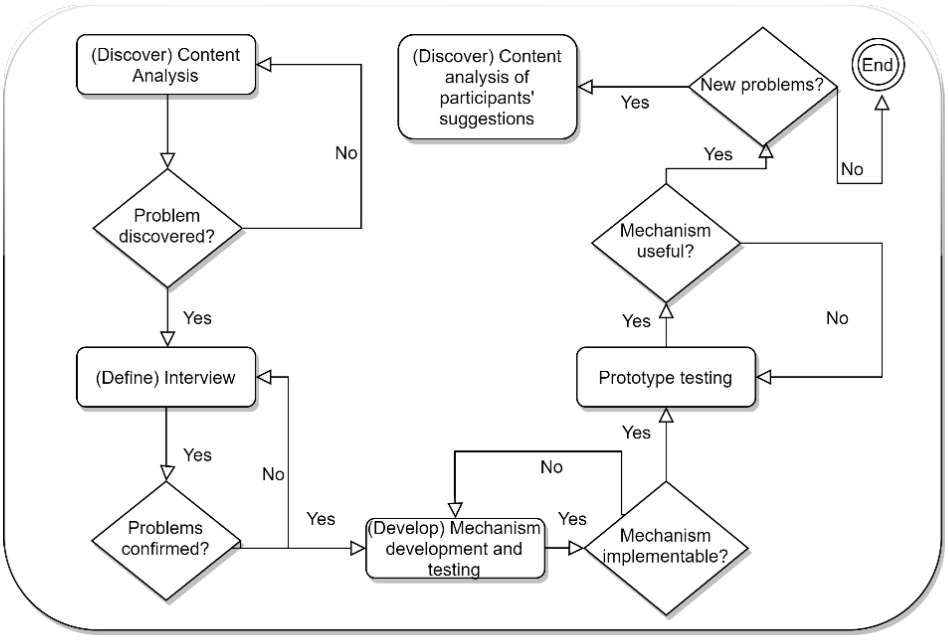


Figure 7. Action Research Spiral—An Iterative Cycle of Planning, Action, and Reflection

Following Bhattacherjee's (2012) guidance, the content analysis stage comprised three phases. The first phase was a sampling of courses. One of the largest MOOC platforms, edX.org, was selected as the subject of this research. Moreover, on that platform, ten courses were randomly chosen for auditing (enrolling without paying a fee) to access the texts in their course forum. The random selection process was based on a full list of the currently available courses obtained by a specialized crawler developed by Shi et al. (2018). The second phase was a unitisation of posts. Posts that entailed the existence of knowledge-sharing problems were selected for analysis and the texts in the posts were divided into segments that were treated as “separate units of analysis”. In the third phase, after analysing those unitized text chunks, I categorized the problems and assigned a name to each category. Potential problems and their examples are summarised in Table 13.

Name of potential problems	Example
No functional forum for knowledge sharing at all	As of 9/4/2018, the course <Introduction to OpenStack>, which opened in 2016, has no post in its forum.
Good-quality posts are “submerged” by low-usability posts	In the course <Introduction to Management Information Systems (MIS): A Survival Guide>, useful posts are effectively hidden by posts of low usefulness, such as greetings and expression of thanks.
Posts with an ambiguous or meaningless title	In the course <CitiesX: The Past, Present, and Future of Urban Life>, a post triggers a meaningful discussion, but the title of that post is “NA”. If the title were more meaningful, it would raise more knowledge-sharing intentions.
Posts are written improperly or use the informal style of writing	A post in <Astrophysics: The Violent Universe> says “Interesting...but it is about telescopes and that”.
Posts that only give an expression of emotions	A post says “ONDE!!!! EXCELLENT..!!!!!! Praise to professors”.
Posts that only contain knowledge unrelated to the current discussion topic	A greeting, which should be posted in a dedicated welcoming thread, instead posted under an academic topic

Table 13. A List of Categories of Knowledge-sharing Problems and Barriers and their Examples

Stage 2: (Define) Online Interview

I then conducted online interviews with voluntary participants. The average duration of the interviews was 23.2 minutes. I used a linear snowballing method to diversify the participants’ demographic backgrounds: the initial participants were summoned from an Australian university during semester break time and asked to refer to a friend or workmate who had a slightly different background. I excluded people from the experiment if they did not have MOOC experiences at the time of this study. The collection stopped when I found there were no new insights given by the participants, and in the end, I obtained a sample size of 46. Table 55 in the Appendix 4 summarises the demographics.

The interview unfolded as follows: The first part of the interview was an icebreaker session discussing participants' MOOC-related learning and sharing experiences (e.g., frequency, time, efforts level, and outcomes, etc.). Questions in the second part checked the validity of the potential problem list. In the third part, the researcher worked with the participants to analyse and find potential causes and possible solutions.

Except one participant stating, "I won't read them anyway" and another stating "MOOC forum is a place where people can discuss freely" and "informal-ness essentially is not a bad thing", all other participants agreed with the knowledge-sharing problems identified in the previous stage. As one participant noted, he only used discussion forums to "ask instructor [*sic*] about assignment things, hoping the problems (questions) are shared by my fellows". He also reported "when it comes to knowledge sharing with peers, one of the problems of those forums is the posts in there are sometimes in very low quality. No one even read them."

Another respondent noted the problem of the low participation rate of those forums and argued the cause of those problems is the long waiting time: "the lecturer didn't pay much attention to the online discussion. It usually may take more than 3 days to get the reply". One respondent argued "for some non-popular courses there is even no comment or post at all.", and this argument corresponded to another respondent's comment, stating "the essential problem is to improve the usage of the forum". To solve these problems, a respondent suggested the forums should be "disciplined and managed timely", though she also said to manage, in real-time, a MOOC forum can be very difficult. Another suggested using tools that ensure effective interaction. Three respondents also suggested providing more guidance to forum users, and the best timing of giving guidance, as one respondent argued, is in real-time.

Stage 3: (Develop) Mechanism Developing and Testing

As Cohn (2004) suggested, functions provided by software should be determined by its user's demands, expectations, and requirements. To achieve an effective system which allows real-time monitoring with minimal costs and prompt incentivization, I deemed that a functional "machine" should be able to calculate the quality of those text-based posts in real-time and immediately report this value to the knowledge editor, and, consequently, to encourage acceptable knowledge-sharing behaviours and to punish undesired ones simultaneously.

I designed a simple prototypical solution that was in the form of a JavaScript-based plugin. It evaluates the quality of a knowledge input by monitoring a set of textual features, including length, readability, and style. The plugin used a Natural Language Processing (NLP) library developed by Kelly (2016) named *NLP_Compromise*.

The system's objective is to motivate people to share more high-quality knowledge and to discourage people to share bad ones. Also, it can automatically determine whether a piece of textual input is merely a junk text. In such cases, it warns the writer not to make such inappropriate input. Moreover, a rule-based mechanism was implemented to monitor and to identify a pre-defined list of problems such as posts without proper netiquette, a set of rules to encourage tolerant, polite and considerate online behaviours amongst Internet users (Sturges, 2002).

As Figure 8 shows, I designed three models of ratings in this prototypical work: that is, a graphic one (Model A), a numeric one (Model B), and a textual one (Model C). Model A estimated a knowledge piece's quality and used a pointer to report it back to the writer. Model B, instead, reported an estimated score to the pointer. Model C tries to catch users' improper behaviours and give corresponding guidance (e.g., "please do not use too many emotional words" and "your post needs further construction") to the users. The nudge has an algorithm based on natural language processing (NLP) embedded in it. The software was developed as a JavaScript and is able to monitor and evaluate users' input and report the evaluation result back to the user in real-time. All three models monitored only the main body area but there may be a chance that the mechanism can also cause a spill-over effect on title-editing, meaning that when people refine their main body based on the mechanism's feedback, they may also want to refine the title, such that participants can perceive the effect of the mechanism not only when they edit the main body but also when they edit the title.

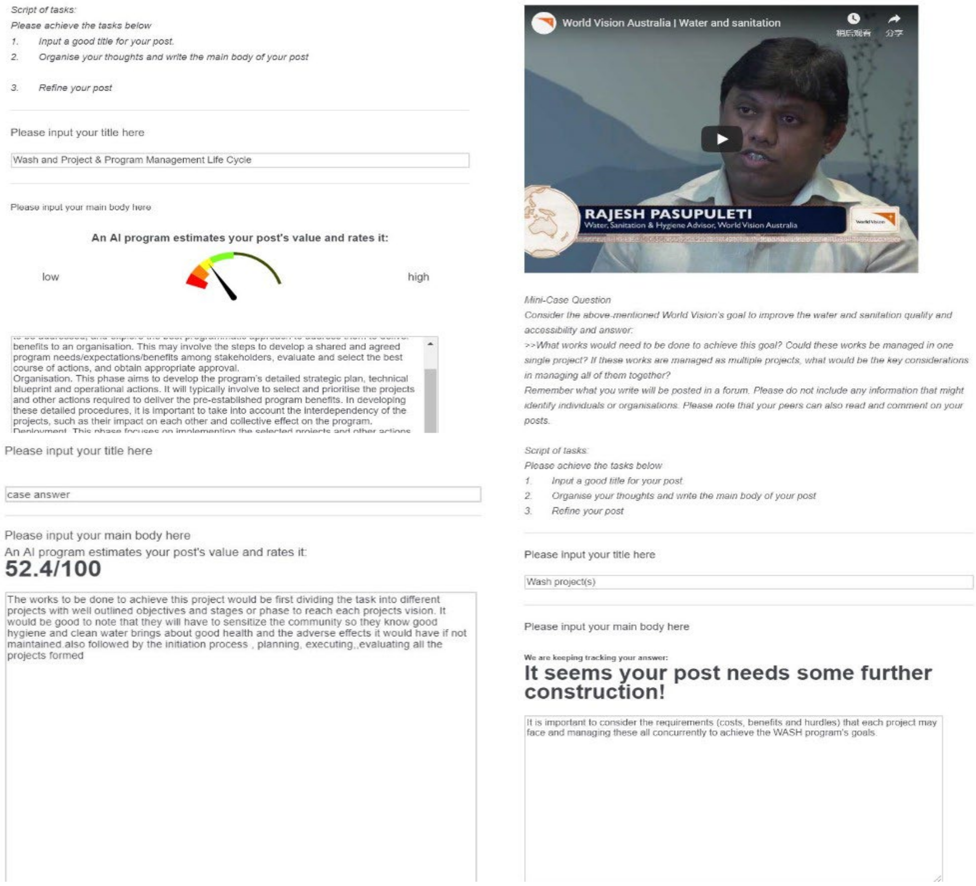


Figure 8. Three Ratings Models: Model A, Upper Left; Model B, Bottom Left; Model C, Bottom Right

Stage 4: (Deliver) Prototype Testing

To analyse the effectiveness of the proposed nudge, I conducted a randomly assigned double-blind experiment. In this experiment, I built a mock MOOC environment, and the participants were asked to access the prototype via a link using their preferred device (i.e., the device they commonly used to log in to a MOOC).

Participants

I called for participants through advertisements in a participant-pool system that a public university in Australia owns and sponsors. The participants should have prior MOOC-related experiences (i.e., taken at least one MOOC before). Note that I have included the demographics information in the Appendix section (see Table 55).

Procedures

The experiment had the following five sections: 1) acknowledging and signing the information sheet and consent form; 2) introduction to community-based question answering; 3) familiarity exercises (to help participants learn to interact with the experimental environment); 4) experimental tests; and 5) demographic questions.

Before the experiment

Before conducting the experiment, I provided participants with an electronic information sheet and a consent form. I explained the mock MOOC environment, and the MOOC discussion forums, then briefly introduced the content of the learning module of a MOOC for Project Management. The sheet also notified participants that I was conducting the experiment to gather information about participants' MOOC learning and knowledge-sharing behaviours in MOOC discussion forums. To avoid the Hawthorne effect, I did not mention the existence of the nudge at this stage.

After reading the sheet and signing the form, participants went to a participant education session that had the following three steps: 1) Two questions that asked participants about their prior experience with MOOCs. 2) A message telling them that their responses would be posted on the discussion forum of a MOOC. 3) An experiment qualification test. Through these steps, I helped the participants to become familiar with the experiment environment and showed them how to interact with it.

During the experiment

To gather evidence that would support a system design that better facilitates knowledge sharing, I also assembled a control group to provide a base of comparison. I followed a random assignment approach to assign participants into different treatment/control groups, and the participants did not know the existence of their peers. During the experiment, I did not know who belonged to the control group and who belonged to the treatment group.

I asked the participants to discuss a mini-case question in this learning module. The mini case was about a charity group, World Vision Australia, which implemented a project in Papua New Guinea to help local residents access improved drinking water and improved sanitation. The question was designed to let the students distinguish the difference between project management and program management, a process of managing several related projects. Both the treatment and the control groups received the same mini-case materials and questions in the same environment. Each participant in the treatment group accessed one model. People who accessed Model A and B saw the questions along with the nudge that showed the sentence: “An AI program estimates your answer's value and rates it: x”, where x reflected the algorithm’s assessment of each participant’s response. For Model A, high-quality inputs caused the indicator to move from the left (the red area) to the right (the green area). For Model B, high-quality inputs resulted in high-quality scores. People who accessed Model C were advised on what they were writing. After that, they rated the prototype on a 5-point Likert scale (5 = definitely yes, 4 = probably yes, 3 = might or might not, 2 = probably not, 1 = definitely not) on eight questions (for details, see Table 2) to test the subjective effects of the prototypical mechanism. The eight questions were adapted from Venkatesh and Davis's (2000) Technology Acceptance Model (TAM2) model.

After that, all the participants received a block of demographic questions. The system they used automatically recorded and saved the text they inputted, so if a participant dropped out in the experiment, the system could still record this participant’s partial responses. All participants could stop the experiment at any time, which I reiterated verbally as they began the experiment. In addition, I did not allow participants to go back to a previous session to edit the writings that they had previously submitted to answer the mini-case questions.

Finally, I asked the respondents to write comments on the solution about the improvements or disadvantages, if any, brought by the prototypical solution. I read comments together with the participants to determine whether they had further suggestions and whether there existed any misunderstandings.

After the experiment

A group of trained research assistants (N=12), who have experience in online teaching and tutoring, judged the quality of the answers that the participants provided. I refer to these research assistants as graders. I used a custom-built designated PHP-based website that was built by one of the authors. I set up different password-protected accounts for different graders so that they could not see or change each other's decisions, and the graders could not interact with each another when grading. The graders assessed two responses to the same question at a time (see Appendix 2) and were required to judge which one had better quality based on the following four factors:

- Accuracy: An response is convincing, that is, it contains valid and reliable factual information and credible sources for references (Jeon et al., 2010). It also pertains to the question (Jeon et al., 2010) and is as complete and objective as possible (Shah & Pomerantz, 2010).
- Helpfulness: A response should have value in use and be perceived as helpful and being polite (Shah & Pomerantz, 2010).
- Richness and informativeness: A response should provide many details and should be presented in a diversified manner and reflect diverse perspectives (Jeon et al., 2006).
- Readability and Presentation: A response should be understandable and clear, and the logic of the response should be coherent and easy to follow (Ghose & Ipeirotis, 2011).

Each answer will appear four times and each answer had an equal chance to appear before the graders accessed it. Therefore, the range of points for each factor will be zero to four. The overall quality score is the average of the four-factor scores, rounded to the nearest integer.

Results

A one-way analysis of variance (ANOVA) was used to determine whether the proposed mechanism can cause a significant increase in the participants' quality scores. I first checked the assumptions required for the analysis and found no major problems. Results showed that my mechanism proved effective in improving contributions' quality ($F(3,37) = 10.218$, $p < 0.001$). As Table 14 and Table 15 indicate, the performance of participants in Model B was the highest among the four groups: my participants spent a longer time and wrote longer responses when they interacted with Model B, and the average score received in this group was also the highest. Also, the participants spent a longer time on editing answers when Model A was presented compared to when Model C was presented. Overall, participants in the treatment group also provided longer answers on average than people in the control group.

	Treatment			Control
	Model A	Model B	Model C	
Length of response (in characters)	M = 906.6 SD = 501.77	M = 1158.0 SD = 494.78	M = 708.1 SD = 466.52	M = 275.1 SD = 122.00
Duration of participation (in seconds)	M = 2023.3 SD = 721.2	M =2250.0 SD = 1316.07	M = 1774.9 SD = 1497.3	M =1144.1 SD = 841.5

Table 14. Prototype Testing Result for Model A, B, C, and Control

Group		Score Mean Difference	SE	Sig.	95% CI (L, U)	
Model A	Model B	-0.231	0.361	0.918	-1.202	0.740
	Model C	0.322	0.407	0.858	-0.772	1.417
	Control	1.655*	0.384	0.001	0.623	2.686
Model B	Model A	0.231	0.361	0.918	-0.740	1.202
	Model C	0.553	0.385	0.486	-0.484	1.590

	Control	1.89*	0.361	<0.001	0.915	2.856
Model C	Model A	-0.322	0.407	0.858	-1.417	0.772
	Model B	-0.553	0.385	0.486	-1.590	0.484
	Control	1.33*	0.407	0.012	0.238	2.427

Table 15. Multiple Comparisons of the Response Average Quality Scores for Model A, B, C, and Control, Using a Tukey Post Hoc Test (* means the mean difference is significant at the 0.05 level)

Specifically speaking, as Table 16 shows, the participants in the treatment group also outperformed the people in the control group in terms of their accuracy scores. Specifically, Model B slightly outperformed others but it did not reach statistical significance.

Group		**Score Mean**	**SE**	**Sig.**	**95% CI (L, U)**	
Model A	Model B	-0.308	0.371	0.840	-1.304	0.689
	Model C	0.083	0.418	0.997	-1.041	1.207
	Control	1.700*	0.394	0.001	0.640	2.760
Model B	Model A	0.308	0.371	0.840	-0.689	1.304
	Model C	0.391	0.396	0.757	-0.674	1.456
	Control	2.008*	0.371	0.000	1.011	3.004
Model C	Model A	-0.083	0.418	0.997	-1.207	1.041
	Model B	-0.391	0.396	0.757	-1.456	0.674
	Control	1.617*	0.418	0.002	0.493	2.741

Table 16. Multiple Comparisons of the Accuracy scores for Model A, B, C, and Control, using a Tukey post hoc test (* means the mean difference is significant at the 0.05 level)

In terms of the Helpfulness scores, Table 17 also shows the treatment group outperformed the control group and that among the three models. Model B performed better than the others. However, this also did not reach statistical significance.

Group		**Score Mean Difference**	**SE**	**Sig.**	**95% CI (L, U)**	
Model A	Model B	0.042	0.389	1.000	-1.005	1.089
	Model C	0.131	0.439	0.991	-1.050	1.312
	Control	1.958*	0.414	<0.001	0.845	3.072
Model B	Model A	-0.042	0.389	1.000	-1.089	1.005
	Model C	0.089	0.416	0.996	-1.030	1.208
	Control	1.916*	0.389	<0.001	0.869	2.963
Model C	Model A	-0.131	0.439	0.991	-1.312	1.050
	Model B	-0.089	0.416	0.996	-1.208	1.030
	Control	1.827*	0.439	0.001	0.646	3.008

Table 17. Multiple Comparisons of the Helpfulness scores for Model A, B, C, and Control, using a Tukey post hoc test (* means the mean difference is significant at the 0.05 level)

As Table 18 shows, participants in the treatment group also performed better than the control in terms of their Richness and Informativeness scores, and Model A significantly outperformed others in this regard. Similarly, Table 19 also shows the treatment group outperformed the control group in terms of the Readability and Presentation scores. Interestingly, among the three models, Model C performed better than the others. Yet, this also did not reach statistical significance.

Group		Score Mean Difference	SE	Sig.	95% CI (L, U)	
Model A	Model B	1.169*	0.367	0.015	0.182	2.157
	Model C	2.025*	0.414	<0.001	0.911	3.139
	Control	2.600*	0.390	<0.001	1.550	3.650
Model B	Model A	-1.169*	0.367	0.015	-2.157	-0.182
	Model C	0.856	0.392	0.147	-0.199	1.911
	Control	1.430*	0.367	0.002	0.443	2.418
Model C	Model A	-2.025*	0.414	<0.001	-3.139	-0.911
	Model B	-0.856	0.392	0.147	-1.911	0.199
	Control	0.575	0.414	0.514	-0.539	1.689

Table 18. Multiple Comparisons of the Richness and Informativeness scores for Model A, B, C, and Control, using a Tukey post hoc test (* means the mean difference is significant at the 0.05 level)

Group		Score Mean Difference	SE	Sig.	95% CI (L, U)	
Model A	Model B	-0.423	0.325	0.568	-1.298	0.451
	Model C	-0.458	0.367	0.600	-1.444	0.528

	Control	1.600*	0.346	<0.001	0.670	2.530
Model B	Model A	0.423	0.325	0.568	-0.451	1.297
	Model C	-0.035	0.347	1.000	-0.969	0.899
	Control	2.023*	0.325	<0.001	1.149	2.897
Model C	Model A	0.458	0.367	0.600	-0.528	1.444
	Model B	0.035	0.347	1.000	-0.899	0.969
	Control	2.058*	0.367	<0.001	1.072	3.044

Table 19. Multiple Comparisons of the Readability and Presentation scores for Model A, B, C, and Control, using a Tukey post hoc test (* means the mean difference is significant at the 0.05 level)

Moreover, following Mohammadhassan et al.'s (2022) tradition, I also used Venkatesh and Davis's (2000) Technology Acceptance Model (TAM2) model to measure the participants' opinions of the usefulness of the proposed nudges, using the Likert scale from 1 (lowest) to 5 (highest). The result (see Table 20) also shows that, among the three models, Model A outperformed others in terms of its perceived usefulness in improving the performance and productivity of writing their responses in the mock discussion forum. Model B was perceived to be easier to interact with. All of the models obtained a low score in the title-editing question, indicating that the anticipated spill-over effect might not happen: although the participants agreed the mechanism might encourage them to make a better-quality response when editing the main body part, it probably would not encourage them to do so for the title part. Model C received lower ratings in all measuring items. Particularly, I found the participants deemed Model C would probably not encourage them to spend more time on editing nor refining knowledge contributions. That said, Model C's large SD values implied the users had conflicting judgments on it.

Item	Treatment	Control	t

	Model A	Model B	Model C		
Perceived usefulness in improving performance when making contributions	M = 4.12	M = 3.93	M = 3.38	N/A	1.474
	SD = 0.35	SD = 0.92	SD = 1.30		
Perceived usefulness in improving productivity when making contributions	M = 4.00	M = 3.71	M = 3.00		2.442
	SD = 0.53	SD = 0.99	SD = 1.07		
Perceived engagement to write good quality contributions	M = 3.63	M = 3.93	M = 3.38		2.158
	SD = 0.74	SD = 1.14	SD = 0.74		
Learning to interact with the mechanism is easy	M = 3.75	M = 3.79	M = 3.25		1.892
	SD = 0.46	SD = 0.97	SD = 0.71		
Becoming skilful at using the mechanism is easy	M = 3.50	M = 4.21	M = 2.75		6.195
	SD = 1.07	SD = 0.89	SD = 1.28		
Be encouraged to have better quality response when editing the title	M = 2.63	M = 2.93	M = 2.88		0.579
	SD = 1.19	SD = 1.27	SD = 0.83		
Be encouraged to have better quality response when editing the main body	M = 3.88	M = 3.43	M = 2.75		2.282
	SD = 0.64	SD = 1.34	SD = 0.71		
Be encouraged to spend more time on refining the knowledge response	M = 4.25	M = 3.50	M = 2.88		2.868
	SD = 0.71	SD = 0.85	SD = 1.36		

Table 20. TAM Result for Model A, B, C, and Control

In assessing the consistency among the graders, I found a substantial level of agreement. This was evidenced by the Intra-class Correlation Coefficient (ICC) score, which stood at an impressive 0.978 (for ICC (3, 12)). The accompanying 95% confidence interval ranged from 0.967 to 0.987 and the p-value was less than 0.001. These strong statistics underscored the reliability of the scores produced through the proposed mechanism, providing solid statistical support for the grading process adopted in the research.

I analysed the comments that the participants wrote during the last part of the prototype testing time. Based on the comments, I found the participants primarily appreciated the straightforwardness and easiness of the mechanisms in Model A and B. Several participants mentioned that the mechanism (the AI) was "sufficiently smart". As one respondent put it, "it (the mechanism) remind [sic] to write a quality answer at all times. So, when I was typing, I feel more pressure or responsibility to write a good answer." Two participants reported the mechanism "mitigates the boringness of writing answers" and "gamifies the process of sharing", and it would "especially suitable for people who always want to win and get a better ranking or score".

The participants also pointed out several potential problems. One respondent mentioned their concern was about the computational burdens, as they found the computer became slow after they inputted a lot of words. A similar concern was raised by another participant who accessed Model A, reporting a bug that "the indicator stopped running when my paragraph went long". After I traced and reproduced this bug, I concurred with the idea of the computational burden as I found the waiting time became significantly longer when a response was over 1,500 words. As another respondent commented, "the machine gives me an impression that it push *[sic]* me to share my knowledge or then make me feel that I am forced to do this, which makes me feel really unhappy and uncomfortable." Respondents also gave suggestions for improvements. For instance, a respondent argued that a "turn-off" button should be added to satisfy the demands of the users who disapprove of such a sharing motivator. A computer-science background participant suggested using mobile web content adaptation techniques so that the software can run on devices perfectly with screens of different sizes.

Implications

Prior research has pointed out that whilst many educators and practitioners recognised the importance of having students actively share knowledge in MOOCs' forums, the level of participation among MOOC learners is low, which can yield negative effects on students' learning. In some MOOC forums, while many learners contribute to the forums, the quality of most of the contributions remains low, resulting in a crowding-out effect on those high-quality ones and an increase in knowledge seekers' searching costs for the right knowledge on these forums (Galikyan et al., 2021; Kizilcec et al., 2013).

Nudge theory proposes that purposeful interface designs can trigger users' desired behaviours if non-conscious heuristics and well-known biases are successfully applied. Guided by this theory and referencing several previous interface design studies, I modified the mechanism that I proposed in the previous chapter and validated its three prototypical variations for motivating learners' knowledge exchanging behaviours in MOOC forums. Prior research generally agrees that there is a need to design motivational mechanisms (e.g., digital nudges) that give immediate extrinsic rewards and recognitions to increase users' engagement levels, enabling them to perform more knowledge-sharing behaviours. My previous study as well highlights the importance of immediacy. However, little is known about how to design a functional nudge to achieve that.

The prototypical design is a success. Participants were found to be more likely to contribute more high-quality knowledge on MOOC platforms when the intervention of the proposed mechanism presents. High perceived usefulness and perceived ease of use were reported by the participants. Also, the participants spent a significantly longer time on writing longer knowledge contributions once the proposed mechanism presents.

In the investigation, three variations of nudge designs were closely examined–Model A (graphical interface), Model B (numerical interface), and Model C (textual message interface). Intriguingly, this study discovered that both Model A and Model B drove substantial improvements in performance, with Model A excelling in amplifying response helpfulness scores, whereas Model B shined in improving presentation and readability. This is likely due to Model B's numerical interface's simplicity, which participants found the most accessible to interact with.

Model A's graphical interface design seemed to lend itself well to a layer of subtlety and uncertainty that may benefit user experience. On the contrary, the AI in Model C, which delivers explicit instructions to users, was not as well received. This direct, text-based feedback risked creating a controlled environment, which could have been detrimental to the user's sense of autonomy and control.

However, it is also noted that not all participants had a negative response to Model C's explicit AI-generated instructions. Some individuals, likely due to their cognitive styles, were more amenable to following algorithmic guidance. For these individuals, the explicitness, transparency, and reduced ambiguity that Model C offers could be beneficial in facilitating efficient user-algorithm collaborations. Still, I found that in the overall landscape, maintaining a layer of vagueness can play a critical role in managing user expectations and preserving a sense of human autonomy and control in AI (i.e., the nudge) interactions.

In terms of quality components, generally speaking, participants presented with Model B performed significantly better. Model B's numerical interface's straightforwardness was a crucial factor in its success. Meanwhile, Model A's graphical interface design seemed to significantly enhance the richness and informativeness of responses, which correlates with the high level of perceived usefulness that Model A's users reported.

Many participants refined their contributions after drafting their initial responses, across all models. Interestingly, it was noted that those who received feedback from the proposed mechanism (treatment group) could potentially save time refining their answers due to explicit feedback indicating areas of potential improvement.

This study demonstrates that real-time feedback can motivate users to improve the quality of their contributions. This aligns with the advent of commercial solutions such as Grammarly, Read & Write, and Gold Write Away, underlining the practical application and market potential of real-time processing tools.

This research brings to light several implications. Firstly, it offers empirical evidence on using a present-time bias nudge to enhance knowledge-sharing in MOOC forums, addressing the need identified by C. Wang et al. (2015). Secondly, by comparing three different interface designs, this study provides valuable insights into the format of presenting nudges in real-world applications. Lastly, the findings contribute to the theoretical understanding of extrinsic motivation mechanisms in online knowledge-sharing contexts, marking a significant advancement in the design and application of intelligent computer-assisted learning environments.

This research has several limitations. First, due to the limitation of time and money, this study only audited ten courses for unitisation of the potential knowledge-sharing problems in MOOC forums. Also, currently it contains a limited number of respondents, and the selection of respondents is not randomized, which may entail biases. In addition, all of the respondents are from the same country (i.e., Australia) which weakened the representativeness. Third, as mentioned in the literature review section, people's attitudes towards motivational factors change over time, but at this stage, there is no data collected to monitor within-sample intertemporal changes. Fourth, the testing environment of this study is in a simulated project management course, but field works on a cross-courses environment are recommended. To mitigate those problems, there is a need to identify more MOOC-specific knowledge-sharing problems from more courses, from a larger student sample, by repeating the design approach in several different courses and evaluating accordingly. Also, I shall aim to conduct an experiment with control and treatment groups to investigate whether the mechanism would improve a students' learning performance and perceived learning gain via enjoying an increased level of knowledge sharing in MOOC forums regulated by a mechanism as such. Fifth, although the participants agreed the mechanism might encourage them to make a better-quality contribution when editing the main body part, I did not see a spill-over effect on encouraging the users to do so for the title part. This implies that, in the future, I may need to design a separate mechanism for helping people write their titles.

Summary

Massive Open Online Courses (MOOCs) have become a prominent platform for online education. While the potential for knowledge sharing within these forums is clear, prior studies highlight the limited participation of MOOC learners. Moreover, many forum contributions are of low quality, challenging learners to extract relevant and valuable knowledge. These observations necessitate an innovative mechanism that can inspire and direct students to share high-quality knowledge.

Grounded in the Nudge theory, which promotes purposeful design to shape user behavior, this study explores the design of digital nudges. Focusing on immediate extrinsic rewards and recognitions, the research aims to boost user engagement and knowledge-sharing behaviors. Despite the recognized significance of immediacy in such nudges, the literature reveals a gap in crafting a functional nudge to exploit this feature.

Three prototypical interface designs—Model A (graphical), Model B (numerical), and Model C (textual message)—were developed to ascertain their impact on learner behavior. The findings showcase:

- **Model A**: Enhanced response helpfulness scores.
- **Model B**: Promoted presentation and readability due to its straightforward nature.
- **Model C**: Garnered mixed reactions. Some appreciated the AI-driven explicit instructions, while others felt it encroached on their autonomy.

Across the board, participants refined their initial responses after drafting, with real-time feedback playing a pivotal role in enabling improvements.

It is expected that the product of this study eventually will lead to the invention of a real-time Artificial- Intelligence-based knowledge evaluation tool with high accuracy, semantic-aware capability, and comprehensive pre-defined problem lists. It shall also consume less computational power on the client side. Mobile friendliness is also important. By utilizing machine learning techniques (e.g., Latent Dirichlet Allocation), the future machine shall be able to check a post's topic relevancy. However, to the best of my knowledge, so far, only "supervised learning algorithms" are viable to calculate factors such as topic-relatedness, which implies the necessity of forcing the practitioners to prepare data (e.g., large corpora of textual documents) to train the machine even before the launch of the course. In terms of this problem, one speculative remedy could be to base predictions on documents extracted from analogous courses that have been recently offered. However, this proposal, while promising, is not a panacea. It underscores the pressing need for more intensive design science research in this realm.

Transitioning into the next chapter, I argue it is pertinent to consider how these advancements and challenges in knowledge evaluation tools intersect with broader ecosystems of knowledge exchange. If one envisions knowledge as an expansive, interconnected web, then the nodes and threads of this web are not just about creating and evaluating knowledge but also about how effectively it can be shared, accessed, and repurposed by a wider audience. This is particularly true for open science knowledge, a domain burgeoning with untapped potential and value. However, the very ethos of 'open' suggests that this knowledge should be accessible, findable, disseminated, and reusable to truly be of service.

In Chapter 6, I delve into the vast domain of open science knowledge exchange, navigating its complexities and highlighting its finer details. By analyzing data from a major Australian science repository, I uncover key findings that offer a nuanced understanding of how open science data is accessed and reused on open science knowledge exchange portals. Thus, this thesis unlocks value for users on another common type of knowledge exchange platform by ensuring open science knowledge is not only available but also effectively accessed and utilized.

Chapter 6: Study 3 - On the increase of open science knowledge exchange: Evidence from an investigation into a large international data portal

This chapter delves into the distinct architecture of centrally organized platforms, contrasting sharply with the largely decentralized ethos of CQAs and MOOC forums. Specifically examining Australia's largest open knowledge and data exchange portal, this section underscores the inherent structural and functional divergences between community-driven platforms and their centrally governed counterparts. This exploration unfurls invaluable insights on enhancing retrievability in open science data and knowledge, presenting a layered understanding of the dynamics and nuances associated with diverse platform typologies.

Open science knowledge has significant value, yet this value can only be realised if the information is accessible, findable, disseminated and reused. This research examines attributes of open science data and enablers for users to access this data. I collect data from this major Australian science repository, and results show:

1) The trendiness of a dataset's keywords is a significant predictor of whether a dataset becomes a top-downloaded dataset;
2) traditional factors, including metadata richness, contributor network and reputation, age, and fields of research, mostly have significant positive but small effects on retrieval rates;
3) metadata completeness has a stable positive effect.

With these results, I advance the literature on exchange of open science knowledge and provide insights on how science organisations can enhance their platforms for users through better accessibility and findability of data. I also provide insights about how to increase retrieval rates, unlocking greater value for users.

Context

This poses the question “How can managers of open science platforms increase the value of their data and knowledge by improving user accessibility and findability?”

The literature suggests that to increase findability and accessibility, managers of open science portals should follow good data-archiving policies. For instance, from an information technology perspective, common data-archiving approaches include ensuring meta-data richness and completeness (Lee et al., 2002), providing relevant documentation and information to potential retrievers and requiring mandated open access (Curty & Qin, 2014; Niu, 2009). However, as Dunning et al. (2017) argue, the effectiveness of these approaches is often questioned for not being sufficient. In this regard, I argue there is a lack of empirical insights into why certain open science data are generating higher impact than others.

Specifically, with this research I quantitatively examine the findability and accessibility of open science knowledge. I use an open science data portal from CSIRO, Australia’s National Science Agency. I analyse how users access and retrieve data collections from the open data portal and examine metadata associated with each collection, over a 26-month period. The results offer important insights for theory and practice of knowledge exchange, and specifically, based on the results, I posit that, to increase research data collections' visibility and to better unlock research data's value, data sharers and portal administrators should prioritise the importance of keywords' topicality.

As I mentioned in the previous literature review section, prior studies clearly show that despite the need to better understand how users can better find and access open data, the extant knowledge management literature and literature review offers few insights how organisations can help to add value. Hence, organisations may underinvest in data sharing practices and not provide appropriate incentives for individuals researchers. Although, I acknowledge that it may not be able to entirely resolve restrictions regarding time and assessment systems, yet I may a find cost-efficient way to mitigate the problem. I now proceed with a case study on open science data with the aim to identify metadata features which may increase the retrieval rate of datasets without imposing significant workloads on data uploaders.

The CSIRO's open science knowledge exchange portal

This research presents a case study and evaluates data from Australia's Commonwealth Scientific and Industrial Research Organization (CSIRO) Data Access Portal (DAP). CSIRO's DAP is a major platform that provides open scientific data to researchers from CSIRO and external users, who either collaborate with CSIRO staff or strategically align with CSIRO's mandates. The platform allows users to share their data collections and digital publications (CSIRO, 2019). The purpose for choosing this particular open science data case is motivated by four reasons:

1. High diversity of available data, as CSIRO carries out a wide range of pure and applied scientific research across most science disciplines and domains, which is shared through the DAP.
2. Large data volume; by the end of 2019, the portal had accumulated more than 4,000 data collections from more than 400 individual data contributors and reached 146 terabytes in size.
3. Open access of scientific data, as CSIRO researchers work on a large number of publicly funded projects. CSIRO is focussed on disseminating data publicly in order to achieve impact from its research.
4. High value of data sharing, with a recent study conservatively estimating the benefits of sharing CSIRO's data at around AU$67m per year (Sanderson et al., 2017). This figure indicates the value that one could generate from increasing the rate at which people reuse data.

CSIRO uses Google Analytics to monitor DAP users' activities, such as viewing and downloading datasets and their geolocation. CSIRO also allows public users to access the data collections via webpage interactions and via an application programming interface (API). For direct webpage interactions, each data collection in DAP has a publicly accessible webpage on which users can find metadata information such as discipline, publishing year, and data descriptions. Per the API method, the DAP uses a Web Service Interface (WSI) for accessing public data collections, which supports Cross Origin Resource Sharing (CORS). However, CSIRO cannot distinguish these two types of access when monitoring users' activities. The data collections vary in their metadata's comprehensiveness and content.

Method

The aim of this research is to examine how users find and access open science knowledge. To achieve this aim, I use the dataset from CSIRO's information management & technology team that recorded DAP dataset's retrieval numbers over a period of 26 months (from 1 January, 2017, to 28 February, 2019). This dataset contains data collections that accumulated at least one retrieval as of the final record-keeping day. Each data collection contained a unique name and the number of times it was retrieved during the period (where collections are split into multiple files, a value of one was recorded for each user whether they downloaded some or all the files). As such, I had an opportunity to test for associations between a dataset's documentation attributes and the rate at which people retrieved it.

After performing a preliminary analysis, I confirmed a highly skewed retrieval rate: a small number of data collections had hundreds of downloads, while most had only one download ----or none at all. The research design used in this study includes two stages. *First,* I test and measure the effectiveness of six metadata quality factors with the DAP dataset. *Second,* I test for the impact of the topicality that a data collection's keywords had in determining whether the data collection would become a top-downloaded data collection. Crawling data through an API is the primary data collecting method, and SPSS 24.0 is the tool for performing statistical analysis. The current study contains three stages.

Initially, I test five metadata factors with the DAP dataset; the narrative table (Table 21) and data flow diagram (DFD) (Figure 9) illustrate the procedures.

#	Activity
1	I extract details from a dataset that was provided by the CSIRO DAP admin team
2	I use the data-titles as search terms to retrieve the metadata details (i.e. identifiers, published dates, lineages, descriptions, contributors' details, lead researchers' names, and fields of research) through the DAP API.

3 I use the names of the lead researchers and the contributors to retrieve their h-indexes which were used to estimate researchers' reputation. I use Scopus as the source of the h-indexes, and the process was automatically accomplished through the Scopus Interactive API.

4 For cases where multiple people share the same name, I select the one labelled with a CSIRO affiliation. Since some of the researchers changed their names or used a different name internally from the ones they use in Scopus, I cooperate with an internal CSIRO staff member to determine the identity of the person manually.

5 If I still cannot find a person through the above-mentioned approach, I search people in Scopus labelled with an Australia location. This is due to the fact that CSIRO primarily collaborates with Australian partners, so if there is an external data contributor, then the possibility of the contributor being affiliated with an Australian organisation at the time of creating the dataset is high.

6 I then retrieve the research field classification details from the Australian and New Zealand Standard Research Classification Scheme (FoR) and categorise the DAP data collections based on that scheme.

7 I create a dummy variable matrix based on the retrieved FoR information.

8 I aggregate the fields of study to their top-level-domains. This step increases the group size of each disciplinary group. For example, for data collections who had integrable systems (Classical and Quantum) as their research field, a very specific discipline, I aggregated it to mathematical sciences, its top-level domain according to the FoR scheme.

9 I merge all the data I collected (i.e., reputation and field of research information) together using “dataset title” as the key.

10 I clean and analyse the data using SPSS 24.0. Detailed cleaning procedures are introduced in the next section.

Table 21. Narrative Table for Procedures of Stage 1

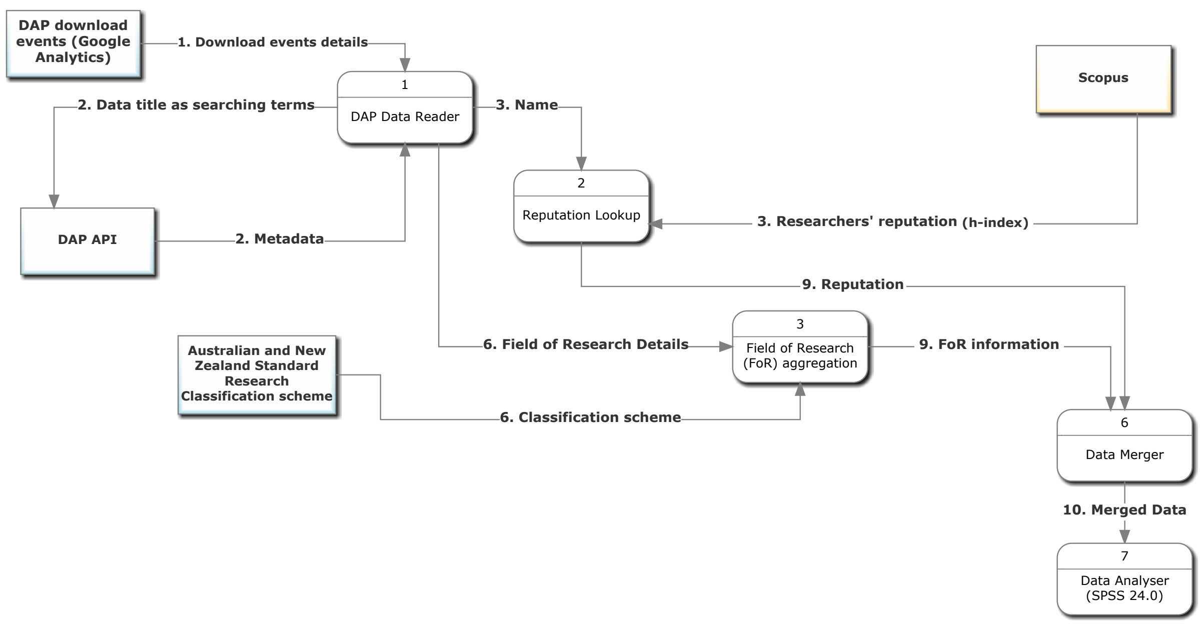


Figure 9. Research Dataflow Diagram of Stage 1

Factor	Variable	Definition	Measure	Mean	Std.D	Range
Metadata richness	Lineage richness	The length of the lineage field (an optional field). Long lineage usually means informative provenance details, rich versions information, clear history, etc.	The number of characters in the lineage field, if exists.	776.49	1055.04	4007
	Description richness	The length of the description field (a required field). Long description field often means richer contextual information, such as research backgrounds, coverages, potential relevance, etc.	The number of characters in the data description field, if exists.	865.23	744.16	3895
Reputation and network	Lead researcher's reputation	The reputation of the lead researcher (typically the supervisor or the leader of a research group who published the data collection)	H-index	21.02	14.06	59
	Contributors' reputation	The total reputation scores of the contributors of a research data collection	H-index	66.83	80.40	611
Metadata completeness	Optional fields completeness	The proportion of optional fields that is not null against the total number (14) of optional fields	Ratio of the optional fields filled in divided by the total number of optional fields	0.84	0.18	1.00
Age	Years	Number of years since the data collection gets published	The year number	3.46	3.32	7.52

Field of research (FoR)	Big science	The disciplines that tend to have large research teams, long-term projects, and significant instrumentation, including Astronomy and Physics, Chemistry, Earth Sciences, Computer and Engineering, and Biomedicines.	1 = is a big science discipline 0 = is not a big science discipline	N/A	N/A	N/A
	ANSRC field of research	The discipline(s) of the dataset, classified according to the Australian and New Zealand Standard Research Classification (Statistics, 2008)	1 = in the discipline 0 = not in the discipline	N/A	N/A	N/A
	Gregory's aggregated field of research	Disciplinary domains that were aggregated using Gregory's et al. (2019) classification scheme. I combined math and physics, computer and engineering, medical and biology, economics commerce and social sciences because of low case number.	1 = in the domain 0 = not in the domain	N/A	N/A	N/A
Retrieval rate	Unique download event value	Data retrieval is operationalised by data download number (i.e. the unique event value).	Number of events that a user retrieves a data collection	15.5	42.992	805.00

Table 22. Variable Definitions and Descriptions

In Table 22, I summarise these variables that were collected in the first stage.

Metadata richness. I use the length (in characters) as a proxy to measure a data collection's contextual quality (i.e., the richness of the lineage data and the description data). Granted, one may argue using the length of the fields to measure richness can be misleading. However, I found length has been used in many previous researches as an objective proxy variable to measure richness and quality of data and information. For example, as Adamic et al. (2008) report, if they used content length to determine an information's quality, they could achieve a 62% determination accuracy. A previous empirical research also indicates that, in a certain range, an information piece's length positively correlates with its quality (Jeon & Rieh, 2013)[5] .

Contributor network and reputation. I assume a higher overall contributor reputation would imply more researchers with high prestige or a bigger network, or both, which could positively correlate with the unique download value. H-index scores were used to estimate the lead researchers', as well as the contributors', reputation. I assigned a "none" value to denote people who did not have a findable h-index. The name list contains 1,207 individual contributors, and 1,099 (91%) have a non-zero h-index. I acknowledge that measuring scholarly structural impact and reputation is a complex task, but, as Wagner et al. (2017) stated, h-index is the most prominent measurement for author reputation and impact, so in this research I use it as a proxy.

Metadata completeness: I calculated an optional-field-completeness by dividing the number of the optional fields filled by the total number of optional fields, and I estimated that data collections with high optional-field-completeness would have higher download values.

Age: I calculated the age (measured by years) of a data collection since its publishing date. I assume the age of a data collection plays an important role in accumulating downloads over time. A data collection's accessibility is higher when the collection exists longer. Therefore, I keep this factor in this research model as a control.

Retrieval rate: I calculated the retrieval by the number of times a data collection is downloaded. Similar to previous research, I also find that the retrieval rate of data collections to be highly skewed (skewness = 11.75).

[5] Note that, by browsing the metadata I collected, I did not find any verbose descriptions, though that may be due to the fact that I lack expertise in information from academic disciplines other than Information Systems and Computer Sciences. Also, due to resource limitations, I could not find and hire enough experts from the various academic fields to judge the quality of each individual metadata description.

Moreover, I retrieved the data collections' research fields that were originally labelled by DAP data uploaders. Because several research fields only had one or two data collections, I aggregated them using two methods. *First,* I aggregated the data collections into top-level disciplinary domains based on their specific research fields that was labelled in each collection. *Second,* I aggregated the disciplines using Gregory et al.'s (2019) classification scheme. Two variables, "ANSRC fields of research" and "Gregory's aggregated field of research", contained the aggregation result--both in the form of two dummy matrices.

In this research, I hypothesize the following:

H1 Metadata richness has a significant positive correlation with the retrieval rate of data collections

H2 Contributors' reputation has a significant positive correlation with the retrieval rate of data collections

H3 Metadata completeness has a significant positive correlation the retrieval rate of data collections

H4 Age of data collection has a parabolic relationship with the retrieval rate of data collections (, i.e., a new data collection need time to accumulate downloads, and the accumulate rate matured at some time, so a very old data collection will not accumulate many downloads during the observation period of this study).

H5 Big science data collections have higher retrieval rates than data collections of other fields of researches

H5a Big science data collections (based on ANSRC fields of research classification scheme) have higher retrieval rates than data collections of other fields of researches

H5b Big science data collections (based on Gregory et al.'s (2019) classification scheme) have higher retrieval rates than data collections of other fields of researches

I performed a generalised linear model (GLM) in this stage. When running the model, I chose to exclude 27 cases with missing leader's reputation values. Since the dependent variable is a count variable, I cannot use the traditional ordinary least square model as the assumptions of homoscedasticity and normal distribution of the errors are violated. A common model to account for the discrete and nonnegative nature of the count data is the Poisson model (C. Wang et al., 2015). An equidispersed Poisson distribution assumes the variance has the same value as the mean, but I found that the data have an overdispersion problem, and in this case, I should use a negative binomial distribution model which allows for overdispersion of the count variable (Hausman et al. 1984). I use log for link function as many other scientometric studies did (Wagner et al, 2017). I followed Ford (2016)'s guidance to determine the dispersion parameter for running the negative binomial regressions.

I summarise the results from the stage 1 analysis in Table 23. Initially, I tested the main effects of the traditional metadata factors (Model A), showing that all traditional factors (except for description richness, $p = 0.262$) identified previously in the literature review show a statistically significant positive correlation with the data-retrieval rates for the DAP datasets. However, the coefficients are all small, except for metadata completeness ($\beta = 2.492$, 95% CI, 2.195 to 2.788, $p < 0.001$) and age ($\beta = 0.127$, 95% CI, 0.077 to 0.177, $p < 0.001$). This may be due to the diverse research represented in the dataset, as certain fields tend to accumulate larger download numbers than other fields (e.g., big science) (Birney, 2012). Subsequently, I build the second model (Model B) in which I put the big-science factor into consideration. After I added this dummy variable in the model, I found that big science can bring a significantly positive effect on data collections' download rate. However, this factor also makes four metadata factors' effect less significant, including lineage richness, description richness, contributors' reputation and network, and lead researchers' reputation. Next, in Model C, I tested the field of research dummies. I found data collections that belong to fields including Maths and Physics, Earth Sciences, Computer Sciences and Engineering are expected to have significantly higher number of downloads. Lastly, in Model D, I tested those interaction effects that Gregory et al.'s (2019) conceptual study suggests (e.g., Earth and Environmental Sciences with lineage richness; Math, Physics, and Chemistry with metadata description richness; and Biomedicine with description richness). The results suggested that the lineage and description richness are significantly positive for datasets that belonged to Biomedicine subjects, but given the small coefficient numbers, the scale of effect is relatively small. One exception is metadata completeness: it is significant for datasets that belonged to Earth and environmental studies, and the scale of effect is reasonably high. However, note that, with this model, goodness of fit factors are not as good as previous models, implying a lower quality of that model, compared to Model A, B, and C.

Variable	Model			
	A	B	C	D
	N=574	N=574	N=574	N=574
	Beta (std. e.) Sig.	Beta (std. e.) Sig.	Beta (std. e.) Sig.	Beta (std. e.) Sig.
Lineage richness	<0.001**(<0.0001) <0.001	<0.001 (<0.0001) 0.186	<0.001 (<0.0001) 0.190	0.001** (0.0004) 0.004
Description richness	<0.001 (<0.0001) 0.262	<0.001 (<0.0001) 0.862	<0.001 (<0.0001) 0.496	<0.001 (0.0004) 0.947
Contributors reputation & network	0.001 (<0.0001) 0.083	0.001 (0.0005) 0.265	0.002** (0.0006) 0.005	0.001 (0.0012) 0.556
Lead researcher's reputation	0.007* (0.0031) 0.027	0.003 (0.0031) 0.381	0.009** (0.0031) 0.007	-0.007 (0.0135) 0.581
Metadata completeness	2.492** (0.1515) <0.001	0.747** (0.2729) 0.006	0.809** (0.2980) 0.007	1.730** (0.1714) <0.001
Age	0.127** (0.0256) <0.001	0.094** (0.0264) <0.001	0.105** (0.0264) <0.001	0.089** (0.0262) 0.001
Big science		1.727** (0.2250) <0.001		
Maths and Physics			8.172** (1.7353) <0.001	
Chemistry			0.120 (0.3454) 0.727	
Earth sciences			0.765* (0.3011) 0.011	
Environmental studies			0.578 (0.3003) 0.054	
Agriculture			0.123 (0.3190) 0.669	
Computer science and engineering			1.647** (0.3121) <0.001	
Biomedicine			0.023 (0.3797) 0.951	
			0.584 (0.4428)	

Humanitarian studies			0.187	
Aggr. Math, physics and chemistry (including astronomy) * contributors' reputation				-0.001 (0.0014) 0.406
Aggr. Math, physics, and chemistry (including astronomy) * lead researcher's reputation				-0.019 (0.0134) 0.167
Aggr. Math, physics, and chemistry (including astronomy) * description richness				0.0004 (0.0004) 0.229
Aggr. Biomedicine * description richness				0.0003** (0.0001) 0.001
Aggr. Earth and environmental studies * lineage richness				0.001** (<0.0001) <0.001
Aggr. Earth and environmental studies * Metadata completeness				1.280** (0.1485) <0.001
Aggr. Social science and economics * lineage richness				0.001** (0.0004) 0.003
Aggr. Social science and economics * description richness				-0.0002 (0.0002) 0.226
Pearson Chi-Square	4044.61	3410.85	2947.06	3138.74
Omnibus test (Sig level)	<0.001	<0.001	<0.001	<0.001

Table 23. Estimations of Parameters in Model A (Pure Metadata Factors), B (Metadata Factors plus Academic Field of Research Dummies), and C (Metadata Factors plus Gregory-inspired Dummies). *p < 0.05. ** p < 0.01.

The second stage of this research aims to test the impact of the topicality of keyword selection on frequency of downloads. To investigate other possible factors that might explain the large differences in the download event numbers, I hypothesise the download number might relate to a data collection's topicality. That is, does a data collection attract more downloads if it used a more popular keyword at the time a user retrieved it compared to those that did not? Inspired by the fact that Google refers users to access the DAP more than any other source (Lawrence, 2018), in this stage, I assume those data collections with keywords that had higher trending scores on average may receive a higher number of downloads.

According to Vaughan and Romero-Frías (2014), Google Trends provides a qualified proxy for researchers to estimate a term's topicality. A Google trend score, as Ginsberg et al. (2009) argue, represents a useful way to monitor social phenomena and provide more timely information than traditional data do. For instance, Cook et al. (2011) and Carneiro and Mylonakis (2009) used Google Trends data to assess, estimate and surveil disease trends (e.g. flu, pertussis) in the US, though some asserted scepticism towards the power of estimation and surveillance (Pollett et al., 2015) and argued that the success may be short lived (Lazer et al., 2014). Vaughan and Romero-Frías (2014) used trend data to estimate or predict academic fame and found a strong positive correlation between search volume data and university ranking data. Preis et al. (2013) found that an increase in Google search volumes for keywords correlates to stock market falls in financial markets, therefore, suggested that one can use trend scores to build up profitable trading strategies. I have not found any studies that have investigated the possible relationship between keywords' trending scores and data-retrieval rates. Thereby, I hypothesize the following:

H6 The trendiness of a data collections' keywords significantly differed among data collections that had different download numbers.

Table 24 summarises the research activities for Stage 2; Figure 10 presents a data flow diagram which explains the procedures used to collect the data for this stage.

#	Activity
1	I retrieved all "keywords" and "published date" metadata via the DAP API (each data collection in the DAP had a set of keywords that its contributors defined and a published date that the system automatically created when contributors uploaded it).
2	I stored the keywords in a temporary data store.
3	I used Pytrends[6] to lookup the keywords' trend scores over a certain period (i.e., from the day that the data collection got published till the day I finalised the research; that is, 29 July, 2019).
4	If a data collection had multiple keywords, I calculated the average score of all keywords and used that score to represent the data collection's topicality. For keywords that I could not search on Google Trends, I assigned the score 0.
5	I randomly choose 100 keywords from the temporary keywords data store and used them as the search terms to retrieve some random data collections

[6] For detailed information about Pytrends API, see: www.github.com/GeneralMills/pytrends

6	I deleted keywords that the original dataset already included. In doing so, I obtained a dataset that comprised data collections that had not yet accumulated downloads (recall that the original dataset comprised collections that had accumulated at least one download). In the unique download event value column (i.e. the column I selected as the retrieval rate), I labelled these data collections as “0”, which means that these data collections did not accumulate any downloads during the download-monitoring period. Step 5 and 6 are used to eliminate the pre-selection effect. That is, I wanted not only to include the data that had accumulated some downloads but also to contain the collections that had accrued no downloads.
7	I then merged all the data that I had collected into one file. I selected the top 60 data collections (in terms of the download numbers) with their keywords' trending scores (time range = from the data publish date to the date I started this research). Then, I randomly chose 60 data collections from the datasets with no or one download and extracted their keywords. Then I analysed the data using SPSS 24.0 for an ANCOVA test.

Table 24. Narrative Table for Stage 2

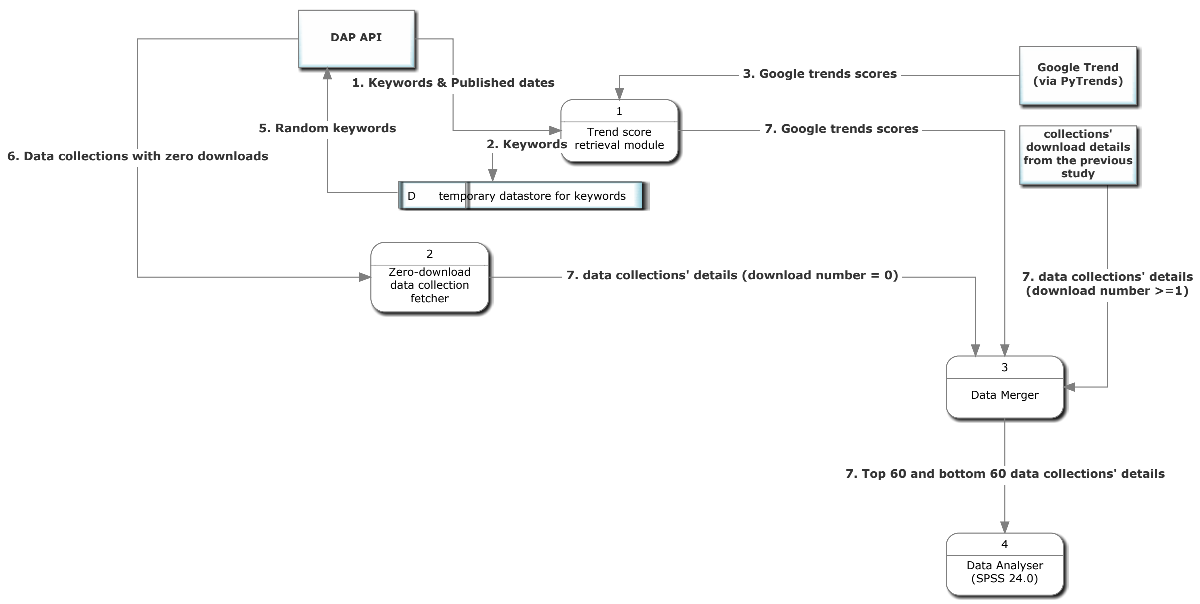


Figure 10. Research Procedures of Stage 2, a Dataflow Diagram

Variable name	Definition	Range
Keywords’ trending scores (topicality)	Google trend scores (a particular term relative to the total number of searches done over time)	[3.347, 47.306]

Group	Whether a dataset belongs to the Top 60 group (= 1) or the Bottom 60 group (= 0)	[0,1]
Trend slope	Positive slope = 1, Negative slope = 0	[0,1]
Trend dispersion	The standard error of the daily trend scores since the dataset got published	[0.6216, 7.2489]

Table 25. Trend Variables Definition

Before the ANCOVA test, I tested whether the data violated any assumptions. I first found that the frequency distributions of the trending scores were normal. I also tested homogeneity of variance based on Levene's test ($p > 0.01$); after doing a log transformation, I found no major concerns. I describe the key variables that I used in this step and summarise the descriptive data in Table 26 and Table 27, respectively.

Group	Keyword Trend Slope	Keyword topicality Mean	Keyword topicality Std. Deviation	Cases
Bottom 60	Negative	16.510	5.773	19
	Positive	15.729	3.913	41
Top 60	Negative	20.959	7.097	27
	Positive	20.485	10.367	30
Total	Negative	19.121	6.880	46

Positive	17.738	7.673	71

Table 26. Descriptive Statistics for Keyword Trend Score Slope, Mean, Standard Deviation, & Number of Cases

Variables	Type III SS	df	F	Sig.
Model	39795.88	5	158.71**	0.00
Group (Reference = Bottom 60)	526.142	1	10.416**	0.00
Trend slope (Reference = negative sloping)	9.205	1	0.184	0.66
Log(trend dispersion)	22.67	1	0.452	0.50
Group * Trend slope	0.78	1	0.016	0.90
Error	5616.43	112	50.14	
Total	45412.31	117		

Table 27. Two-way ANCOVA Test Result for log(trend), Group (top v. bottom 60), and Trend Slope, log(trend dispersion), DV= log(keywords' trending score). $*p < 0.05$. $** p < 0.01$.

A two-way ANCOVA was conducted to test if the keywords' trending scores significantly differed among data collections that had different download numbers. At the same time, I wanted to control for the trend slope and the trend dispersion. Therefore, in this case, I used keywords' trending scores as the dependent variable. I used group as the independent variable, and I controlled for trend slope and dispersion.

Dependent Variable	Beta	Std. e.	t	Sig.
Group (Bottom 60)	2.724**	0.079	34.641	0.000

Group (Top 60)	2.908**	0.090	32.278	0.000
Trend slope (Reference = negative sloping)	0.064	0.107	0.596	0.553
log(Trend dispersion)	-0.003	0.174	-0.017	0.986
Group * Trend slope	-0.059	0.155	-0.381	0.704

Table 28. Parameter Estimation for Group, Trend Slope, log(trend dispersion), and Interaction between Group and Slope, DV = log(keywords' trending score) *$p < 0.05$. ** $p < 0.01$.

Results (see Table 27 and Table 28) showed that the Top-60 group's topicality scores were significantly higher (18.4%) than the Bottom-60 group's scores, and this effect was robust as the results showed the potential moderating factor (e.g., trend slope) or the confounding factor (e.g., trend dispersion) did not influence this effect.

In Stage 3, the keyword topicality factors were examined. Based on the conclusions that I obtained from the previous stages, I decided to add the keyword trend scores into the original models. I h the trend score factor not only has a significantly positive effect on retrieval rate, but also causes an improvement on the models' effectiveness in explaining the variance in retrieval rates. Formally, I hypothesise:

H7 The trendiness factor can improve the models (A-D)' effectiveness in explaining the variance in retrieval rates

I used the Pytrends API again and retrieved the trend scores for keywords of all the data collections. With the trend scores, I then re-ran all the models.

	Model A		Model B		Model C		Model D	
	Old	New	Old	New	Old	New	Old	New
Independent variables	See Table 3	Model A factors +	See Table 3	Model B factors +	See Table 3	Model C factors +	See Table 3	Model D factors +

		Trend score		Trend score		Trend score		Trend score
Trend Score	N/A	β = 0.025 t =11.015 p < 0.001	N/A	β = 0.020 t = 8.683 p < 0.001	N/A	β = 0.024 t =10.574 p < 0.001	N/A	β = 0.026 t =11.334 p < 0.001
| Log-Likelihood |	3134.7	2489.6	3089.5	3048.9	2974.2	2919.1	3051.3	2169.9
AIC	6281.41	6159.89	6193.01	6113.81	5974.47	5866.24	6130.60	6009.67
BIC	6308.12	6191.04	6224.15	6149.41	6032.33	5928.54	6192.91	6076.43
Omnibus test (Sig level)	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Pseudo R-squ.	0.0301	0.1525	0.0980	0.2068	0.3796	0.4788	0.2086	0.3482

Note: the models did not include intercepts; N/A = Not Applicable

Table 29 A Comparison between the Old Models (introduced in stage 1) and the New Models

As expected, the result shows that trend score factor positively predicted retrieval rate, and adding this factor also resulted in a statistically significant improvement in all model measurements (including Akaike Information Criterion (AIC), Bayesian's Information Criterion (BIC) Log-Likelihood, and Cox & Snell Pseudo R^2). For all the four models that I introduced previously. Table 29 presents a summary of the results from Stage 3.

Discussion

The aim of this research was to examine findability and accessibility of open science data. Large public research organisations play a critical role in transferring open data, and they should reduce the transaction costs of knowledge and data exchange (Gans et al., 2017). In terms of this, data documentation and metadata maintenance are important in establishing and enabling the knowledge exchange process between data producers and their secondary users and in ensuring the findability and availability of open science data (Niu, 2009). Thus, I focussed on finding answers to the question on how administrators of open science knowledge can enhance the value of their data platforms, so that users can better find and access data.

I reviewed prior research that used several traditional metadata quality indicators, including metadata richness and completeness, contributor network and reputation, age, and fields of research, and set up generalised linear models to find a relationship between the indicators and the download numbers. Then, inspired by Lawrence (2018)'s report which states that most of the data collections have a landing page from Google search, I hypothesised and tested those data collections with keywords that had higher topicality scores on average may receive a higher number of downloads. To the best of my knowledge, I have not found any studies that have investigated the possible relationship between keywords' topicality scores and data-retrieval rates.

Limitations and implications for future work

As with any study, this thesis has several limitations. First, I included eight state-of-the-art independent variables for predicting data-retrieval rates and tested how usefully they explained highly skewed retrieval rates in datasets. However, given the sheer number of established measurements for estimating meta-data quality that I found in the literature review, eight variables represented a small selection of the potential independent variables. It is of course possible that other variables which I was not able to measure in this study could have a significant effect on downloads.

Second, purely using length of provenance and description information to estimate the richness of description and lineage information may be not sufficient. I therefore recognise that length constitutes an objective proxy of information richness--an important component quality that one can easily measure and quantify. Length is a simple and critical predictor for information quality. In this case, I argue that data collections with longer descriptions and lineage information, which translates to a higher level of richness, tend to offer data users more opportunities to find cues about reusing the data collections. Professional researchers, who are also the primary users of the data collections, should be able to sift through data. That said, some people disagree and argue amateurs and inexperienced information users tend to have this kind of preference towards lengthy description and high richness because they can more easily judge effort than quality and novice users, compared to experienced ones, need more information and a longer evaluation time to judge quality (Chen et al., 2010).

Moreover, due to scope and monetary limitations, I did not perform further in-depth quality estimations for each dataset's metadata. To increase the validity of the quality measurement, I suggest future researchers invite domain experts from different research fields and ask them to read the metadata information for a dataset sample and give reliable qualitative scores. In this way, researchers may be able to observe and summarise several machine-learnable features and to use the qualitative scores as ground truth and training set to build models. By doing so, I would be able to train a model to automatically assess and even predict data collections' retrieval rates based on their meta-data features.

I cannot eliminate the possibility that Google Trends may not be a suitable measurement to estimate research datasets' topicality. I recognise that Google Trends is based on Google Search, which reflects the public's interests over a certain range of time. However, the level of interest of a certain keyword may greatly vary between its public use and its use in academia. For instance, 'Taylor Swift' may be a trending phrase, but arbitrarily adding that word into a research data collection as a keyword may not helpfully improve its retrieval rate. It would be better if I could find a viable topicality indicator based on a popular research-oriented search engine. However, no such specialised search engine exists (albeit the search log of some research repositories such as Scopus may be a reasonable proxy for such an engine).

Implications

I expect that this empirical study provides useful and timely insights to researchers and practitioners in data publishing communities of open science data. First, this study illustrates ways for practitioners (e.g., research data sharers and research data portal managers) to better publicise their data and, thus, to help them unlock its value. With this study, I propose a new robust factor (i.e., keyword topicality) that the results of this study show to be highly useful in explaining why datasets have skewed retrieval distributions. I then tested and confirmed the factor's effectiveness by adding it into the original models. Based on these results, I suggest data sharers and data portal administrators should use and update topical, relevant keywords and terms if they want other users to find their datasets.

Furthermore, these results also show that, for an established research institution, traditional factors that were proposed in previous interview- and survey-based conceptual studies, such as metadata richness, contributors' reputation, and fields of study, can bring significant positive effect on data collections' retrieval rates, but those factors may not sufficiently explain why different data collections have hugely uneven downloads and why some data collections attract significantly more downloads than others. Metadata completeness, however, is an outstandingly important factor.

According to Sanderson et al. (2019), to increase visibility and facilitate retrieval data sharers and portal administrators need to help users draw insights from data when users making decisions, such as by giving more detailed and comprehensive metadata, highlighting the most salient information, and identifying patterns or trends. However, providing additional information would also incur additional costs (e.g., codification costs, which occurs when data sharers need to convert the required information into a store-able and decode-able format (Cowan et al., 2000). Given limited resources, one should prioritise those factors.

This study suggests the following policy recommendations. First, I recommend data contributors and administrators in the DAP, as well as people in other similar data portals, to recognise the importance of metadata completeness and keyword topicality. Particularly, I recommend using more accessible keywords, given the number of interdisciplinary scientists and researchers is increasing and they must be able to find data in the disciplines that they are less familiar with. *Second,* data administrators shall do regular reviews on keywords' topicality and update them, if necessary. A data collection's keywords that were trending when the collection got published might subsequently become obsolete (e.g. 'Grid computing' should have been replaced by 'Cloud Computing'). Therefore, knowing what are trending and obsolete keywords and reacting accordingly is an important task for data portal administrators. *Third,* search engine optimisation is important for DAP and similar institutional repositories that support scientific data sharing and publishing, given that there is an increasing number of people landing on these online repositories from Google. In this regard, as Brickley et al. (2019) also suggest, data managers and uploaders should recognise the importance of using and updating keywords that are agreed upon vocabularies in semantics and knowledge graph (e.g. Schema.org standard).

Summary

In summary, this chapter provides critical insights into the nuanced relationships between various metadata indicators and the download numbers of datasets. While positive correlations were found with most metadata indicators, the influence of these factors, barring metadata completeness, tended to be relatively weak. This challenges some prevalent assumptions and suggests a need for further investigation.

One of the significant findings of this study was the influential role of a data collection's keyword topicality in distinguishing top-downloaded datasets. The study found that top-downloaded data collections incorporated keywords with higher search volumes on Google, compared to datasets with few or no downloads post-publication. This difference was significant even when considering the slope and dispersion of data topicality.

To leverage this finding, a 'trend score' factor was introduced into the original models. This addition not only confirmed that trending keywords could notably enhance data collections' retrieval rates but also improved the overall fitness and validity of the models.

These results significantly contribute to the knowledge management literature by suggesting effective strategies to enhance data retrieval rates, optimise data platform management for superior accessibility and findability, and boost user value. Given the escalating demand for scientific knowledge and quality data to address pressing global issues (e.g., Ylöstalo, 2020), these findings hold immense significance for promoting the exchange of open science knowledge. Therefore, the novelty of this chapter lies in quantifying the relative importance of established factors, reassessing the strength of metadata-based factors, and introducing a new keyword-related factor to significantly bolster the predictive power of the model.

As this chapter draws to a close, it is worth highlighting that enhancing retrievability and reusability is integrally tied to the “optimizing knowledge distribution” problem. Interestingly, marketization methods emerge as potential avenues to remedy this problem. With this in mind, the subsequent discussions will delve into the unique interplay between knowledge exchange and market dynamics. The forthcoming two chapters will pivot the focus towards market-centric platforms, offering a comprehensive exploration. Specifically, I will embark on a discussion into the Massive Open Online Courses (MOOC) market, shedding light on its intricacies and the multifaceted dynamics underpinning it. MOOC markets can be important because they not only democratize access to knowledge but also become hubs of rich interactions, experiences, and exchanges. Consequently, understanding the MOOC market is not merely a detour but a critical focal point for this research. It offers an intricate tapestry of knowledge exchange intricately woven with market dynamics. Thus, the subsequent two chapters will turn the gaze towards these market-centric platforms, offering an in-depth dive into their multifaceted nature. First, I aim to uncover the layers, challenges, and opportunities that define the MOOC market, establishing its central role in the modern landscape of knowledge exchange.

Chapter 7: Study 4 – Real-world knowledge market analysis: A case study of edX

Context

The above platforms were mostly not market-oriented. Scholars has gradually noticed a salient contrast emerges between platforms, with their community-driven ethos and decentralized structure, and the more transactional, market-oriented knowledge platforms. The latter is accentuated by their distinct advantages: unparalleled access to external knowledge sources, cost-effectiveness in knowledge exchange, and an adept fusion of intrinsic and extrinsic motivations. Yet, notwithstanding their apparent potential, scholarly exploration of these market-centric platforms remains in its nascent stages. Bridging this scholarly void, the thesis embarks on an exhaustive exploration of both public and private knowledge market landscapes, shedding light on the intricacies and nuances of knowledge marketization. This chapter presents a public knowledge market, with an emphasis on the pricing dynamics of online MOOCs.

The first MOOC appeared in 2008, but it was not until 2012 that a small number of MOOC initiatives gained "massive" popularity worldwide (Moe, 2015). MOOC, as Moe argues, is hard to usefully define but the term has been used by mainstream media in a conflated manner and has widely been seen as a combination of technological solutionism, disruptive innovation, and a way to "mitigate our educational crisis". He suggests that MOOC refers both to an instrumental learning model and to a social movement. That said, for the purpose of this study, I use a working definition given by Kim (2014) to define and to set up a boundary for MOOC: that is to say, I will not consider MOOC as a social movement but merely as a course that has the capacity to accommodate a very large number of learners, is able to be accessed via online channels regardless of a classroom analogue, and is open for assessment and for curriculum so a learner can choose to have or not to have his or her assignment graded freely and what courses to take at will. As a result, MOOC allows on-demand accreditation and a relatively flexible learning pace.

Now, most MOOC providers charge a price to students (customers) to enrol (rather than to audit) and to obtain a trackable certificate. For instance, in 2015 edX ceased its Honour Code Certificates to its users who take courses for free (Agarwal, 2015), and, in the same year, edX's major competitors, Coursera and Udacity, "phased out" most of their free "Verified Certificates" and "Statement of Achievements". As Shah (2015) reported, in some courses, users who do not pay money are not anymore able to access the whole package of course materials (e.g. taking quizzes). As Rustam and van der Weide (2016) argued, those platforms offering MOOCs, as well as the relevant software mediating and connecting the students and the course providers, can already be seen as "marketplaces for knowledge". That is to say, those platforms allow knowledge buyers and sellers to meet with each other and negotiate transactions. In these platforms, "market information", such as price and reputation, is fundamentally important in the bargaining process and, therefore, vital for achieving a successful and smooth matching process between demand and supply. Ideally, this marketplace of knowledge would optimise the distribution of knowledge resources and maximise the utility level for all market participants. This type of knowledge marketplace is also termed "K-mall" by Skyrme (2012).

A well-functioning market cannot survive without an appropriate pricing mechanism. Yet, the pricing system and the pricing strategies used by major modern MOOC platforms such as edX, Coursera, Udemy, Udacity, and xuetangX, are still under-developed. Until recently there has also been limited research investigating factors influencing the pricing of MOOCs (Jia et al., 2017). This has become an increasing concern to providers, particularly since after 2015 some of the major providers of MOOC courses have gradually dropped their free offerings (MoocLab, 2017).

The pricing structure for MOOCs is still immature, largely, because it is very difficult to price digital products. Economics suggests that prices should be set at a point where the marginal benefit of the product equals its marginal cost (Mankiw, 2014). MOOCs typically have marginal costs close to zero, but the fixed costs are quite high. Therefore, the fixed costs need to be spread across a large number of users; this means that more popular courses should cost less per user. However, according to Shah (2015), as of December 2015, more than half of the courses sold on Coursera are priced at exactly \$49 USD. The precisely same number is also the most popular price on edX, despite differing courses' subjects, offering institutions, number of enrolled students, etc. Also, the average price of courses taught in languages other than English is lower than courses in English, which might be due to the fact that many of those non-English courses are targeted at customers in developing countries. In addition, also in 2015, Udacity adopted a "flat rate" business model by which students need to pay a fixed price, USD 200/Month for gaining a Nano-degree: a 4-12 month program designed for training technical or professional skills (Morell, 2015).

Maintaining and sustaining good-quality courses can be prohibitively costly for universities, because of the high fixed costs. Despite this, MOOC users can still witness the introduction of new or re-offered courses and programs on MOOC platforms (Shah, 2017; Ukueberuwa, 2018), even though the revenue patterns of MOOCs are still not at all clear. Belleflamme and Jacqmin (2016) suggest a "two-sided market" model, i.e., a market aimed at enabling interactions between at least two groups (sides) of its end-users, is appropriate for MOOC platforms because this market model allows the MOOC platforms to continuously provision knowledge goods without excessive use of external subsidies. An asymmetric pricing structure is suitable for this type of market, i.e. a pricing strategy aimed at charging a lower price to the group that has the strongest positive cross-side effect on the other side in order to enlarge the participants' base and to start a positive feedback loop (Belleflamme & Jacqmin, 2016). In the case of MOOC platforms, this theory justifies the logic that they charge relatively low fees (compared to traditional university tuitions) to students to initiate the loop whilst charge a larger fee to suppliers for revenue. In reality, according to Kolowich (2013), as of 2013, edX.org officially uses two methods to generate revenue: either by collecting the first \$50,000 USD generated by a course offered by an institution or by charging the institution a course production assistance fee of \$50,000 USD. In terms of business models, most current MOOC platforms are using a Freemium model (accessing a course for free while charging for certification) or a Subscription model (Gassmann et al., 2014). That said, given the diversity of the MOOC education market, there are also other possible business models, such as the Advertising model, the Subcontractor model, the sub-licensing model and the Job matching model. Those models may have a promising future according to Belleflamme and Jacqmin (2016) and Jia et al. (2017). In practice, courses, together with their certificates, are often sold in bundles (e.g., in form of a micro master program on edX). Taking that into consideration, Jia et al. (2017) present a mathematic model for pricing the bundled certificates. As such, there does exist some sort of pricing structures on MOOC platforms, but the current system's effectiveness is at most questionable, because, according to Kolowich (2013), major MOOC players are still facing challenges in maintaining a free cash flow and a healthy financial return. For the time being, the platforms' survival is still heavily relying on external investments and cross-financing from universities. For example, Shah (2016) mentioned that, to survive, edX obtained $15 million USD from its university partners in 2015 and would gain another $20–30 million in 2016. It is, however, uncertain to see whether this model is viable in the long run.

As aforementioned, although many universities are providing MOOCs for philanthropic purposes, brand building or as a pre-admission and filtering mechanism - universities offer pathway program (mostly via credit redemption) for outstanding performers - it is still worthwhile to investigate if there is a discernible underlying pricing model within MOOC marketplaces to guide courses' pricing. Before addressing this question, it is essential to understand the current pricing structure of MOOC platforms and to investigate what factors would affect course pricing. This is what this study aims to achieve. More precisely, this study attempts to investigate the aforementioned questions by conducting a descriptive statistic study.

This study will first examine the current price structure of an online non-for-profit MOOC site, specifically, edX.org, as it is the largest not-for-profit provider in this industry (Baker & Passmore, 2016). Then, I formulate a model to examine what factors can usefully explain the differences in courses' prices. Further, I want to investigate the "usefulness" of the price data: i.e., what conclusions can be made from a given price information. Intuitively, it is conjectured that price would have a significant correlation with courses' enrolment scale, exploration rate, and completion rate. It also seems plausible that higher priced courses would receive a higher ratio of certificated enrolment compared to overall enrolment. Some previous studies investigated the causal factors of MOOCs' low completion rate issue (Aboshady et al., 2015; Lewin, 2013; Yuan et al., 2013), very few papers focus on the potential relationship between the price and the completion rate. Burd et al. (2015)'s work mentioned money and price issues, but it is only concerned with the course suppliers' perspective. Their argument is that the low completion rate affects the revenue flow generated by MOOCs, but not how a course's price would affect completion rates of students. Henceforth, in this study, I hypothesise the following: first, the higher the price, the lower the demand (in this case, the lower the number of enrolments in a course); second, that participants pay more attention to courses they paid a larger sum of money for earning certificates.

Method

The software I developed for the project[7] consists of two major parts: A Web crawler and a data analyser. Both are written in Python 3.6, and both are specifically designed for crawling and analysing data on edX. I utilised the "selenium.webdriver" module to access the price information, as the information is not directly crawl-able: They are generated by a piece of JavaScript code embedded rather than in plain HTML format. As of 1st February 2018, the crawler visited 1743 courses' web pages and collected information about their recommended course length and suggested efforts (weekly study-load), institution, subject, level, language(s), and video transcript languages. It is worth to mention that there are 1923 courses offered on edX, but some courses are "uncrawlable" because their "courses information" section does not provide useful data fields, which may be due to the fact that the courses have ceased. Furthermore, although some courses do have a sufficient information section, the data shown in the section are not entirely structured: Most courses contain eight data fields, but some contain only seven fields while some have nine fields. Some courses have no "Price" information and some have an extra field named "type". The "type" field usually contains miscellaneous data: For instance, the course "Deals in Project Finance: Case Studies and Analysis" has a "Type" which is labelled "Professional Education and Self-Paced".

In total, I found 673 courses that currently do not contain clear price information, of which 91 courses do not have a price data field, while 582 courses are labelled as "Free Verified Certificate

[7] The project is called edx_crawler and is accessible https://github.com/Xenonshi/Edx_Crawler_V0.git

option closed". Other than that, I also found 42 courses being clearly labelled "free". In the following analysis, the former two categories of courses are excluded, while the third group, the "free courses", are denoted "zero" in the price column of the data-frame. In addition, there exist courses with no "language" information and courses with incomplete information for "length". In such cases, I label them as "NaN" in the dataset (i.e. not being excluded). For the purpose of data analysis, NaN, originally standing for "Not a Number", refers to a "missing data" in this study. I included those data points from the analysis as their level of influence as negligible. Furthermore, as I observed that most of the "length" and "effort" data are in a format of "*n* to *m* weeks" (e.g., 2 to 5 weeks) or "*n* to *m* hours per week" (e.g., 10-12 hours per week), I parsed and split those data points into three columns: max length (effort), min length (effort), and average length (effort).

I also acquired a second-hand dataset which contains data for 290 courses offered by Harvard and MIT, which encompasses subjects in STEM (Science, technology, engineering, and mathematics), CS (Computer Science), GHSS (Government Health Social Sciences) and HHRDE (Humanities, History, Religion, Design, Education). I performed an inner join on those two datasets using the "URL", "course title", and "course number" as keys. I deleted those courses that are not open as of 2nd February 2018 nor provide effective price information on its course introduction webpage. Many courses have also been offered already multiple times, which is readily identifiable as those course entries that have exactly the same URL but different course launch date. For those courses, I only select the most recent one for this research. In the end, 64 courses with active price information are identified and are used for further analysis. Also, for the purpose of this study, I follow Chuang and Ho (2016)'s convention and define that a student becomes a participant after he or she enrolled a course. If a person visits more than half of the course materials, the person becomes an explorer, and the course's exploration rate can be calculated by dividing the number of explorers by the number of participants. Then, if a person earns a certificate via successfully passing quizzes, assignments and exams, the person becomes a certificated student for that course, and by dividing this number against the number of the total participants, I obtain the course' completion rate.

Results and modelling

This section will first provide a series of basic descriptive statistic results based on this study's data analysis. Because all the price data crawled used Australian Dollars, unless it is otherwise noted, the denomination of price is AU Dollars (AUD). At the time of writing the paper, the exchange rate of AUD to USD is ~0.78. A basic analysis of the price of courses is shown in Table 30. It can be noted that the price frequency distribution is right skewed with its median lower than its mean.

Measure	Price		Percentile	Price
count	1070.00		5%	31. 00
mean	115.33		25%	61. 00
std	97.28		50%	93. 00
max	1115.00		75%	123.00
min	0		95%	248.55

Table 30. Basic Price Statistics

In terms of "institutions vs. price", as of February 1st, 2018, there are 115 institutions offering courses, and the provider offering the highest number of courses is, somehow surprisingly Microsoft, which has so far offered 183 courses (either explicitly for free or for a price). The average price is 123.01 AUD (95.57 USD) with a small standard deviation of 0.15. HarvardX and MITx follow Microsoft, providing 68 and 47 courses with an average price of 95.29 AUD (74.03 USD) and 102.49 AUD (79.62 USD) respectively. Also, it can be observed that, while on average the lower-priced courses are not necessarily provided by an institution from a developed country, the most expensive courses are all from developed economies, especially from the US and Australia. The latter finding coincides with Ortiz et al. (2015)'s report which mentions that the US and Australia have also the most expensive (offline) university fees.

In terms of price differences for different subjects, on average, the most affordable subject is "History" while the most expensive subject is "Medicine". Details can be found in Figure 11. The online courses' fee structure seems to be very similar to fee discrimination in the offline world, as in Australia, the government implements a "Student contribution banding and ranging system" in which those "Band 3 degrees" (e.g. medicine, laws, economics, and accounting) are more expensive than "Band 2 degrees" (e.g. computing and engineering) and "Band 1 degrees" (e.g. humanities social studies, and education) (Soutar & Turner, 2002; StudyAssist, 2016).

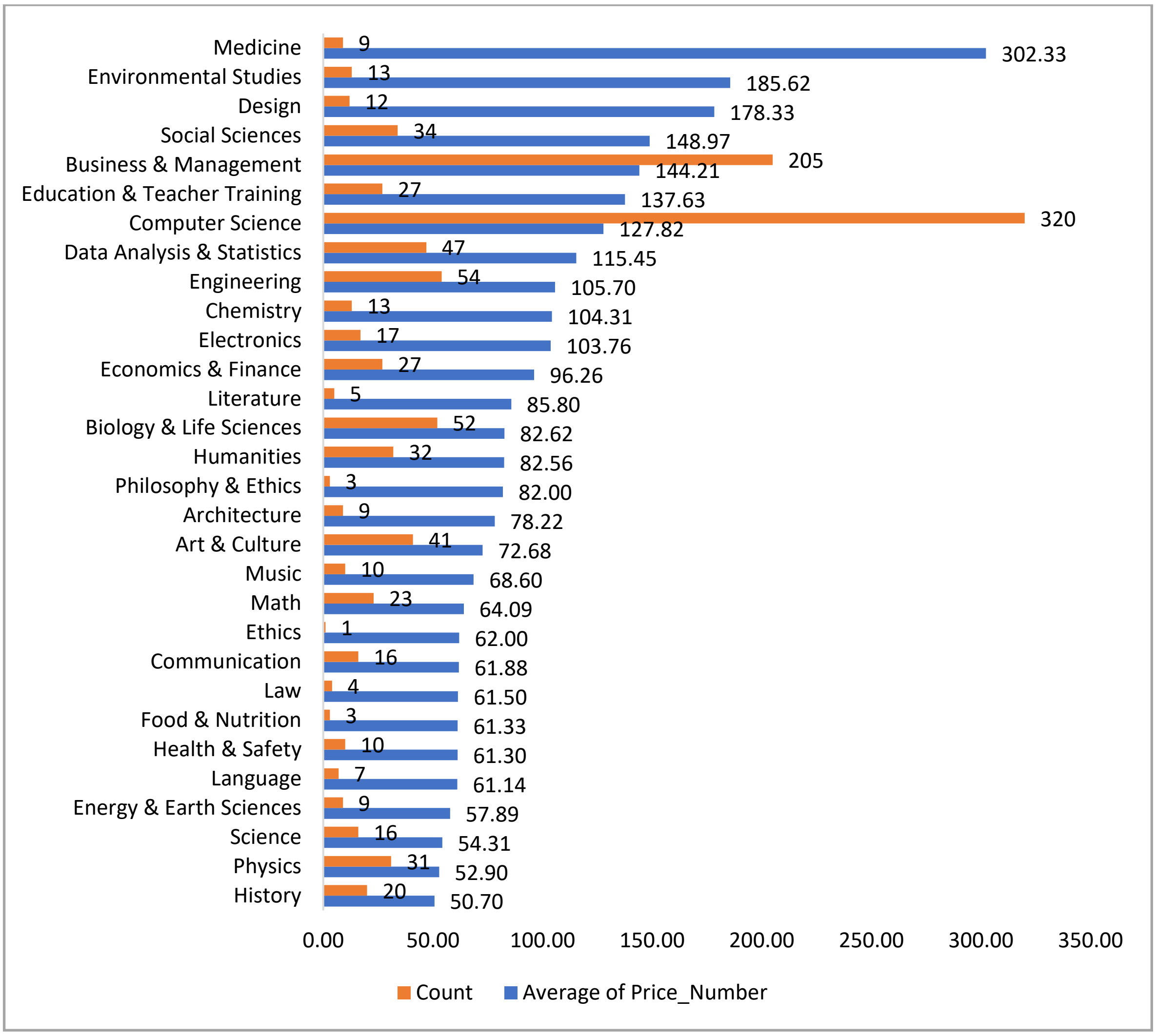


Figure 11. Price vs. Subjects

Level	Average price
Advanced	208.2
Intermediate	123.83

Introductory	82.77
Average	**115.33**

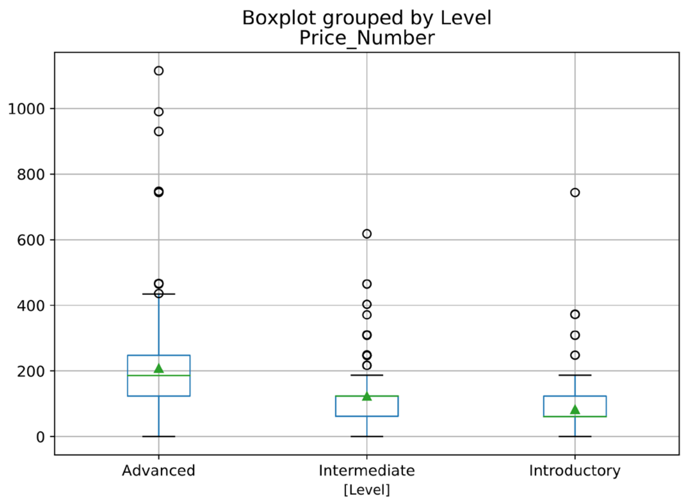


Figure 12. Average Price for Different Levels

I also see a pattern that, on average, the more "difficult" the course, the more expensive (See Figure 12). The average price for advanced level courses is AUD 208.2 (USD 161.42), for intermediate level courses it is AUD 123.83 (96.20 USD), and for introductory level courses it is AUD 82.77 (USD 64.30). However, this correlation does not hold for all subjects. For example, the average price for an "Intermediate" level "Architecture" course is slightly less expensive than the "Advanced" level course in the same subject. The cost of an average "Intermediate" level course in Medicine is unexpectedly lower than the one at the "Introductory level". It can be inferred, that since the large average price difference is not only due to the course per se but also due to the offering institutions, and because the population of Medicine courses is relatively small, such price difference is exacerbated by some extreme outliers.

Language	**Price**	**Count**
English	$ 123.97	867
Japanese	$ 123.00	1
French	$ 94.55	20
English in combination with other languages	$ 92.54	74
Spanish	$ 77.26	66

Dutch	$ 61.50	2
Russian	$ 61.00	4
Japanese and Chinese	$ 61.00	2
Portuguese	$ 61.00	1
German	$ 61.00	1
Arabian	$ 61.00	1
Chinese	$ 34.00	28

Table 31. Price vs. Language

Moreover, as Table 31 shows, the "language" factor seems to play a significant role in explaining the difference in courses' prices, i.e. courses taught in English are more expensive than ones taught in other languages. That said, since the population size of other languages is relatively small, a valid conclusion cannot be made at this stage.

	Introductory	**Intermediate**	**Advanced**
Introductory		-9.467*** (0.000)	-14.762*** (0.000)
Intermediate	9.467*** (0.000)		-7.908*** (0.000)
Advanced	14.762*** (0.000)	7.908*** (0.000)	

Table 32. T-test for Testing Inter-group Difference (price vs level)

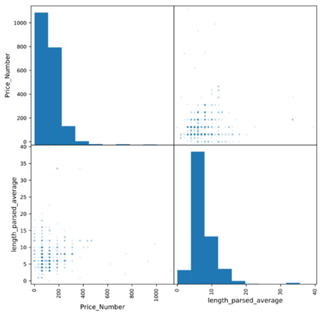
Note: p-value reported in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Factor	**sum_sq**	**df**	**F**	**PR(>F)**
Institution	4.328740e+06	114.0	6.264459***	<0.0001
Subject	1.397242e+06	29.0	5.746238***	<0.0001
Languages	5.009691e+05	31.0	1.738718***	0.008
Effort average	9.443550e+05	1.0	109.813258***	<0.0001
Length average	1.681653e+05	1.0	18.1682***	<0.0001

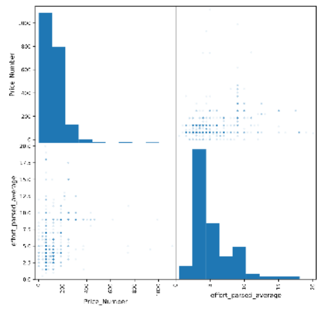
Table 33. Type II ANOVA Result for Factors; Note: * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Also, as demonstrated in Table 32 and Table 33, based on the result of an ANOVA (Type II) analysis, it is found that a significant difference exists among the prices of courses in different levels.

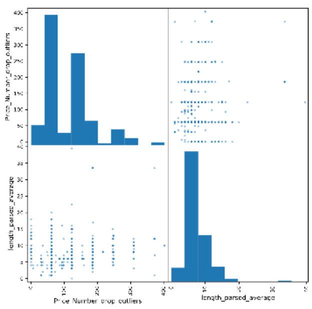
That said, it is surprising to see that the language factor has the lowest significance level, but the effort and the length have the highest. In fact, the result of this study shows that “language” only has a significant effect at an aggregate level. If I take a closer look at the data, I found that, for each individual language, the pricing-predicating power is rather limited. For instance, the coefficient of English courses is 62.96, but the standard error is 96.463, which leads to a t-value of 0.653 and a p-value of 0.514. In contrast, the result verifies one of the previous assumptions claiming some schools provide statistically more expensive courses than others. For instance, the prices of the courses provided by Curtin University and Doane University are significantly higher than the average at the 5% and 1% significance level, respectively, whilst there are universities offering significantly cheaper courses. For example, Cornell University and Edinburgh University’s course price is significantly lower than the average at a 1% significance level.



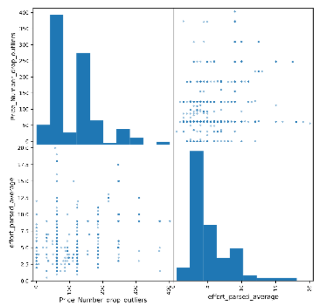
Price vs. Length



Price vs. Weekly Efforts



Price vs. Length after excluding outliers



Price vs. Weekly efforts after excluding outliers

Figure 13. Scatter Plot: Price, Length, and Efforts

The average length and the average effort per course are 6.76 weeks and 5.16 hours per week, respectively, with a standard deviation of 3.80 and 3.04. After excluding the outliers (i.e., retaining only those that are within +/-3 standard deviations), the average length is 6.54 weeks, and the average effort is 4.89 hours. Furthermore, as Figure 13 illustrates, the relationship between "price" and "course length" and "price" and "recommended weekly effort" seem to be weak, i.e., there exists no obvious relationship. Even after excluding extreme outliers in price, in length, and in weekly efforts, no clear correlation can be found.

Based on the result of the data analysis mentioned above, I proposed a model to explain the relationship between the price of a course and the course's six characteristics which were used as predicting factors. I generalised this relationship to the following equation, where $Is(subject)$, $Ii(institution)$, $Ii(level)$, and $Ii(language)$ are matrixes of dummy variables. For example, $Ii(level)$ represents a course's level, and level ∈ ['introductory',' intermediate',' advanced'].

$$price = constant + length + effort + \sum Is(subject) + \sum Ii(institution) + \sum Ile(level) + \sum Ila(language) + \varepsilon$$

I adopted the OLS (Ordinary Least Squares) method for running the regression and used a step-in strategy to formulate the modelling. It can be argued that the model gets an optimised shape at the fourth step: As Table 34 illustrated, the factor, "language", should be dropped from the model, since after I incorporate the "language" factor into the model, the R square value has not been greatly improved, while the significant level of other factors is weakened.

Step	Predicator	Coef	Std.e.	|t|	P>|t|	R-square	F-value	Observations	Durbin-Watson	Jarque-Bera
	Effort	9.83	0.97	10.16***	0.01					
1	Length	2.05	0.78	2.63***	0.00	0.11	62.63	1002.00	0.90	43916.31
	Constant	52.80	7.11	7.42***	0.00					
	Effort	10.40	0.94	11.12***	0.00					
	Length	3.00	0.74	4.06***	0.00					
2	Subject	-72.58	28.66	0.05	0.00	0.26	11.25	1002.00	1.09	34565.91
		250.73	89.09	6.28***	0.96					
	Constant	5.97	29.01	0.21	0.84					
3	Effort	12.70	1.11	11.49***	0.00	0.58	8.51	1002.00	1.45	91211.93

	Length	4.23	0.72	5.85***	0.00					
	Subject	-41.47	26.87	0.01	0.01					
		95.95	72.91	2.80	0.99					
	Institution	-231.50	0.00	0.02	0.00					
		693.37	75.00	12.72***	0.98					
	Constant	-0.51	36.17	0.01	0.99					
	Effort	9.23	1.15	8.03***	0.00					
	Length	3.36	0.70	4.77***	0.00					
	Subject	-24.84	25.86	0.002~	0.00					
		102.10	70.26	12.95***	1.00					
4	Institution	-240.38	0.00	0.05	0.00	0.62	9.57	1002.00	1.49	77780.15
		680.75	73.94	3.08***	0.96					
	Level[T.Intermediate]	-47.87	7.25	6.60***	0.00					
	Level[T.Introductory]	-64.02	7.62	8.40***	0.00					
	Constant	75.33	35.94	2.10**	0.04					
	Effort	9.29	1.19	7.80***	0.00					
	Length	3.63	0.73	4.95***	0.00					
	Subject	-7.74	31.40	0.06	0.02					
		127.49	47.50	2.36**	0.95					
	Institution	-241.80	0.00	0.01	0.00					
5		680.70	78.80	12.80***	0.99	0.62	7.99	999.00	1.48	81043.44
	Level[T.Intermediate]	-48.27	7.41	6.52***	0.00					
	Level[T.Introductory]	-64.68	7.84	8.25***	0.00					
	Language	-99.79	0.00	0.01	0.34					
		29.92	117.55	0.95	1.00					
	Constant	89.16	85.75	1.03	0.30					

Table 34. Result of OLS Regression: Step in. Note: * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

I assumed in the introduction that popular courses should cost less per user as there is a larger user base to share the fixed costs with, which may potentially create barriers to entry, for instance, for starting new courses with uncertain popularity. However, the result showed that this assumption is not valid. Table 35 shows a significantly positive relationship between the price and participants of the courses offered by Harvard and MIT on edX.org. The explanation for this unexpected result is that, according to Armstrong (2016), as in the higher education sector, education is often treated as a credence good where the “high price” implies “high quality” which attracts “high enrolment”: Enrolling in a MOOC is free of any charges after all. Thinking further, higher education, even being provided online, seems to be treated by its users as Veblen Goods. As an idea proposed by Salmon

(2009), for offline courses, an increase in tuition partially raises the enrolment number as the school becomes more desirable in terms of being a symbol of high status.

	Coefficient	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
I	11313.38	1293.25	8.75	0.00	8756.22	13870.53	8756.22	13870.53
Price	48.42	18.42	2.63	0.01	12.00	84.85	12.00	84.85

Table 35. Price and Participants, *I* stands for Intercept

Nonetheless, Table 36 and Table 37 shows that both the exploration rate and the completion rate show no significant differences when there are differences in prices. Admittedly, not all the students enrolled want to earn a certificate. In fact, according to Chuang and Ho (2016), based on a questionnaire for 195 courses offered by MITx and HarvardX, on average, only 54% of the participants self-reported an intention to obtain a certificate. Meanwhile, this divide in intentions may have a negative impact on the meaningfulness of the completion rate and exploration rate, and consequently, negatively affect the correlation analysis presented in this study. I argue that the "ratio of the number of participants who completed all course requirements against enrolled population" may be a better indicator than "certificated rate" in terms of examining completion rate. However, Harvard and MIT did not publish those relevant data in detail. Also, putting price aside, I do understand there are many other technological factors and human agency elements that might affect the exploration rate and completion rate (Chu & Robey, 2008).

	Coefficient	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
I	19.51	2.66	7.33	0.00	14.19	24.84	14.19	24.84
Price	0.01	0.03	0.52	0.61	-0.04	0.06	-0.04	0.06

Table 36. Price and Exploration Rate, *I* stands for Intercept

	Coefficient	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
I	5.86	0.94	6.25	0.00	3.99	7.74	3.99	7.74
Price	0.01	0.01	0.63	0.53	-0.01	0.02	-0.01	0.02

Table 37. Price and Completion Rate, *I* stands for Intercept

In addition, I also notice that, for MOOCs provided by Harvard and MIT, those CS (Computer science) and STEM (Science, Technology, Engineering and Mathematics) courses tend to attract more participants than non-CS and non-STEM courses. Therefore, in order to check whether the correlation between price and enrolment is still valid when a course's subject is under consideration, I categorise the courses based on their curricular areas (either a CS&STEM course or a non-CS&STEM course). As shown in Table 38 and Table 39, it seems that the positive relationship is still valid between the price and the enrolment, though the effect of this relation is slightly smaller for those non-CS&STEM courses, as indicated by a smaller coefficient.

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
I	11303.97	1299.64	8.70	0.00	8733.86	13874.08	8733.86	13874.08
Price	51.60	19.09	2.70	0.01	13.86	89.35	13.86	89.35

Table 38. Price and CS&STEM Courses' Participants, *I* stands for Intercept

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
I	11313.38	1293.25	8.75	0.00	8756.22	13870.53	8756.22	13870.53
Price	48.42	18.42	2.63	0.01	12.00	84.85	12.00	84.85

Table 39. Price and Non-CS&STEM Courses' Participants, *I* stands for Intercept

Finally, I used a polynomial regression to examine the correlations between price and percentage of students who hold a bachelor’s degree or up (i.e. bachelor rate) and between price and the percentage of students who explored the course. In doing so, I first rounded the independent variable to the nearest integer value, then the average of price in each bucket to remove the spikes. In Figure 14, red dots are the actual data, blue dots are the refined data, and the green curve is the output polynomial function. I chose polynomial degrees of 2, 3, and 4. These numbers are chosen as in this stage I only have a dataset with limited tuples, so choosing a higher degree may overfit the regression curve. Moreover, the result of this study indicates that courses with either relatively very high proportion (85%) of highly educated people (bachelor or higher) or low proportion (55%) would have a lower-than-average price, whilst courses that have a bachelor rate at about 65-70% may ask for a higher price. Also, using the same method I noticed that courses with an explored rate of 20-30% have a higher price (See Figure 15). However, it requires a deeper research (e.g. using a more general and comprehensive dataset) to validate this phenomenon. At the current stage, most of the courses in the current dataset are for free, impairing the training model.

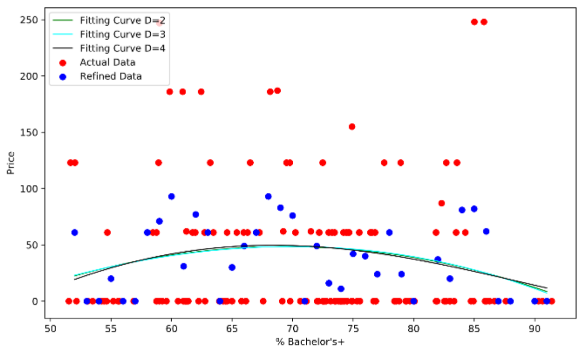


Figure 14. Price vs Percentage of Students with a Bachelor’s and up

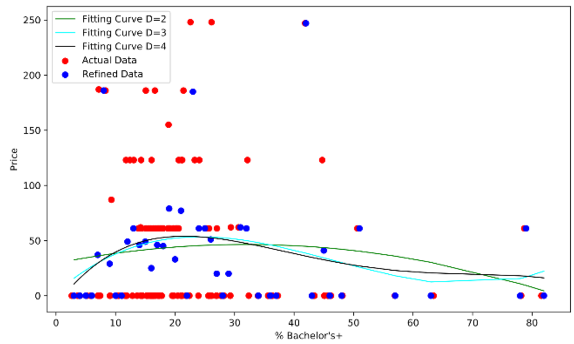


Figure 15. Price vs Explored rate

Summary

Recently, there has been an increase in publications for MOOC-related topics (Zhu et al., 2018), and yet, based on a Google Scholar search (keyword: pricing on MOOCs; timeframe: after 2017) it was found that only a very limited number of papers (even fewer high-cited papers) that discuss the pricing strategies and/or the price structures of MOOCs offered by major platforms. As argued by Daradoumis et al. (2013), the number of studies using data analysis methods on existing MOOC platforms is rather limited. The reasons include that the platforms only offer limited data access and the usability to analyse the data is even lower.

In this study, in order to systematically study the current price structure of the knowledge products sold on a popular knowledge market, i.e., edX.org, this study used crawlers to collect data and performed a descriptive study based on the collected data. I examined the determinant factors for course prices and formulate a model for the prices. It is found that factors, such as effort level, difficulty level, recommended length, offering institutions, and subject, are significantly correlated with courses' price but that "language" only has a significant effect at an aggregate level. I also use a fraction of courses' data to test if there exists a correlation between the prices and the courses' completion rates, but I only found that the price shows a positive correlation with participants' number but no clear relationship with exploration rate nor completion rate.

Due to the limitations in terms of available data and scope, there are several limitations that need further exploration. First, I did not address the multicollinearity problem, which requires procedures such as lasso and ridge regression to remedy or an increase of the dataset size. Second, the existing price structure established by edX, as well as its partners, may not be optimised. Instead, currently, most of the courses' prices are either pre-determined by the platform or follow a certain set of conventions rather than a price determined by the market. To maximise the welfare of all the market participants, I presume that prices for each course would be optimised if the price is set at a level where the highest Willingness-To-Pay (WTP) of a majority of the students meets the lowest Willingness-To-Accept (WTA) of the corresponding course providers. A future study shall devise methods to determine the real WTP of the consumers and the WTP of the course suppliers. Of further interest would be to find and to cluster consumer characteristics that, to some extent, determine or be able to predict the level of WTP and of WTA. Third, the course list on edX is changing, and the research conducted here is based on a snapshot of the data only. It limits the quality of and the depth of the price analysis that was conducted in this chapter because of the lack of time-series data. Therefore, regular future Web crawls are recommended.

I expect this research to be beneficial for MOOC platforms, online learning and e-learning industries, and relevant research areas. I acknowledge that these industries are undergoing major changes both in terms of scope and of scale. For example, in the distance learning sector, there is a notable shift in focus from developed countries to developing countries (Cheney, 2017; Nataf, 2018). There is also a challenge in that most providers are from the Western higher education sector, but a large potential customer base life in developing countries where high-quality education is highly demanded, but who have only very limited access to MOOCs. Hence, it would be useful if I can design a suitable MOOC pricing structure which can better serve the learners from developing countries. I expect that this study provides a starting point for future research into discriminative pricing practices. Also, as I suggested earlier in this paper, I argue the current pricing of many MOOCs may be suboptimal. Therefore, an empirical analysis of the current MOOCs' pricing structure will support the development of a more advanced pricing mechanism that can help both the MOOC providers and platforms' owners to achieve a more accurate price-setting system and, as a result, to make the MOOC platforms become a better knowledge marketplace to allocate the knowledge resources in a more-optimized manner. Henceforth, the idea to correlate price and statistics data is useful to design an algorithm to dynamically adjust the price of the future courses based on the previous statistics to maximize the gross revenue, a potential direction for future work.

Overall, this chapter investigates the role of pricing as a quality signal in the context of Massive Open Online Courses (MOOCs). Using signalling theory as a theoretical underpinning, the study explores how the price of MOOCs affects user enrolment decisions. The findings reveal that higher prices may indeed act as a quality signal, influencing user perceptions and enrolment behaviors. However, the relationship is not as straightforward as traditional supply and demand dynamics, with various factors mediating the effect of price on user behaviour. The chapter concludes with a discussion on the implications of these findings for both academia and practitioners, suggesting that MOOC providers need to carefully consider their pricing strategies to effectively attract and retain users.

Upon concluding the exploration of the MOOC market, a vibrant and expansive public knowledge domain, it's essential to balance the understanding by shifting the lens towards private knowledge markets. While public platforms like MOOCs democratize access and catalyse widespread knowledge dissemination, private knowledge markets offer a distinct set of dynamics and interactions worth investigating. Often characterized by more tailored knowledge exchanges, specialized content, and unique user behaviours, these private markets possess their own set of challenges and opportunities that can significantly influence the broader ecosystem of knowledge exchange. They become instrumental in understanding the nuances of knowledge sharing in a controlled, specialized, and often proprietary environment. Therefore, in the forthcoming chapter, the focus will pivot to this often less-charted territory, providing a holistic view of the diverse landscape of knowledge markets. Through this juxtaposition, the thesis aims to furnish a comprehensive understanding of both public and private knowledge exchange platforms, emphasizing their unique characteristics and shared challenges. Consequently, the thesis showcases insights from a private knowledge market in the next chapter.

Chapter 8: Study 5 - A quasi-experimental study of effective market-based knowledge transfer in a growing Chinese company

Context and research questions

The culmination of this thesis is seen in this chapter, where the myriad insights find real-world application in the case study of Yichen—a testament to the tangible benefits and areas ripe for improvement in a private knowledge marketplace. This chapter offers a practical application of all the theories and practices discussed, through the knowledge marketisation case, by designing a knowledge market, emphasizing the real-world implications and benefits of digital tools and strategies for knowledge sharing.

Knowledge is a critical resource that aids in problem-solving, innovation, and developing competitive advantage within organizations (Goswami & Agrawal, 2019). Despite firms investing heavily in knowledge management systems, the internal knowledge flow remains 'sticky', with minimal user-to-user knowledge transfer (Jeong et al., 2013; S. Zhao et al., 2020). This 'black box' nature of intra-organizational knowledge transfer, noted by Argote & Ingram, (2000), has since been a major theme in Management and Information Systems research (Benbya, 2016).

Prior studies showed that knowledge transfer is a two-way movement on the inter-personal level. It involves an exchange between a knowledge source (i.e., an individual who possesses knowledge) and a knowledge recipient (i.e., an individual who receives the knowledge from a knowledge source) and an assimilation and learning after the recipient understands the details and implications of knowledge so that the recipient can utilise the knowledge in practice (Argote et al., 2003; Srisamran & Ractham, 2020; Szulanski, 1996). To successfully transfer knowledge from source to recipient, a knowledge source must be willing to dispose of or share the knowledge and be able to distribute the knowledge to a recipient, and a knowledge recipient must be able to find and be willing to receive that knowledge (Hermans et al., 2017). Nevertheless, although many firms have noted that it is important to support the knowledge transfer activities of their workers, many found managerial supports often failed to ensure a successful knowledge transfer process because knowledge sources tended to hide, hoard, and withhold knowledge and knowledge recipients' adoption intention and absorptive ability were low (Lin & Huang, 2010; Strik et al., 2021; Sussman & Siegal, 2003).

Benbya (2016) mentioned there are two streams of research focusing on motivating knowledge transfer activities. While the strategy and organization literatures mostly focused on knowledge transfer within and across units, IS (Information Systems) researchers mostly investigated the role of knowledge platforms in supporting the transfer of knowledge between individuals within a firm and its value creation implications. Prior IS studies have extensively relied on a range of theoretical perspectives, such as the theory of reasoned action and theory of planned behaviour (Dong et al., 2022; Singh et al., 2018), social exchange and social capital theories (H. C. Huang et al., 2018; Jin et al., 2010; Lin & Huang, 2010; Wang & Liu, 2019; Zhao et al., 2020), and knowledge governance theories (Benbya, 2016; Fang et al., 2013). More recently, exploring the potential of knowledge markets has begun to emerge as an effective knowledge management topic (Serrat, 2017).

Although a large number of studies from various perspectives have been conducted attempting to unpack the black box of intra-organizational knowledge transfer, according to Zhang et al. (2022), so far there has only been a small (but increasing) number of researchers and practitioners becoming interested in using an internal knowledge market to mitigate the internal knowledge stickiness problem. A knowledge market is a market-based knowledge management mechanism for distributing knowledge via bringing together knowledge suppliers and consumers who, via interacting, collectively determine the price of commercialized knowledge. Such a market allows market participants to evaluate price knowledge through market mechanisms, and, by using these mechanisms, a company that runs these internal markets can motivate its employees to take advantage of these mechanisms, increase suppliers' utility via monetary rewards, support an environment amiable for sharing knowledge, stimulate learning activities, and, eventually, reach an optimal point for distributing knowledge resources (Desouza et al., 2006; Zhang & Sundaresan, 2010; Z. J. Zhang et al., 2016). As Van Alstyne (2013) argue, a well-designed, -launched, and -sustained internal knowledge market can cause valuable knowledge resources to speak up and self-identify and these resources can be used to identify new product development, problems and opportunities, and arbitrage the gap between these problems and opportunities. Overall, new knowledge markets focusing on firms' innovation agendas offer a digital space to generate, explore, enrich, and evaluate knowledge, and by doing so, increase the overall economic return for the firms.

Researchers still know little about how to design a specific incentive mechanism for internal knowledge markets to enable knowledge transfer. First, knowledge markets entail using financial incentives to encourage knowledge transfer. Although overall financial incentives were found to influence individuals' incentivised knowledge-transfer-related behaviours (Dong et al., 2022; Hsieh et al., 2010; N. Huang et al., 2017; Kuang et al., 2019), there are some inconsistent conclusions on the effects of financial incentives. Garnefeld et al. (2012) found that financial incentives can increase knowledge platform users' engagement behaviours, but the effect was short-lived. After a knowledge platform launches a function offering financial incentives, a fierce competition will be triggered and therefore an overall negative impact will be exerted upon knowledge sharing as well as team cooperation (Goh, 2002). Sun et al. (2017) mentioned that after financial rewards for posting reviews are introduced, the contribution of reviews decreased, in particular for those who were highly connected in the community. Second, although some prior empirical studies reported the early adopters, such as Infosys, McKinsey and Eli-Lilly, they agreed that knowledge markets, compared to traditional knowledge management solutions, can better manage information flows and bring some of the aforementioned benefits (Van Alstyne, 2013). Some studies also reported the opposite. For instance, Benbya (2015) mentioned two cases, Siemens AG and the Hewlett-Packard company, in which the market-based approaches they adopted could not reach satisfactory results. This implies that an internal knowledge market cannot fit every firm and that there are still theoretical and methodological issues that need to be addressed before the role of the knowledge market can be fully explained and understood.

Also, it is argued that more research attention should be dedicated to investigating how market-based approaches can be used in the transition of a small & medium-sized company growing into a big one. Working with Diamond Lease (which was later merged into Mitsubishi HC Capital Inc), Benbya and Van Alstyne (2010) summarized that, employees in small companies work side-by-side, which fosters an intimate environment that helps employees share knowledge across the organization with no need for augmentation. As a business grows, however, knowledge silos are readily formed across branch offices and divisions, and the transfer of knowledge deteriorates. However, relevant research on emerging companies is lacking. Few empirical studies exist in this field, and the few studies that do exist have focused only on large transnational enterprises (such as Simens, SAP, Allianz and AECOM) and not on emerging companies (Benbya, 2015, Desouza and Awazu, 2003, Dev et al., 2017, Van Alstyne, 2013).

In this chapter, I will present a quasi-experimental fieldwork study. This study was conducted within an emerging, medium-sized company. In collaboration with the firm, a knowledge market was designed. Surveys and real-world data were used to observe its effectiveness. After launching an online knowledge platform with a market-based mechanism, extrinsically motivated knowledge sharing increased but intrinsic motivation did not drop significantly. Also, voluntary transferring activities increased. This market has been subject to the power law in that a few items received most of the monetary rewards, views, and comments, whereas a long tail of items received relatively fewer monetary rewards, views, and comments. Most income came from voluntary post-viewing contributions rather than ticket fees at entrance, which suggests that the suppliers in this market need to fight for attention to maximize profits. This study contributes to a deeper explanation of how internal knowledge markets can boost intra-organizational knowledge transfer. Specifically, the study aimed to explore the following research questions:

RQ1: Does a market-based knowledge platform decrease voluntary knowledge-sharing activities among employees in an emerging medium-sized company?

RQ2: What factors (e.g., sex, seniority, department, income, etc.) affect such a market's impact?

RQ3: Do employees increase their online and offline knowledge-sharing-related social interactions after a firm forms a market-based knowledge platform?

RQ4: Does a knowledge market lead to better match between receivers' knowledge demands and contributors' knowledge supplies?

As I discussed in the literature review section, one of the main problems encountered by many knowledge management practitioners is that, although they know knowledge is valuable, they always find it difficult to efficiently distribute knowledge (i.e., to unlock the value of knowledge) (Tippmann et al., 2017). To find a better way of distributing valuable knowledge resources and address the research questions as listed above, the researcher of this study cooperated with a company, Yichen Consultancy, a fast-growing construction advisory company in Shandong, China.

In initial interviews, senior employees reported that, in recent years, the company had grown its headcount very quickly, resulting in its departments and branches becoming segmented in terms of their physical locations and expertise, and its internal knowledge transfer encountering barriers that caused knowledge silos to appear.

Aiming to mitigate this problem, in the first quarter of 2021, the company established a new role (a chief knowledge officer (CKO)) and established a knowledge management platform—its first formal initiative to tackle the knowledge silo problem. However, the chief executive officer (CEO) still claimed the new arrangement did not meet her expectations, with low utilization rate, low sharing rate, and unsatisfactory learning performance problems existing.

At the time this study was conducted, Yichen was using a cloud-based SaaS platform (i.e., *Little Penguin*) as its knowledge management platform. Every employee could contribute to the platform by uploading knowledge, such as electronic books, case studies, know-how reports, work reviews, business process models, templates, etc. They could also socially interact with each other on the platform by, for example, commenting on their co-workers' posts or messaging them. However, as I found in the initial interview with senior leaders, the executives and the chief knowledge officer played a dominant role in distributing knowledge items. Before 1st June, 2021, either the executives, their secretaries, or the chief knowledge officer prepared and uploaded all knowledge, but, as the employees reported, many could not find the right knowledge in the knowledge management system. Co-workers customarily transferred knowledge informally in their inner or small professional circles possibly due to the Chinese cultural factor called *guanxi*, which refers to a special personal relationship/connection that one has with other people and constitutes a prerequisite for most information and business exchanges in China (Davies, 2017). Specifically, whether people share and transfer knowledge in these social circles depends on whether they have guanxi with other people in it (H. Chen et al., 2019). In Yichen, these private and guanxi-based transfer channels also existed, and they often enabled workers with similar job descriptions or shared interests to communicate timely and effectively mainly within those private channels, which resulted in knowledge silos. Each silo contained valuable but effectively untapped knowledge (knowledge resources are owned by most people, regarded as a free public good, but not yet effectively exploited or used), and workers could not formally contribute their valuable organizational knowledge to the knowledge management platform that the company owned. Since there was no formal index for knowledge resources that were scattered around different silos, knowledge seekers had to ask around people and drop by different work teams to obtain what they want. These problems further pushed up searching costs for knowledge.

Furthermore, the knowledge's ephemeral nature meant the organization could easily lose it especially when those valuable knowledge pieces were stored in software which was not designed for managing organizational knowledge. Therefore, facing an insufficient knowledge flow, the research team and the interviewees in the initial interview agreed that just establishing a knowledge platform that allowed knowledge to circulate is not enough. Also, finding knowledge-sharing champions can mitigate the problem but still cannot sufficiently address the knowledge-transfer problems that Yichen faced. Rather, I and the company senior management agreed to attempt a new way to interconnect knowledge owners and seekers: the company would provide a knowledge market with minimal friction that would allow participants to exchange knowledge resources to maximize their utilities based on a more market-oriented approach.

I engaged in a field study with the company and followed the research procedures that Benbya (2016) recommends. First, I worked with the company and defined the study's scope. By conducting preliminary interviews with the company's senior employees, I confirmed current problems in the company's knowledge-transfer processes. Second, I conducted surveys to confirm the problems with employees regarding knowledge transfer that I identified in the first step. After that, based on a preliminary analysis, I designed a knowledge market and set up relevant protocols to regulate and increase knowledge transfer. Then, I used weekly interviews and surveys to evaluate the proposed design's effectiveness.

After the initial interview with senior employees, I conducted the first survey with employees. Specifically, this study surveyed 92 employees and surprisingly found that most employees recognized that the company had a culture that fostered knowledge sharing and that employees were eager to learn new work-related skills. However, they also reported several problems. For example, they reported that employees in the company did not create sufficient new knowledge on the knowledge management platform that the company purchased, that they faced difficulties in finding useful work-related knowledge materials inside the company, and that they often used private chats or group chats to share knowledge, which created knowledge management and archiving problems. Moreover, employees reported that the learning materials provided by the company sometimes were not useful to them, indicating a mismatching problem between what knowledge recipients' demanded and what the knowledge suppliers provided.

Hypotheses

As previously discussed, previous studies have found that incorrect financial incentives or incentives offered in incorrect ways cannot improve, and sometimes will even reduce people's knowledge supplying intentions and behaviours. As Yan et al. (2018) explained, this is partially because a financial incentive can have two effects (i.e., the direct price effect and the psychological effect) at once. While these two effects can sometimes complement each other and increase users' satisfaction, continuance, and knowledge-supplying intentions (Mochon et al., 2016; Qi et al., 2021b; Yan et al., 2018); sometimes they can contradict each other and result in an undesirable scenario where a financial incentive has no impact or even crowds out voluntary knowledge-sharing behaviours (Fischer, 2021; Gneezy et al., 2011; Kettles et al., 2017; Liu et al., 2011; Mettler & Winter, 2016). By and large, researchers agree that an incentive must exceed the total costs (e.g., money, time, effort, psychological burden, etc.) that knowledge supplies incur in creating the value in question—at least for the single point in time when the knowledge exchange occurs (Benbya, 2011).

Recent studies show that the extent to which introducing a marketplace for knowledge that provides financial incentives to knowledge suppliers encourages their desired knowledge-supplying behaviours effectively depends on how many financial incentives it provides and the way that the market distributes such incentives to suppliers. Specifically, Yan et al. (2018) argued that knowledge suppliers increased their voluntary knowledge-sharing behaviours after the platform introduced a financial incentivization scheme, even if the amount of the incentive is small, since the knowledge suppliers viewed it as the platform acknowledging their psychological self-efficacy, which subsequently increased their intrinsic motivation and further encouraged them to reciprocate to other users on the platform. However, the means of any financial incentivization scheme needs to be settled correctly. A further research conducted by Qi et al. (2021b) showed that if a platform simultaneously presents two types of monetary incentives (one with high-yield monetary return and one with low-yield monetary return), then the low-yield option will not play an incentive role and sometimes can turn into a negative factor on experts' free knowledge contribution behaviours. I expect that with the guidance of the market design theory, the incentivisation scheme designed in this study can be implemented correctly. Thus, I hypothesize:

H1a: *Introducing a market-based knowledge platform can increase incentivised knowledge-sharing activities.*

H1b: *Introducing a market-based knowledge platform does not reduce voluntary knowledge-sharing activities.*

As I mentioned above, a knowledge market and the financial rewards it brings may incentivize market participants to supply more knowledge products, but the effect may differ when it comes to different groups of people. Previous empirical studies showed that a person's social status in a community and how much knowledge a person supplies positively correlate with each other (Benbya & Leidner, 2017; Fischer, 2021). Senior and experienced workers naturally share more knowledge compared to comparatively lower-ranking workers with less expertise; as such, incentives also have a lower effect on the former (El-Den, 2007; Lin, 2007). A more recent study showed that this effect may be reversed if the form of platform is changed (Pu et al., 2022). Unlike a wiki or a discussion forum-based knowledge exchange platform, a question-answering-based platform may encourage more junior knowledge suppliers to share their knowledge especially when the question is asked by a senior employee because they expect sharing more and better-quality knowledge to senior workers can lead to a higher promotion probability. Ziemba & Eisenbardt's (2016) empirical research found younger workers need more social incentives than seniors, but the difference is not as significant as in the case of tangible incentives. Thus, I hypothesize:

***H2a**: When introducing a market-based knowledge platform, employees' seniority may affect a market reward's impact.*

Moreover, Eisenbardt's (2020) empirical research found that there was a small but significant difference in financial incentives expected by males and females to share knowledge on intra-organizational websites, and in their study, they found that females were expecting higher financial incentives than males. Ziemba & Eisenbardt (2016) also found that tangible incentives were needed more by females for them to share knowledge. However, Mallasi & Ainin (2015) argued that males usually work more competitively than females in a mixed environment (men and women) to emphasize their dominance, whereas females are less likely to behave competitively and can be classified as cooperative, so a market-based rewarding scheme, which increases the level of competition, would increase male workers' willingness to supply knowledge.

***H2b**: When introducing a market-based knowledge platform, employees' gender may affect a market reward's impact.*

Workers from different departments may react to a new *market-based* mechanism differently. Kettles et al. (2017) found that a rewarding system has less chance to increase how much knowledge people from supporting departments share compared to people from core revenue-generating departments. This is due to the fact that workers who receive compensation on a piece-rate basis feel hesitant about spending time on secondary tasks, which includes sharing knowledge, and that such departments usually contain proportionally more workers who receive compensation on a piece-rate basis.

H2c*: When introducing a market-based knowledge platform, employees' current department may affect a market reward's impact.*

Also, prior research showed that employees' compensation schemes for their primary work task affects how they react to a new monetary incentivization framework. A new monetary incentivization framework would not necessarily encourage workers who already receive a high salary to share more knowledge (Salameh & Zamil, 2020). After all, individuals transfer knowledge largely on a discretionary basis, and researchers often categorize it as extra-role behaviour. That is to say, such behaviours may prove helpful, but job requirements do not formally specify them in advance (Bartol & Srivastava, 2002). Kettles et al. (2017) argued that the nature of an employee's compensation scheme for performing their primary work task will likely influence how they perceive the value of being paid to share knowledge (a secondary task). Producing knowledge and transferring it can often entail that knowledge suppliers make considerable sacrifices (Bartol et al., 2009), and for lower-income earners, the opportunity costs of making these sacrifices is lower than the ones who receive higher income. Thus, they will be more willing to react positively to the new knowledge market arrangement compared to people who already receive a high compensation package. Introducing a market-based knowledge platform may change such the situation as it may also change how people perceive knowledge transfers. Many people's knowledge sharing and transferring actions are mainly intrinsically motivated, and if these individuals cannot perceive an external incentive that can complement their existing internal motivations to transfer knowledge, the degree of their knowledge transfer will decrease (Minbaeva, 2008). The token payment that a knowledge market provides may not be able to complement the sacrifice that high-income earners made, so it would be economically irrational for them to share more knowledge. Henceforth, I hypothesize the following:

***H2d**: When introducing a market-based knowledge platform, employees' current income level may affect a market reward's impact.*

Internal knowledge sharing and exchange involve important social processes and mechanisms, and, by changing the reward structure and the way people use a knowledge platform, one can influence these processes and mechanisms such as organizational norms, which may impact overall knowledge sharing and transfer level in the organization (Benbya, 2016). A knowledge market may result in more satisfied users via giving them more exposure and greater self-efficacy perceptions—important intrinsic motivations (Ergün & Avcı, 2018). Enhancing intrinsic motivation can increase users' social interactions (Chiu et al., 2006; Hung et al., 2011; Yan et al., 2018). Thus, the following hypothesis is formulated:

H3: *Employees increase their knowledge-sharing-related social interactions after their organization implements a market-based knowledge platform.*

A knowledge market, as Van Alstyne (2013) argued, can match content receivers and suppliers: compared to a centrally managed knowledge management system whose system administrators usually lack resources and even the know-how to produce all the specialty content that knowledge seekers need. A functional intra-organizational knowledge market ideally encourages the entire employee population to participate in storing and retrieving knowledge out on the long tail. Previous research emphasized the importance of matching and argued that a slowed matching rate can cause a market failure (especially at scale) (Dev et al., 2018), and the most prohibitive factors include high searching costs, information asymmetries, and the threat of knowledge expropriation (Dushnitsky & Klueter, 2011). However, introducing sanction policies and market agents such as regulators, sponsors, monitors, and matchmakers can mitigate these drawbacks (Dignum & Dignum, 2003; Dushnitsky & Klueter, 2011).

***H4**: An internal knowledge market leads to better matching between knowledge receivers and suppliers than if such a market does not exist.*

Method

Knowledge market arrangement

This study followed market design theory and devised a range of requirements for Yichen's knowledge market (see Table below).

Market design requirement	**Knowledge market arrangement**
Rapid reaching the critical mass	Yichen shall sponsor the knowledge market this study examined.
Dynamic pricing	It is also suggested that Yichen allow the prices to float. Specifically, a knowledge supplier could earn money from the market in two ways. First, they could upload their knowledge items to the platform and set up a price for them. The platform used 5 CNY (approximately $US0.77) as the default price, but the uploaders could choose to change the price arbitrarily. They could also choose to set the price to zero (i.e., others could access the knowledge piece for free). Second, suppliers could also accept a monetary reward after a receiver accessed the knowledge item regardless of whether they paid money or not, and the knowledge receiver could give an arbitrary amount of money to the supplier.
Use currencies (absolute rewards)	In this specific study, the company set up a special account (CNY 200, approximately

	US$70) for every employee, except for the CEO.
Use market to heal itself	I also asked the managers of Yichen to not intervene in the market during the experiment.
Rules against market manipulations	I followed Benbya's (2015) suggestions and implemented two mechanisms to counter market manipulations: First, it is important to provide transaction transparency. Yichen mandated that its knowledge market's transactions data are made publicly accessible. Second, it is also critical to allow a company's employees to align individual goals with the firm's goals, and Yichen reiterated this goal-alignment suggestion in its weekly all-hands meetings.
Communal motivation preservation	Compared to employees' income, the amount of money that they can spend on the knowledge market (CNY 200, US$70) is minimal, so I expect this small token of monetary incentive will not incur fierce competition that may significantly hurt communal motivation.

Table 40. Knowledge Market Design Summary

Research timeline

This study adopts a one-group pretest-posttest design (Cook et al., 1979). This study has two posttests, which enables the researcher of this study to observe longitudinal changes and also increases the validity of the treatment effect. The following table summarises the timeline of this research.

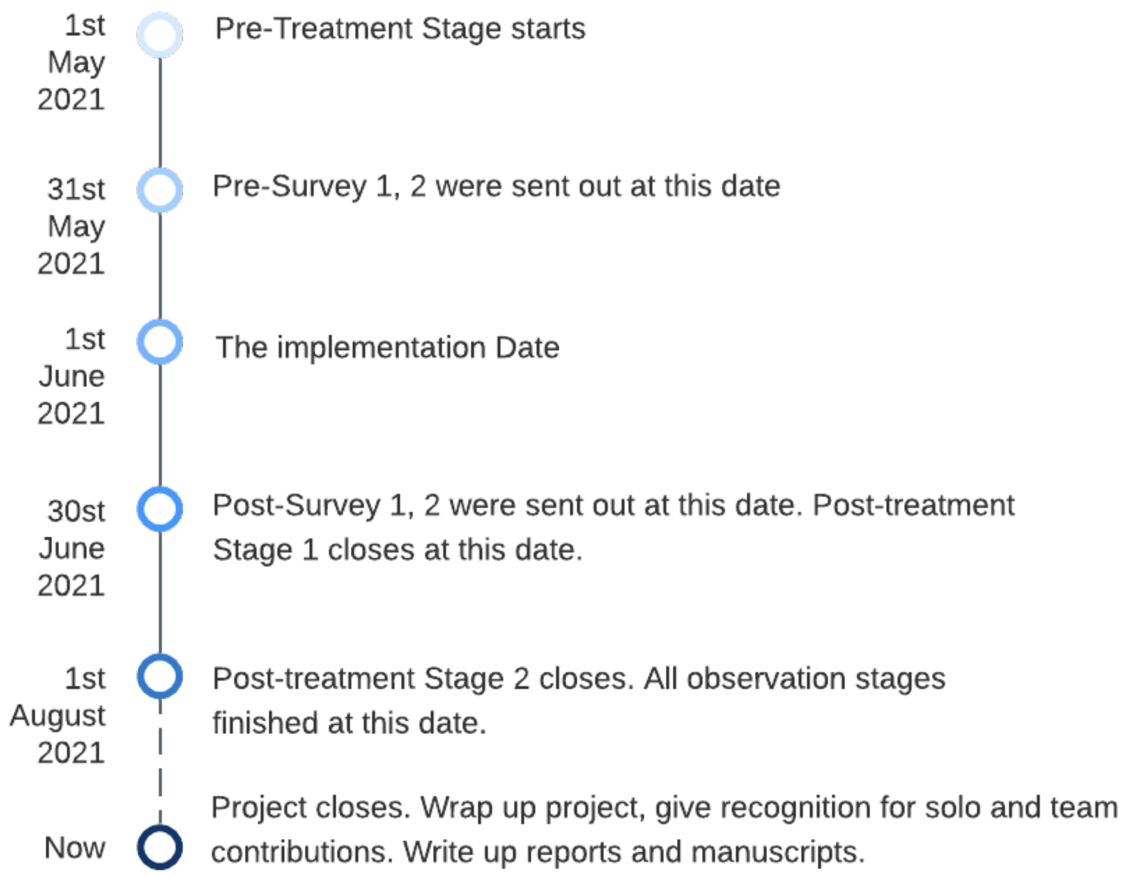


Figure 16. Research Timeline in this Study

I started monitoring the platform's activity on 1 May 2021 and stopped on 1 September 2021. Each stage (including pre-treatment stage, post-treatment stage 1 and post-treatment stage 2) had a one-month data collection period and a two-month observation period (note that the observation period included five days off for Labour Day holidays and three days off for the Dragon Boats' Festival).

During the data collection period, I recorded all the knowledge pieces that were contributed to the market-based knowledge platform during the period (one month for each stage). On the last day of the observation period of each stage, I recorded all the associated information about the knowledge pieces that were generated during the stage.

Furthermore, I conducted two types of surveys to check my knowledge market's impact on the participants' knowledge-sharing- and transferring-related behaviours. Specifically, the first survey was a self-report survey (adapted from Lee et al.'s (2005) KMPI scale and H. Liu et al.'s (2014) scale), and the second survey was a supervisor-rated survey (adapted from Bartol et al.'s (2009) scale).

The two surveys were distributed twice. The first round was conducted on the implementation date (i.e., 1 June), and this round's purpose was to test Yichen employees' knowledge sharing and transferring activities before I implemented the knowledge market. Moreover, on the 1st July, I conducted another round of survey to test the knowledge-transfer level after I implemented the knowledge market. Thus, I implemented a time-lagged design, which reduces common method bias (Podsakoff et al., 2003). Ma et al. (2020) contended that a two-week time lag is reasonable to reduce common method bias while maximizing participation retention. I used a one-month lag, which is effectively longer than their two-week time window, so I considered the time lag chosen in this study as appropriate. Also, this multi-source methodology can also help me avoid potential common method bias.

In order to maintain overall consistency, I also measured all variables that I collected from surveys using a five-point Likert scale that ranged from "strongly disagree" (1) to "strongly agree" (5). Table 7 shows the items for each variable.

Douglas and Craig's (2007) method was used to ensure translation validity. In addition, I addressed all missing cases before I began analysing the data.

Participants

In this study, participants were recruited with the support of the company's Chief Executive Officer as well as the newly appointed Chief Knowledge Officer. The HR (Human Resources) department of the company contacted the employees, explained to them that the study was being conducted to test the knowledge transfer situation of the company, and told them that the conclusions of the study will be hugely important for the company's future. The Chief Knowledge Officer also helped to inform respondents that the responses would be confidential. The Chief Knowledge Officer managed reminders throughout the data collection period and prompted employees to complete the surveys. All employees were invited to join the study. Although they were informed that they could withdraw from the survey at any time during the data collection period, there were no attritions between the two stages. Besides the CEO, 91 employees participated in the self-report survey at stages 1 and 2.

Measurements

The table below gives details of the variables included.

Category	Concept name	Definition	Measure (s)	Range
knowledge suppliers	Voluntary knowledge sharing	The number of “free” items shared by employees	Automatically calculated by system	[0, 423]
	Incentivised knowledge sharing	The number of "for-fee" items shared by employees	Automatically calculated by system	[0,166]
	Knowledge-sharing level (self-reported)	The degree of a person’s ability to diffuse knowledge and to contribute to making the work process astute and knowledge-intensive	Survey questions	[1,7]
	Knowledge-sharing level (direct supervisor rated)		Survey questions	[1,7]
	Intrinsically-motivated knowledge sharing	An employee’s reporting that his or her knowledge-sharing behaviours are driven by intrinsic motivational factors (e.g., feeling pleasurable)	Survey questions	[1,7]
	Extrinsically-motivated knowledge sharing	An employee’s reporting that his or her knowledge-sharing behaviours are driven by extrinsic motivational factors (e.g., financial rewards)	Survey questions	[1,7]
	Knowledge creation	The degree of a person’s ability to produce new knowledge pieces	Survey questions	[1,7]
knowledge recipients	Knowledge utilization	The degree of a person’s ability to adopt and apply knowledge	Survey questions	[1,7]
	Knowledge accumulation	The degree of a person’s ability to access and systematically obtain relevant knowledge to aid in their work and decision making	Survey questions	[1,7]
	Knowledge internalization	The degree of a person’s ability to discover explicit knowledge and embody it into tacit knowledge	Survey questions	[1,7]
Both	Perceived matching	An employee’s perception that the platform is useful for matching information seekers and sources and that if the employee contribute knowledge to the platform, the contributor believes that the shared knowledge item can be matched with knowledge seekers	Survey question	[1,7]
	Social interactions (online)	The number of comments that a knowledge piece received	Automatically calculated by system	[0, 2772]
	Social interactions (offline)	An employee’s perception of the level of users’ knowledge-exchange-related social interactions via offline channels	Survey question	[1,7]
	Views	The number of times that a knowledge piece is accessed	Automatically calculated by system	[0, 15901]
External factors	Seniority	The current ranking of an employee	Survey question	1 = interns/casual workers 2 = juniors 3 = team leaders

				4 = managers/branch head
				5 = CXOs
	Department	The main department that an employee is working in	Survey question	1 = Quantity Survey
				2 = Engineering
				3 = Accounting
				4 = Marketing
				5 = General (incl. CEO office)
				6 = HR
				7 = Others
	Income	An employee's self-reported current monthly income level	Survey question	1 = 0,4000 RMB per month
				2 = 4001 to 8000 per month
				3 = 8001 to 12000 per month
				4 = 12001 to 16000 per month
				5 = 16001 ~ per month
	Gender	The biological sex of an employee	Survey question	1 = Female
				0 = male

Table 41. Factors' Description

Results

Multiple tests were conducted with the various constructs to help answer the research questions. The results shown in Table 42 confirmed the convergent validity by Cronbach α, Composite Reliability (CR), and Average Variance Extracted (AVE). Note that Chin's (1998) rule of thumb was followed: The rule claims that constructs' CR should exceed 0.7 and AVE should exceed 0.5.

Construct	**N of items**	**Std. deviation**		**Cronbach's α**		**CR**		**AVE**	
		pre	**post**	**pre**	**post**	**pre**	**post**	**pre**	**post**
Knowledge-sharing level (self-report)	4	0.87	0.98	0.9	0.95	0.92	0.94	0.74	0.79
Knowledge-sharing level (direct supervisor rated)	8	0.82	0.89	0.94	0.94	0.95	0.96	0.71	0.73
Intrinsically motivated knowledge sharing	3	0.65	0.7	0.81	0.87	0.76	0.86	0.51	0.67
Extrinsically motivated knowledge sharing	4	0.74	0.89	0.9	0.92	0.89	0.93	0.54	0.76
Knowledge creation	4	0.64	0.96	0.79	0.93	0.82	0.94	0.53	0.81
Knowledge utilization	5	0.62	0.66	0.86	0.88	0.89	0.88	0.62	0.61
Knowledge accumulation	4	0.57	0.64	0.85	0.89	0.88	0.83	0.66	0.55

Knowledge internalization	5	0.57	0.72	0.8	0.89	0.81	0.89	0.58	0.63
Matching	2	0.82	0.86	0.91	0.92	0.84	0.91	0.73	0.75
Social interactions (online)	2	0.83	0.93	0.88	0.9	0.84	0.78	0.73	0.65
Social interactions (offline)	2	0.75	0.81	0.8	0.83	0.81	0.89	0.77	0.68

Table 42. Standard Deviations, Cronbach α, Composite Reliability (CR) and Average Variance Extracted (AVE); Note: pre = the first round of surveys which were conducted before the knowledge market launched; post = the second round of surveys which were conducted after it launched

In terms of the knowledge market performance, it was found that employees contributed more than six times as many knowledge pieces than before and that the number of views of these knowledge pieces increased 8.5 times. They also made more than five times as many comments than before. However, the increases did not follow an equal distribution ($Skewness_{views} = 6.983$ and $Skewness_{comments} = 3.890$). These high skewness numbers indicate that the most popular items attracted the most attention and comments.

Also, for the 15 most popular knowledge items, eight were in video format. For comparison, less than 15.6 percent of the total knowledge items were in video format. Thus, the video items seemingly attracted more attention than other items.

Employees made most knowledge pieces (71.83%) free for receivers to access them. For the first month of the post-treatment stage, the total amount of ticket income (i.e., income that employees generated from fees to access knowledge pieces) was CNY 7,905 (approximately US$1,236.9), while the total amount of tip income (i.e., incomes that employees generated during and after accessing knowledge pieces) was CNY 21,115 (approximately US$3,304.0). Income also followed a highly skewed distribution (skewness(tips) = 6.99, skewness (ticket) = 4.75). For the second month of the post-treatment stage, the highly skewed pattern continued, and the total amount of tip income increased to CNY 25,459 (approximately US$ 3983.7), while the income for ticket income decreased to CNY 814 (US$ 127.4).

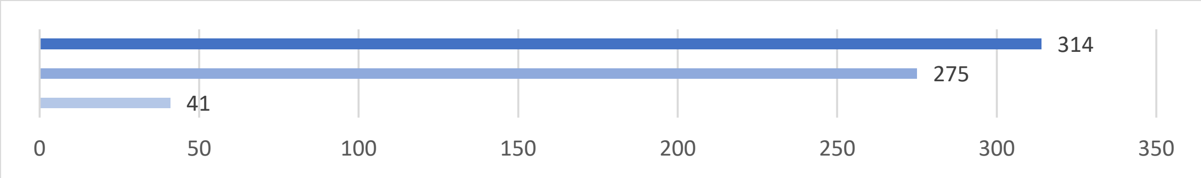


Figure 17. Number of Knowledge Pieces (Pre (Below) vs. Post-treatment stage 1 (Middle) vs. Post-treatment stage 2(Upper))

	Stage		
	Pre	Post - 1	Post - 2
Views	1560	13298	15901
Average Views	38.04	48.35	48.06
Median Views	18	7	3
Comments	503	2772	1824
Average Comments	12.27	10.08	5.81
Median Comments	1	1	1
Voluntary knowledge sharing	41	228	295

Table 43. An Increase in Total Number of Views and Comments; A Decrease on Average Number of Comments each Knowledge Piece Receives; Voluntary Knowledge Sharing (the Number of Free Items Shared) Plateaued

As for the survey results (see Table 43), the employees used the knowledge platform, and accumulated and shared more knowledge items after the company implemented the market-based knowledge platform mechanism. Extrinsic motivations significantly influenced the increase in the knowledge-sharing level. Employees reported slightly lower intrinsically motivated knowledge sharing after the implementation of the new reward scheme, but the difference did not meet statistical significance. The knowledge internalization level remained largely unchanged after the implementation, but the perceived matching between receivers and suppliers significantly increased. The supervisor-rated knowledge-sharing scores also confirmed what was found from the self-report survey (see Table 44).

Supervisor's rating	Difference (post survey-pre survey)	Sig.
This employee can always pass along information that may be helpful to the work of the group.	0.75	< 0.001***

This employee actively seeks helpful information to share with the group.	0.46	0.006***
This employee keeps others in the work group informed of emerging developments that may increase their work effectiveness.	0.44	0.005***
This employee shares his/her expertise to help resolve work group problems.	0.52	< 0.001***
This employee willingly aids others in the group whose work efforts could benefit from his/her expertise	0.56	< 0.001***
This employee shares information that he/she has when it can be beneficial to others in the work group.	0.39	0.019**
This employee offers innovative ideas in his/her area of expertise that can benefit the group's work.	0.11	0.500
This employee frequently shares his/her expertise by making helpful suggestions that benefit the work group.	0.27	0.085*

Table 44. Supervisor Rated Knowledge Sharing Score p<0.1 *; p<0.05**; p<0.01***

Construct	Item	Mean difference (post survey-pre survey)	Sig	Std. e. mean
Knowledge utilization	There are research and educational programs with rewards in my company	1.05	<0.001***	0.129
	There exist incentive and benefit policies for new idea suggestions in utilizing existing knowledge in my company			
	There exists a culture encouraging knowledge sharing and utilization			
	Electronic communication, rather than paper-based communication is extensively used to facilitate processing tasks in my company			
	In my company, teamwork is promoted by utilizing organization-wide information and knowledge			

Knowledge accumulation	I refer to corporate database/knowledge base before processing tasks	0.55	<0.001***	0.091
	I try to store expertise on new tasks design and development			
	I often try to store knowledge about legal guidelines and policies related to tasks			
	I document and summarise such knowledge needed for the tasks and training and education results provided by the company			
Knowledge internalization	… I have a unique mastery of the tasks	0.06	0.780	0.064
	… in the company, professional knowledge such as customer knowledge and demand forecasting are managed systematically			
	… the company has an organization-wide standard for knowledge resources which are built, and these are updated regularly and maintained well			
	…. employees are given educational opportunities to improve adaptability to new tasks			
	… I can learn what is necessary for new tasks			
Knowledge sharing	I share information and knowledge necessary for the tasks	0.64	<0.001***	0.150
	I improve task efficiency by sharing information and knowledge			
	I developed my company's knowledge systems to share information and knowledge			
	I promote sharing of information and knowledge with people in other project teams and departments			
Knowledge creation	I often use my current knowledge management system to analyse tasks	0.47	<0.001***	0.105
	My predecessor adequately introduced me to my tasks			

	I fully understand the core knowledge and skills that are necessary for my tasks			
	I am ready to accept new knowledge and apply it to my tasks when necessary			
Intrinsically motivated knowledge sharing	Sharing my knowledge with colleagues is pleasurable.	-0.02	0.049**	0.062
	It feels very good to help someone by sharing my knowledge			
	I am confident in my ability to provide knowledge that others in my organization			
Extrinsically motivated knowledge sharing	I will receive a higher salary and bonus in return for my knowledge sharing.	0.58	<0.001***	0.126
	I will receive increased promotion opportunities in return for my knowledge sharing.			
	After sharing my knowledge, I also expect to receive knowledge in return when necessary.			
	After sharing my knowledge, I expand the scope of my association with other organization members.			
Social interactions online	I spend a lot of time interacting with some members of the company's online knowledge platform	1.3	<0.001***	0.178
	I make frequent communication on the company's online knowledge platform			
Social interactions offline	I have frequent communication with my co-workers and share information and knowledge offline	0.4	0.859	0.121
	I maintain close social relationships with some co-workers through sharing information and knowledge offline			
Perceived matching	On my company's knowledge platform, I can find the knowledge resources that I need.	0.74	<0.001***	0.141

I know that I can create knowledge resources that my colleagues need and upload them onto my company's knowledge platform.

Table 45. Self-reported Knowledge Transfer Level, $p < 0.1$ *; $p<0.05$**; $p<0.01$***

I also tested whether external factors (such as sex, seniority, income, and department) caused any significant differences in the knowledge-transfer level before and after the implementation. To do so, a least significant difference (LSD) post hoc analysis was conducted. As Table 46 shows, sex did not exert a significant impact on any knowledge-transfer factor before the market-based mechanism was implemented. That being said, after the implementation, female workers' intrinsically motivated knowledge-sharing level was marginally greater than male workers. Before the implementation, lower-income workers' intrinsically motivated knowledge-sharing level was significantly lower than higher-income workers. After the implementation, the difference became insignificant. It is also found that there are lower values for several knowledge-transfer factors (e.g., knowledge accumulation, extrinsically motivated knowledge sharing, online social interactions, and matching) for workers in the accounting department than for people in quantity survey, marketing, general (including CEO office), and HR departments, which indicates that the market-based mechanism affected people in the accounting department less than the others. These findings concur with Kettles et al.'s (2017) conclusion. Seniority also had a significant role in knowledge utilization at an aggregate level after the company implemented the new mechanism. However, in the post hoc analysis, the result of this study also shows that less senior employees (junior, intern, and casual workers) had a lower knowledge utilization level compared to more senior employees, though the difference did not reach statistical significance. Moreover, this difference became even smaller after the company implemented the knowledge market. The results also shows that casual, interns, and junior workers were more extrinsically motivated to share knowledge after the implementation. The perceived matching rate between receivers and suppliers was significantly higher for the top-level management before the implementation but not after it, compared to the people in other seniority statuses. Employees in the HR department and CEO office also perceived a higher matching before the implementation, and this difference became less salient after the implementation. This finding might reflect a discrepancy between the people who publish knowledge items and the people who receive them, especially before the company implemented the knowledge market. After all, the organization centrally controlled the knowledge-transfer platform before the company implemented the knowledge market (i.e., when the CEO and HR arranged the knowledge items that employees should have learned). The market implementation allowed more horizontal knowledge transfers. Note that, in the above analysis, the Levene's statistic method was used to test the homogeneity of variances and found no problems.

Table 47 summarises the support for the hypotheses.

Factor	Survey Timepoint	Sex		Income		Department		Seniority	
		t	Sig.	t	Sig.	t	Sig.	t	Sig.
Knowledge sharing (self-report)	Pre	1.556	0.216	0.857	0.493	1.401	0.224	0.321	0.863
	Post	0.593	0.443	0.146	0.964	2.651	0.021	0.903	0.466
Intrinsic motivated knowledge sharing	Pre	0.526	0.47	2.113*	0.086	2.145	0.056	1.643	0.171
	Post	4.417*	0.038	0.916	0.458	0.691	0.657	1.172	0.329
Extrinsic motivated knowledge sharing	Pre	0.058	0.811	0.721	0.58	2.372**	0.036	1.268	0.289
	Post	0.64	0.426	1.264	0.291	3.297***	0.006	1.935	0.100
Knowledge creation	Pre	0.395	0.532	1.835	0.129	1.732	0.123	1.353	0.257
	Post	0.014	0.906	1.846	0.127	1.823	0.104	0.03	0.998
Knowledge utilization	Pre	0.305	0.582	0.207	0.934	2.141	0.057	2.511**	0.047
	Post	0.726	0.397	1.084	0.37	1.395	0.226	1.279	0.284
Knowledge accumulation	Pre	1.45	0.232	2.107	0.087	2.254	0.046	2.315	0.064
	Post	0.003	0.958	2.806*	0.03	6.727***	<0.001	1.212	0.312
Knowledge internalization	Pre	1.789	0.184	0.745	0.564	1.305	0.264	1.862	0.124
	Post	0.956	0.331	1.113	0.355	0.934	0.475	2.477*	0.050
	Pre	0.123	0.727	0.913	0.46	1.953	0.081	0.629	0.643

Social interactions-online	Post	0.54	0.465	1.417	0.235	3.044***	0.01	0.437	0.781
Social interactions - offline	Pre	0.545	0.462	1.81	0.134	2.004	0.074	2.472*	0.050
	Post	2.992	0.087	1.757	0.145	1.052	0.398	2.268	0.068
Perceived matching	Pre	0.001	0.983	1.197	0.318	5.384***	<0.001	4.395**	0.003
	Post	0.013	0.909	1.482	0.215	3.954***	0.002	1.344	0.260

Note: $p < 0.05$*; $p < 0.01$**; $p < 0.001$***

Table 46. Sex, Seniority, Income, and Department Influence on Knowledge Transfer, p<0.1*; p<0.05**; p<0.01***

No	Hypothesis	Support
H1a	Introducing a market-based knowledge platform can increase incentivised knowledge-sharing activities.	Yes
H1b	Introducing a market-based knowledge platform does not reduce voluntary knowledge-sharing behaviours.	Yes
H2a	When introducing a market-based knowledge platform, employees' seniority may affect a market reward's impact.	Yes
H2b	When introducing a market-based knowledge platform, employees' gender may affect a market reward's impact.	Yes
H2c	When introducing a market-based knowledge platform, employees' current department may affect a market reward's impact.	Yes
H2d	When introducing a market-based knowledge platform, employees' current income level may affect a market reward's impact.	Yes

H3	Employees increase their knowledge-sharing-related social interactions after their organization implements a market-based knowledge platform.	Partial
H4	An internal knowledge market leads to better matching between knowledge receivers and suppliers than if such a market does not exist.	Partial

Table 47. Hypothesis Testing Results of Study 5

Implications

In my collaborative work with an emerging Chinese medium-sized knowledge-intensive company, Yichen, I designed a knowledge market and set up relevant protocols to regulate and boost knowledge transfer in the company. To ensure the validity of the market design that was proposed in this study, I conducted a comprehensive literature review and summarised useful functional features from previous market designs. Also, during the study, weekly interviews were conducted, and two surveys were used to evaluate the effectiveness of the design of a new market-based knowledge management scheme. To further verify the results' robustness, I also crossed-checked the results from the surveys and the performance data about the knowledge market.

In general, the knowledge market promoted knowledge-transfer practices and behaviours, an effect that extrinsic motivations largely drove. The perceived matching rate between knowledge supply and demand also increased significantly. These results generally confirm the conclusions that previous studies of knowledge markets have drawn. That said, the intrinsic motivation for knowledge sharing did not decrease dramatically as Hung et al. (2011) and Janssen and Mendys-Kamphorst (2004) believed. As for why, the reward possibly worked both as an extrinsic and an intrinsic motivator for the workers, especially the less senior ones. Also, I found even a small amount of monetary incentive can cause a positive effect on knowledge suppliers' sharing and creation behaviours, which contradicts Qi et al.'s (2021) empirical finding arguing that only a high-yield monetary incentive leads to an increase in suppliers' sharing and creation behaviours while a small incentive leads to a decrease in sharing and creation of knowledge. I suspect this is because in Qi et al.'s (2021) research, the focal point is a public knowledge-sharing platform, but in my research, the research subject is an internal platform. As Chen et al. (2010) explain, post-purchase payments are more likely to be viewed as an indication of "niceness" rather than real monetary compensation. The former factor is a necessary part of building meaningful reciprocity which, based on social exchange theory, can build a higher level of knowledge exchange (Bartol et al., 2009). Compared to a public platform whose knowledge suppliers are more likely to rely on a pure economic exchange, a firm's internal platform relies more on the social factors. That being said, I argue there is still a need for future research to investigate this question further.

Moreover, the results also show that the knowledge market mechanism can significantly boost knowledge creation, sharing, accumulation and utilization levels but not knowledge internalization nor increase users' offline knowledge-sharing interactions. The former is an important process of transforming explicit knowledge into tacit knowledge and the latter one is a critical path for transferring tacit knowledge (Nonaka, 2008). This, as I postulate, reflects that a knowledge market alone cannot sufficiently facilitate this explicit-tacit knowledge-transformation process.

I also found that the market-based mechanisms' effect is slightly different for different groups of people. For instance, among the less senior workers, the increase of perceived matching rate brought by the market mechanism is higher than other groups. I argue this is because a knowledge market allows more horizontal knowledge transfers to occur and allows platform managers to manage the market like a market maker rather than a central planner (Serrat, 2017). This horizontal system replaced the old vertical transfer mode (i.e., the top managers and the HR department decided the knowledge supply), and these results show that the horizontal system increased the perceived matching rate, and the less senior workers' perception of this change was much stronger than senior workers.

It was also found that knowledge receivers' attention followed a highly skewed distribution in that few knowledge items received most of the monetary rewards, views, and comments. After launching a market-based knowledge platform mechanism, the company's online knowledge-transfer-related interactions increased in frequency of interacting on the knowledge platform the company provides, yet offline interactions largely remained unchanged in frequency, as the employees reported. Voluntary knowledge-sharing activities did not decrease after the researcher of this study introduced the market-based knowledge platform. In fact, most income came from voluntary post-viewing contributions rather than ticket fees, which suggests that the knowledge market followed a busking fashion. From the data collected during this study, it is also apparent that the knowledge suppliers and the recipients seemed to adapt to this fashion quickly by offering a higher number of items that were free of any access charges upfront and waiting for people to contribute tips. Accordingly, one may hypothesize that the key success factors for knowledge suppliers in this market included increasing knowledge availability by demolishing the paywall, increasing content interactivity and arousing audiences' behavioural response, and producing a large bandwagon effect (Anglada-Tort et al., 2019). However, this also needs further research to confirm this hypothesis.

This study also offers some theoretical contributions for literature. I confirm the market design theory's usefulness in guiding the design of knowledge markets. So far, previous knowledge market studies sometimes gave inconsistent findings, and in this study, guided by the market design theory, I systematically summarised the strengths and the weaknesses of the design features recorded in literature of this field and provided a new design paradigm with theoretical underpinning for knowledge market design research. By doing so, this study validates and reconciles various theoretical findings pertaining to the effect of market-based mechanisms on their users' knowledge exchange behaviours. Moreover, this study offers a road map for other companies who want to provide internal knowledge-exchange and knowledge-trading platforms. In doing so, this study answers calls in the recent literature for researchers to take urgent steps toward investigating how firms can use digital technologies (such as multi-sided digital platforms) to deliberately steer a complex sociotechnical system (such as an internal knowledge management system) from a given state through phase transitions toward a desired new state (Benbya et al., 2020). Finally, this study empirically suggests that the online knowledge market that was designed in this study could induce a positive extrinsic motivational effect without crowding out intrinsic motivations, and cause a positive but insignificant spill-over effect on offline knowledge-sharing interactions, which further enriches the research literature on knowledge market designs.

This study also has practical implications. As I mentioned previously, the arising need for augmenting the knowledge network of their organizations has led to the invention of various types of first-generation market-based knowledge management platforms. Most of the previous knowledge market practices focused on multinational companies, and in this study, a timely practical contribution was made to a medium-sized company. Specifically, this study outlined details about how a knowledge market can be used and designed to increase activities within the whole knowledge transfer process (e.g., knowledge creation, knowledge sharing, knowledge accumulation, and knowledge utilisation). Thus, it showed that a market-based knowledge platform can increase the perceived matching rate between knowledge suppliers and recipients. However, this study also showed that if a knowledge platform administrator wants to increase the level of knowledge internalisation and also promote offline knowledge-sharing-related interactions, the knowledge market design that this study proposed cannot achieve it alone, and other mechanisms should be jointly used to increase the transfer and the internalisation of tacit knowledge.

Also, practitioners might learn from this study of market participants' behaviours. As this study shows, users can quickly adapt to the market mechanisms and develop suitable money-making strategies. Specifically, voluntary post-viewing contributions are more preferable than entrance ticket fees which maybe partially be explained by the fact that, as my literature review shows, knowledge is a typical kind of experience product whose real value is difficult to calculate because it involves many uncertainties when evaluating the quality of it, particularly in online environments (Qi et al., 2019). Also, the findings of this study suggest a role for knowledge platform administrators in selecting top knowledge sharers who can maximise their knowledge's spreadability. The knowledge market practitioners can also help the suppliers to increase their content interactivity and their ability to entertain their audiences so as to arouse their behavioural response, eventually being capable of finding a balance between professionalism and popularity.

Similar to other studies, this study contains several weaknesses, but I believe these shortcomings open doors for future research. First, due to time and scope limitations, I conducted the study in a single company. However, many organizational factors such as company culture, norms, structure, size, and so on can influence knowledge transfers (Alavi & Leidner, 2001). Thus, future work should replicate this study in organizations with different cultures, norms, structures, and sizes. Second, this study considered only two time points and made observations for only three months in each stage. A longer observation period would be ideal because it will help researchers and practitioners to clarify whether this market scheme's impact would be minimalized as the time passes by and whether its incentivisation has a significant fatigue effect. Also, if such an effect does exist, future researchers need to see when it will appear and whether platform managers can use any mitigation methods (e.g., change of incentive structure, creating new types of recognitions, and create dedicated work group to manage and motivate transfer) to ensure its longevity.

Summary

In an extensive collaboration with Yichen, an emerging medium-sized knowledge-intensive company in China, the researcher embarked on designing a novel knowledge market to streamline and enhance knowledge transfer processes within the organization. A rigorous literature review was undertaken to distill functional attributes from prior market designs, complemented by weekly interviews and dual surveys to assess the effectiveness of the introduced knowledge management system. The findings revealed that while the knowledge market amplified knowledge-transfer activities, primarily driven by extrinsic motivations, it could not drive up knowledge internalization and offline tacit knowledge exchange at the same effective scale. That being said, interestingly, even minimal monetary incentives emerged as potent catalysts for knowledge sharing, particularly within an internal organizational context, with junior employees reaping pronounced benefits from horizontal knowledge transfer mechanisms.

The study thus underlined the vital role of market design theory in shaping knowledge markets, presenting a detailed blueprint for organizations navigating the digital technology landscape in complex sociotechnical systems. Furthermore, the research transcended the confines of Yichen's experience, delving into broader theoretical and practical implications for the wider realm of knowledge markets. Despite its comprehensive scope, the study recognizes its limitations, primarily its singular focus on Yichen and its relatively brief temporal span, advocating for more extended research engagements in the future to unveil deeper insights and long-term trends.

So far this thesis presents a labyrinthine journey through the complex nature of online knowledge exchange platforms. By examining various incarnations of these platforms, it endeavours to furnish readers with both a theoretical understanding and a practical handbook, ensuring the next generation of platforms is not only thriving but also optimized for high-quality knowledge exchange. In reflection, as knowledge continues to be an invaluable asset in the evolving digital age, the importance of effective, efficient, and equitable online knowledge exchange platforms cannot be overstated. This work stands as a testament to the depth and breadth of exploration and innovation possible in this domain. I envision that future scholars, developers, and educators draw inspiration from this investigation, recognizing both the profound responsibility and boundless opportunity they hold in shaping the future of knowledge dissemination. May the five empirical studies presented in this thesis serve not just as a chronicle of what has been but as a beacon illuminating the path forward.

Chapter 9: Overall discussion

This thesis, spanning eight chapters, delves into the contemporary challenges and innovations surrounding knowledge exchanges. It offers an exhaustive review of pertinent literature, complemented by empirical studies exploring modern knowledge exchange dynamics, mechanisms to enhance knowledge contribution, and the leveraging of knowledge marketplaces to bolster knowledge-sharing behaviors. Rooted in a multidisciplinary framework, I will now elucidate the overarching implications of my findings, subsequently charting potential avenues for future research.

Overall implications of this research

Knowledge exchange is critical for many modern companies because knowledge has been considered by those companies as the most important resource for staying competitive. As this thesis shows, there are many new challenges and trends emerging in this area. To fit the new features and trends of knowledge exchange platforms and to face the new challenges, through this thesis, I firstly achieved a comprehensive, state-of-the-art literature review of the theories and the current empirical research on knowledge-exchange-related topics. Using motivation theory as the overall guiding theory, five empirical studies were performed to achieve the three research objectives that I formulated in the first chapter (see the summary table below).

#	Research objective	Summary
1	Develop and Evaluate an Innovative Design Paradigm {Study 1 and 2}	I achieved this research objective by designing and validating a nudge that highlights the factor of immediacy and applies a well-known bias – present time bias. This nudge proved useful in achieving the said objectives in different contexts.

2	Identify Motivating Features for Open Knowledge Retrieval {Study 3}	I achieved this research objective by traditional factors that were proposed in previous interview- and survey-based conceptual studies, such as metadata richness, contributors' reputation, and fields of study. These can have a positive effect on data collections' retrieval rates, but those factors may not sufficiently explain why different data collections have hugely uneven downloads. Then a new robust factor (i.e., keyword topicality) was proposed and I tested and confirmed the factor's effectiveness by adding it into the original models comprising the traditional factors.
3	Examine and Analyse Real-World Knowledge Exchange Cases and Market Practices {Study 4 and 5}	I achieved this research objective by observing two real world knowledge markets (including a public market and an internal market). Specifically, in a knowledge market that sells MOOCs, I found that factors, such as effort level, difficulty level, recommended length, offering institutions, and subject, are significantly correlated with courses' price but that "language" only has a significant effect at an aggregate level. Also, it appears that there exists a correlation between the prices and the courses' enrolment and completion rates.

Table 48. A Summary of the Research Objectives and Findings in this Thesis

By achieving those objectives, this thesis contributes to the knowledge exchange literature and also generates several implications for the practices of online knowledge exchange platforms in a number of ways.

Specifically, in Study 1, combined with the nudge theory and use and gratification theory, I reveal that a digital nudge that highlights the immediacy factor in motivational feedback designs can promote knowledge-sharing behaviours, positive engagement behaviours, and, at the same time reduce negative engagement behaviours. Gratifications, theoretically speaking, drives and regulates people's knowledge exchange behaviours, and previous studies show that knowledge exchange platforms need to maintain the gratification level of their users, especially the knowledge contributors so as to stimulate sustainable engagement and positive contributions. However, maintaining the gratification level is not always successful and can be very costly, and the extant literature remains unclear about what types of gratification-conferring mechanisms are most effective. As mentioned in the literature review, to date, most of the studies in this area focused on the *ex-post* motivational mechanism's effect on promoting knowledge-sharing and knowledge contribution behaviours. To the best of my knowledge there is no research focused on the importance of the *ad hoc* and immediacy factor in designing motivators. In Study 1, I utilised Nudge theory and designed a mechanism which can provide immediate motivational feedback to knowledge contributors so as to promote their knowledge-sharing behaviours. This nudge aims to apply a well-known bias—present time bias—and the result shows it can increase the quality of contributions as well as the overall proportion of quality knowledge contribution in the knowledge pool. Moreover, this study also help reconciles the inconsistent findings about extrinsic motivations from previous online knowledge-sharing and knowledge-management research by highlighting the importance of the immediacy factor. Thus, my research contributes to the exploration of a new stream of research that highlights the importance of utilising *ad hoc* and immediacy factors in designing motivators. As I explained in the corresponding chapters, theoretically the immediacy factor can amplify the motivational power that extrinsic motivators offer, and in practice, a digital nudge that highlights immediacy indeed can increase the probability of contributors writing better knowledge contributions. Furthermore, in the practical sense of these findings, I not only present a new applicable, robust, and rigorous design paradigm but also add to theoretical knowledge of extrinsic motivation mechanisms in an online knowledge-sharing context.

In Study 2, using an action research approach, I not only verified the effectiveness of the digital nudge design that was proposed in Study 1 but also extended the existing knowledge exchange literature by applying several existing theoretical concepts and models, such as the utilization of the theoretical knowledge-sharing enablers and inhibitors, people's time preference for rewards, and system evaluation of users' acceptance to new technologies. Also, the study makes a novel contribution by applying an action research approach to the design of a viable prototype for motivating MOOC learners' sharing behaviours such that they will contribute more high-quality knowledge on MOOC platforms when the intervention of the proposed mechanism presents.

In Study 3, I focused on open science knowledge exchange and, based on examining the current knowledge retrieval rate of Australia's Commonwealth Scientific and Industrial Research Organization (CSIRO) Data Access Portal (DAP), which perhaps is one of the largest publicly funded open science knowledge portals, I found empirical evidence to support new ways for practitioners and knowledge owners to better publicise open science knowledge. Specifically, I found traditional factors, such as metadata richness, contributors' reputation, and fields of study, can bring a significant positive effect on data collections' retrieval rates, but those factors may not sufficiently explain why different data collections have hugely uneven downloads. Further, I found the usefulness of use and update topical, relevant keywords and terms. That is to say, if data suppliers want other users to find their datasets, they need to take care of the trendiness of their datasets' keywords. By doing so, to increase the overall efficiency in exchange open science knowledge. Practically, as Sanderson et al. (2019) pointed out, methods such as giving more detailed and comprehensive metadata, highlighting the most salient information, and identifying patterns or trends, indeed drive up retrieval rates, but asking contributors to provide additional information also means asking contributors to bear additional costs. Henceforth, policy makers should consider prioritising the factors that have proved to be useful in boosting accessibility and findability. My study suggests the particular importance of metadata completeness and keyword topicality. A data collection's keywords that were trending when the collection was first published might subsequently become obsolete (e.g., 'Grid computing' should have been replaced by 'Cloud Computing'). Therefore, knowing what are trending and obsolete keywords and reacting accordingly is an important task for data portal administrators. Lastly, this study confirms many people land on open knowledge science portals from search engines such as Google, which suggests the importance of search engine optimisation for DAP and other similar endeavours for open science knowledge exchanges, and, therefore, it is a must for knowledge contributors to use keywords that are agreed upon vocabularies in semantics and knowledge graphs (e.g., Schema.org standard) as they have been extensively used in search engines.

In study 4 and 5, I contribute to the knowledge market literature by presenting critical results and new outcomes from observing two important real-world knowledge exchange platforms. As mentioned in the literature review section, till now, there is only a small but emerging number of researches exploring the functionalities and the mechanisms of market-based knowledge exchange approaches. Specifically, in Study 4, based on examining the current price structure of edX.org, an online non-for-profit MOOC site, I found that five factors, such as effort level, difficulty level, recommended length, offering institutions, and subject, are significantly correlated with courses' price but that "language" only has a significant effect at an aggregate level. Also, the prices of MOOCs and the enrolment numbers of courses have a positive correlation, suggesting price may be a salient quality feature. However, my hypothesis that participants pay more attention to courses to which they paid a larger sum of money for earning certificates was not supported because no significant statistical relationships between price, exploration rate and completion rate were found. These findings extend the current understanding of knowledge markets' price structures and effects.

Finally, I present my empirical study in Study 5. In this study, a real-world market-based knowledge exchange platform was designed and implemented, and the result of the study suggests that, empirically, the knowledge market can increase the matching rate between knowledge suppliers and receivers and promote knowledge transfer practices and behaviours where the promotion effect was largely through the extrinsic motivation venue. The market-based platform can also facilitate knowledge-transfer-related interactions as well as the process of explicit-tacit knowledge transformation by allowing a higher number of horizontal transfers of knowledge. I also found that the benefits of the market-based platform are not reaped equally. That is, the distribution of income and viewership is highly skewed, with a small number of knowledge items receiving most of the attention and rewards and a large sum of items receiving minimal attention, which is often seen as an indication of low quality (Sha et al., 2020). Therefore, this study contributes to the knowledge market design literature by providing additional empirical support, confirming the overall effectiveness of the knowledge market in increasing employees' knowledge exchange behaviours such as extrinsically-motivated knowledge transfers, online knowledge-transfer-related social interactions, and perceived matching rate between knowledge supplies and demands. Some prior studies suggested that the firms that use a knowledge market mechanism, which effectively introduces new explicit monetary rewards, to govern their knowledge management platforms may lessen the effect of non-monetary recognition on increase the quality of knowledge transferred from sellers to buyers, resulting in a "crowding-out" effect (Bock et al., 2005; Lombardi et al., 2020). However, this study suggests this might not be the case if the market mechanism is designed in a proper manner. These findings also contribute to the market-based knowledge exchange literature by providing insights of users' knowledge trading behaviours as well as people's reactions towards market signals. Moreover, future practitioners can also use the empirical findings about designing and implementing new market-based mechanisms to boost their knowledge platforms' overall efficiency.

Overall suggestions for future research

With a broader lens, the studies collectively pave the way for future research on knowledge exchange in online platforms, specifically focusing on the roles of motivational mechanisms, metadata optimization, and market-based approaches.

Each study, with its unique focus and insights, contributes towards a holistic understanding of online knowledge exchange while simultaneously unveiling areas that require further exploration. In this discussion, I will revisit each study to outline future research opportunities and explore the interconnectedness of these distinct yet complementary studies.

Study 1's primary focus is on the role of behavioural nudges in promoting knowledge sharing behaviour, particularly through the lens of immediacy in motivational feedback, provides ample scope for subsequent research. An array of possibilities can be envisioned where researchers could delve deeper into the dynamics of varying types, timing, or intensity of nudges. The interaction between these nudges and the user's intrinsic motivations presents another intriguing facet to explore. A thorough understanding of these motivational mechanisms can provide valuable insights to enhance user participation in online knowledge exchange platforms.

Building on the findings from Study 1, Study 2 examined the effectiveness of digital nudges in different contexts like MOOCs. The outcomes of this study can influence future research on the design and implementation of such nudges in various platforms like social media, professional networks, and even in different cultural contexts. Exploring how these nudges interact with specific platform dynamics or cultural nuances can lead to a more effective application of motivational mechanisms in these contexts.

Study 3's focus on metadata and keyword optimization to improve knowledge discoverability opens up possibilities for further research into online search and retrieval mechanisms. Future research could examine the intricacies of metadata optimization across different platforms or fields. Investigating how platforms and users can keep abreast of evolving keyword trends to maintain the relevance of their content could also be a valuable area of study. These insights could contribute towards building more user-friendly and effective knowledge discovery mechanisms.

Study 4 provided critical insights into the dynamics of market-based knowledge exchange. It also raised intriguing questions about how price structures and market mechanisms affect knowledge exchange behaviors and outcomes. Future research could investigate the interplay between pricing strategies and perceived quality. A more nuanced exploration of the application of economic principles in knowledge exchange, including the impact of market structures like monopoly, oligopoly, and perfect competition, could further enhance the understanding of market-based knowledge exchanges.

Complementing Study 4, Study 5 demonstrated the practical implications of market-based knowledge exchange. This leads to exciting avenues for future research on how to create balanced market mechanisms and mitigate the risk of skewed markets. Potential studies could look at the effects of reputation systems on market behaviour or strategies to address inequality in market outcomes.

While these studies can individually contribute to the understanding of online knowledge exchange, collectively, they provide a more integrated view. For instance, the insights from Studies 1 and 2 on motivational mechanisms can inform the market-based approaches to knowledge exchange in Studies 4 and 5. Similarly, the findings from Study 3 on metadata optimization can enhance the design of motivational nudges and market-based platforms. This interconnectedness between motivation, accessibility, and economics in online knowledge exchange presents an exciting landscape for future interdisciplinary research.

The research findings also have profound implications for various stakeholders involved in online knowledge exchange. For platform designers, these insights can guide the integration of behavioural nudges into the user interface and development of search-friendly design elements. Knowledge contributors can leverage these strategies to enhance the visibility and impact of their contributions. Educators and policy-makers can also find valuable guidance in these studies to enhance online learning outcomes and promote fair and efficient knowledge markets.

In sum, this thesis advances the understanding of online knowledge exchange and offers a promising foundation for future research. It is essential to continue expanding this knowledge base to improve the effectiveness and inclusivity of online knowledge exchange platforms.

However, it is also noted that establishing a market-based knowledge exchange system and transferring into it is not easy. As Pentland et al. (2020) and Benbya et al. (2020) suggested, rapid and unexpected changes are increasingly common in information systems development and implementation processes, and unexpectedly changing requirements and incremental endogenous changes can cause non-linear bursts of complexity. Problems emerging from the complexity of sociotechnical systems are called “wicked problems” (Tanriverdi & Du, 2020). A wicked problem, as Dakova et al. (2018) argued, involves a large number of stakeholders having different objectives, diverse needs, and distinct priorities and therefore, such a problem is complex, uncertain, and contested. Designing, developing and implementing a knowledge exchange platform that fosters online knowledge transfer digitally induced such problems, and as Benbya et al. (2020) suggested, there usually are no right answers to fundamentally “solve” such problems; however, IS scholars can use big data, machine learning, and AI algorithms to “tame” them.

In my research, I attempted to adopt a multidisciplinary method to tame the problems that are existing in knowledge exchange platforms and knowledge exchange marketplaces. Through empirical observations, I also attempted to discover potential useful causalities existing in complex knowledge exchange systems, a significant research challenge for IS research as Benbya et al. (2020) introduced. Although I believe the current research, including mine, is far from sufficiency, I still contend that this thesis points to several avenues of future research to investigate issues such as how to ensure the longevity of knowledge exchange platforms and markets, how to manage the fluctuations and complex sociotechnical problems during the knowledge exchange systems’ evolution, and how to use advanced technologies to intervene knowledge exchange behaviours and relevant performance outcomes given the complex interdependencies among the organization-platform-people dimensions

As I reviewed in the previous chapters, the valuation of knowledge products involves high subjectivity (Raban et al., 2019). The users’ utility should be the base for calculating the price of knowledge products, but as an experience good, the utility obtained from consuming knowledge products often varies greatly by person-specific factors and context-related variables (Rafaeli & Raban, 2003).

Henceforth, I argue there is need to investigate the impact of people’s emotion on their evaluation of knowledge products. On one hand, it seems intuitive to assume that some negative emotions (such as anxiety emotion) would increase people’s willingness to pay towards knowledge products. On the other, it is also conjectured that, after people registered a negative emotion, the emotion may also trigger a defensive mechanism which results in people taking actions to avoid information intake. Hence, knowledge buyers' willingness to pay for a knowledge product may decrease due to the introduction of a negative emotion factor. Moreover, even if a negative emotion may motivate people to purchase an information good, this emotional motivating effect may not be sustainable as this emotion maybe short-lived. Also, there may be an optimal level for emotion to trigger high purchase intention and willingness to pay. However, despite the interesting theme and potentially huge outcomes from these topics, so far, to the best of my knowledge, there is no prior study investigating this, which implies new opportunities for IS research.

References

Abdallah, Y. O., Shehab, E., & Al-Ashaab, A. (2021). Understanding digital transformation in the manufacturing industry: a systematic literature review and future trends. *Product: Management and Development*, *19*(1), 1-12.

Abhinav, K., & Dubey, A. (2017). Predicting budget for Crowdsourced and Freelance Software development Projects. the 10th Innovations in Software Engineering Conference, New York.

Aboshady, O. A., Radwan, A. E., Eltaweel, A. R., Azzam, A., Aboelnaga, A. A., Hashem, H. A., Darwish, S. Y., Salah, R., Kotb, O. N., & Afifi, A. M. (2015). Perception and use of massive open online courses among medical students in a developing country: multicentre cross-sectional study. *BMJ open*, *5*(1). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4289712/pdf/bmjopen-2014-006804.pdf

Acquisti, A., Adjerid, I., Balebako, R., Brandimarte, L., Cranor, L. F., Komanduri, S., Leon, P. G., Sadeh, N., Schaub, F., & Sleeper, M. (2017). Nudges for privacy and security: understanding and assisting users' choices online. *ACM Computing Surveys*, *50*(3), 44.

Adamic, L. A., Zhang, J., Bakshy, E., & Ackerman, M. S. (2008). *Knowledge sharing and yahoo answers: everyone knows something* Paper presented in the 17th international conference on World Wide Web, Beijing, China. https://doi.org/10.1145/1367497.1367587

Adams, J. S. (1963). Towards an understanding of inequity. *Journal of Psychopathology and Clinical Science*, *67*(5).

Adger, W. N., Brown, K., Cervigni, R., & Moran, D. (1995). Total economic value of forests in Mexico. *Ambio*, 286-296.

Adomavicius, G., Bockstedt, J., Curley, S., & Zhang, J. (2019). Reducing Recommender Systems Biases: An Investigation of Rating Display Designs. *MIS Quarterly*, 19-18.

Adomavicius, G., Bockstedt, J., & Curley, S. P. (2015). Bundling effects on variety seeking for digital information goods. *Journal of Management Information Systems*, *31*(4), 182-212. https://www.tandfonline.com/doi/pdf/10.1080/07421222.2014.1001266?needAccess=true

Adusumalli, S., Aragam, G., & Patel, M. (2020). A Nudge towards cardiovascular health: applications of behavioral economics for primary and secondary cardiovascular prevention. *Current Treatment Options in Cardiovascular Medicine*, *22*(9), 1-17.

Agarwal, A. (2015, 10th Feb.). News About edX Certificates. *edX learner news*. https://blog.edx.org/news-about-edx-certificates

Agrawal, A., Bhattacharya, S., & Hasija, S. (2016). Cost-reducing innovation and the role of patent intermediaries in increasing market efficiency. *Production and Operations Management*, *25*(2), 173-191.

Agrawal, A., Cockburn, I., & Zhang, L. (2015). Deals not done: Sources of failure in the market for ideas. *Strategic management journal*, *36*(7), 976-986. https://onlinelibrary.wiley.com/doi/pdf/10.1002/smj.2261

Ahituv, N. (1989). Assessing the value of information: Problems and approaches. *ICIS 1989 Proceedings*.

Ahmed, A., & Elhag, M. (2017). SMART KM model: The integrated knowledge management framework for organisational excellence. *World Journal of Science, Technology and Sustainable Development*.

Ahn, J.-H., & Chang, S.-G. (2004). Assessing the contribution of knowledge to business performance: the KP3 methodology. *Decision Support Systems*, *36*(4), 403-416. https://doi.org/10.1016/S0167-9236(03)00029-0

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. *MIS Quarterly*, *25*(1), 107-136. http://www.jstor.org/stable/3250961

Alexa. (2021). *Top Sites, Alexa*. https://www.alexa.com/topsites/

Allam, H., Bliemel, M., Spiteri, L., Blustein, J., & Ali-Hassan, H. (2019). Applying a multi-dimensional hedonic concept of intrinsic motivation on social tagging tools: A theoretical model and empirical validation. *International Journal of Information Management*, *45*, 211-222.

Almatrafi, O., Johri, A., & Rangwala, H. (2018). Needle in a haystack: Identifying learner posts that require urgent response in MOOC discussion forums. *Comput. Educ.*, *118*, 1-9.

Ames, M., & Naaman, M. (2007). Why we tag: motivations for annotation in mobile and online media. Proceedings of the SIGCHI conference on Human factors in computing systems,

Anderson, A., Huttenlocher, D., Kleinberg, J., & Leskovec, J. (2012). Discovering value from community activity on focused question answering sites: a case study of stack overflow. The 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining,

Anderson, C. (2008). Free! Why $0.00 is the future of business. *Wired Magazine*, *16*(3), 16-03.

Andreoni, J. (1995). Cooperation in public-goods experiments: kindness or confusion? *The American economic review*, 891-904.

Andrews, K. M., & Delahaye, B. L. (2000). Influences on knowledge processes in organizational learning: The psychosocial filter. *Journal of Management studies*, *37*(6), 797-810.

Anglada-Tort, M., Thueringer, H., & Omigie, D. (2019). The busking experiment: A field study measuring behavioral responses to street music performances. *Psychomusicology: Music, Mind, and Brain*, *29*(1), 46.

Aparicio, M., Bacao, F., & Oliveira, T. (2014). MOOC's business models: Turning black swans into gray swans. Proceedings of the International Conference on Information Systems and Design of Communication,

Argote, L. (2012). *Organizational learning: Creating, retaining and transferring knowledge*. Springer Science & Business Media.

Argote, L., & Ingram, P. (2000). Knowledge transfer: A basis for competitive advantage in firms. *Organizational behavior and human decision processes*, *82*(1), 150-169. https://ac.els-cdn.com/S0749597800928930/1-s2.0-S0749597800928930-main.pdf?_tid=41c15f79-b17e-4e5c-ab0e-0d80ad83b5a4&acdnat=1528877182_71c20599a9a7222b9b4971301dbc7b0a

Argote, L., McEvily, B., & Reagans, R. (2003). Managing Knowledge in Organizations: An Integrative Framework and Review of Emerging Themes. *Management Science*, *49*(4), 571-582. http://www.jstor.org/stable/4133958

Armstrong, L. (2016). Barriers to innovation and change in higher education. *TIAA-CREF Institute*. https://s3.amazonaws.com/academia.edu.documents/35995620/TIAA_-_barriers_to_change.pdf?AWSAccessKeyId=AKIAIWOWYYGZ2Y53UL3A&Expires=1519

725046&Signature=9MMEqDPIY3GISsNuIjCmV4HDZJE%3D&response-content-disposition=inline%3B%20filename%3DBarriers_to_Innovation_and_Change_in_Hig.pdf

Arzberger, P., Schroeder, P., Beaulieu, A., Bowker, G., Casey, K., Laaksonen, L., Moorman, D., Uhlir, P., & Wouters, P. (2004). Promoting access to public research data for scientific, economic, and social development. *Data Science Journal*, *3*, 135-152. https://doi.org/ 10.2481/dsj.3.135

Ashenfelter, O., Harmon, C., & Oosterbeek, H. (1999). A review of estimates of the schooling/earnings relationship, with tests for publication bias. *Labour economics*, *6*(4), 453-470.

Attali, Y., & Burstein, J. (2004). Automated essay scoring with e-rater® v. 2.0. *ETS Research Report Series*, *2004*(2).

Auerbach, A. J., Chetty, R., Feldstein, M., & Saez, E. (2013). *Handbook of public economics* (Vol. 5). Newnes.

Azadeh, A., Songhori, M., Saberi, M., Hosseini, S., Salarvand, F., & Pazhoheshfar, P. (2014). Deterministic bundle pricing of two products with limited stock. 2014 Iranian Conference on Intelligent Systems, Bam, Iran.

Ba, S., Stallaert, J., & Whinston, A. B. (2001). Optimal investment in knowledge within a firm using a market mechanism. *Management Science*, *47*(9), 1203-1219.

Baker, R., Evans, B., & Dee, T. (2016). A randomized experiment testing the efficacy of a scheduling nudge in a Massive Open Online Course (MOOC). *Aera Open*, *2*(4), 2332858416674007.

Baker, R. M., & Passmore, D. L. (2016). Value and pricing of MOOCs. *Education Sciences*, *6*(2), 14.

Bakos, Y. (1998). The emerging role of electronic marketplaces on the Internet. *Communications of the ACM*, *41*(8), 35-42. https://dl.acm.org/citation.cfm?id=280330

Bakos, Y., & Brynjolfsson, E. (1999). Bundling information goods: Pricing, profits, and efficiency. *Management Science*, *45*(12), 1613-1630.

Balfour, S. P. (2013). Assessing writing in MOOCs: Automated essay scoring and calibrated peer review (tm). *Research & Practice in Assessment*, *8*.

Bandura, A. (1990). Perceived self-efficacy in the exercise of control over AIDS infection. *Evaluation and program planning*, *13*(1), 9-17.

Bansler, J. P., & Havn, E. (2004). Exploring the role of network effects in IT implementation: The case of knowledge repositories. *Information Technology & People*, *17*(3), 268-285. https://www.emeraldinsight.com/doi/abs/10.1108/09593840410554184

Barachini, F. (2009). Cultural and social issues for knowledge sharing. *Journal of knowledge management*, *13*(1), 98-110. https://www.emeraldinsight.com/doi/abs/10.1108/13673270910931198

Baralis, E., Cagliero, L., Jabeen, S., Fiori, A., & Shah, S. (2013). Multi-document summarization based on the Yago ontology. *Expert Systems with Applications*, *40*(17), 6976-6984.

Bargh, J. A., Gollwitzer, P. M., Lee-Chai, A., Barndollar, K., & Trötschel, R. (2001). The automated will: nonconscious activation and pursuit of behavioral goals. *Journal of Personality and Social Psychology*, *81*(6), 1014.

Barrett, D. J. (2008). *MediaWiki: Wikipedia and beyond*. " O'Reilly Media, Inc.".

Barro, R. J. (1991). Economic growth in a cross section of countries. *The quarterly journal of economics*, *106*(2), 407-443.

Bartol, K. M., Liu, W., Zeng, X., & Wu, K. (2009). Social exchange and knowledge sharing among knowledge workers: The moderating role of perceived job security. *Management and Organization Review*, *5*(2), 223-240.

Bartol, K. M., & Srivastava, A. (2002). Encouraging knowledge sharing: The role of organizational reward systems. *Journal of Leadership & Organizational Studies*, *9*(1), 64-76. https://doi.org/10.1177/107179190200900105

Bascavusoglu, E., & Zuniga, M. (2002). Foreign patent rights, technology and disembodied knowledge transfer cross borders: An empirical application. *Unpublished manuscript. University of Paris I, France*.

Baskerville, R., & Myers, M. D. (2004). Special issue on action research in information systems: Making IS research relevant to practice: Foreword. *MIS Quarterly*, 329-335.

Bateman, P. J., Gray, P. H., & Butler, B. S. (2011). Research note—the impact of community commitment on participation in online communities. *Information Systems Research*, *22*(4), 841-854.

Bateson, G. (2000). *Steps to an ecology of mind: Collected essays in anthropology, psychiatry, evolution, and epistemology*. University of Chicago Press.

Beaven, T., Hauck, M., Comas-Quinn, A., Lewis, T., & de los Arcos, B. (2014). MOOCs: Striking the right balance between facilitation and self-determination. *MERLOT Journal of Online Learning and Teaching*, *10*(1), 31-43.

Beck, R., Pahlke, I., & Seebach, C. (2014). Knowledge exchange and symbolic action in social media-enabled electronic networks of practice: A multilevel perspective on knowledge seekers and contributors. *MIS Quarterly*, *38*(4), 1245-1270.

Beckert, J. (2009). *Beyond the market: The social foundations of economic efficiency*. Princeton University Press.

Belanger, Y., & Thornton, J. (2013). Bioelectricity: A quantitative approach Duke University's first MOOC. https://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/6216/Duke_Bioelectricity_MOOC_Fall2012.pdf

Belkin, N. J. (1978). Information concepts for information science. *Journal of documentation*, *34*(1), 55-85. https://doi.org/10.1108/eb026653

Belleflamme, P., & Jacqmin, J. (2016). An economic appraisal of MOOC platforms: business models and impacts on higher education. *CESifo Economic Studies*, *62*(1), 148-169. http://dx.doi.org/10.1093/cesifo/ifv016

Bello-Orgaz, G., Jung, J. J., & Camacho, D. (2016). Social big data: Recent achievements and new challenges. *Information Fusion*, *28*, 45-59. https://doi.org/10.1016/j.inffus.2015.08.005

Benbya, H. (2008). *Knowledge management: systems implementation: lessons from the Silicon Valley*. Chandos Publishing. https://dx.doi.org/10.1533/9781780632032

Benbya, H. (2011). Valuing Knowledge-Based Initiatives: What we know and what we don't know. *International Journal of Knowledge Management*, *7*(1), 1-15. http://dx.doi.org/10.4018/jkm.2011010101

Benbya, H. (2015). *Exploring the design and effects of internal knowledge markets* (1 ed.). Springer. http://dx.doi.org/10.1007/978-3-319-14517-4

Benbya, H. (2016). Mechanisms for Knowledge Transfer in the Context of Knowledge Platforms: A Governance Perspective. *Systèmes d'information & management*, *21*, 39. https://doi.org/10.3917/sim.161.0039

Benbya, H., & Leidner, D. (2017). Harnessing Employee Innovation in Idea Management Platforms: Lessons from Allianz UK. *MIS Quarterly Executive*, *2017*. https://ssrn.com/abstract=3041319

Benbya, H., Nan, N., Tanriverdi, H., & Yoo, Y. (2020). Complexity and information systems research in the emerging digital world. *MIS Quarterly*, *44*(1), 1-17.

Benbya, H., & Van Alstyne, M. W. (2010). How to find answers within your company. *Sloan Management Review*, *52*(2), 66-77. https://ssrn.com/abstract=1652432

Berger, B., Matt, C., Steininger, D. M., & Hess, T. (2015). It Is Not Just About Competition with "Free": Differences Between Content Formats in Consumer Preferences and Willingness to Pay. *Journal of Management Information Systems*, *32*, 105 - 128.

Bernstein, P. A., Madhavan, J., & Rahm, E. (2011). Generic schema matching, ten years later. *Proceedings of the VLDB Endowment*, *4*(11), 695-701.

Bettman, J. R., & Kakkar, P. (1977). Effects of information presentation format on consumer information acquisition strategies. *Journal of Consumer Research*, *3*(4), 233-240.

Bhatt, G. D. (2000). Organizing knowledge in the knowledge development cycle. *Journal of knowledge management*, *4*(1), 15-26. https://www.emeraldinsight.com/doi/abs/10.1108/13673270010315371

Bhattacharyya, S., Banerjee, S., Bose, I., & Kankanhalli, A. (2020). Temporal effects of repeated recognition and lack of recognition on online community contributions. *Journal of Management Information Systems*, *37*(2), 536-562.

Bhattacherjee, A. (2012). Social science research: Principles, methods, and practices.

Bilgihan, A., Barreda, A., Okumus, F., & Nusair, K. (2016). Consumer perception of knowledge-sharing in travel-related online social networks. *Tourism Management*, *52*, 287-296.

Bimba, A. T., Idris, N., Al-Hunaiyyan, A., Mahmud, R. B., Abdelaziz, A., Khan, S., & Chang, V. (2016). Towards knowledge modeling and manipulation technologies: A survey. *International*

Journal of Information Management, *36*(6, Part A), 857-871. https://doi.org/10.1016/j.ijinfomgt.2016.05.022

Birney, E. (2012). The making of ENCODE: lessons for big-data projects. *Nature*, *489*(7414), 49. https://doi.org/10.1038/489049a

Bock, G.-W., Kankanhalli, A., & Sharma, S. (2006). Are norms enough? The role of collaborative norms in promoting organizational knowledge seeking. *European Journal of Information Systems*, *15*(4), 357-367. https://www.tandfonline.com/doi/full/10.1057/palgrave.ejis.3000630

Bock, G.-W., & Kim, Y.-G. (2001). Breaking the myths of rewards: An exploratory study of attitudes about knowledge sharing. *Proceedings of PACIS 2001* 78.

Bock, G.-W., Zmud, R. W., Kim, Y.-G., & Lee, J.-N. (2005). Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate. *MIS Quarterly*, 87-111.

Bockstedt, J. C., & Goh, K. H. (2014). Customized bundling and consumption variety of digital information goods. *Journal of Management Information Systems*, *31*(2), 105-132. https://www.tandfonline.com/doi/pdf/10.2753/MIS0742-1222310205?needAccess=true

Bonn, N. A., & Pinxten, W. (2020). Advancing science or advancing careers? Researchers' opinions on success indicators. *PloS one*, *16*(2). https://doi.org/10.1101/2020.06.22.165654

Borck, R., Frank, B., & Robledo, J. R. (2006). An empirical analysis of voluntary payments for information goods on the Internet. *Information Economics and Policy*, *18*(2), 229-239. https://ac.els-cdn.com/S0167624506000163/1-s2.0-S0167624506000163-main.pdf?_tid=3adb2478-a026-4fde-9e3b-b260bd962efb&acdnat=1528877683_9419036eb41d4056f456ecfd869a1d4c

Bordia, P., Irmer, B. E., & Abusah, D. (2006). Differences in sharing knowledge interpersonally and via databases: The role of evaluation apprehension and perceived benefits. *European Journal of Work and Organizational Psychology*, *15*(3), 262-280. https://www.tandfonline.com/doi/pdf/10.1080/13594320500417784?needAccess=true

Borgman, C. L., Scharnhorst, A., & Golshan, M. S. (2019). Digital data archives as knowledge infrastructures: Mediating data sharing and reuse. *Journal of the Association for Information Science and Technology*, *70*(8), 888-904.

Boroujeni, M. S., Hecking, T., Hoppe, H. U., & Dillenbourg, P. (2017). *Dynamics of MOOC discussion forums* Proceedings of the Seventh International Learning Analytics Knowledge Conference, Vancouver, British Columbia, Canada.

Bourdieu, P. (2018). The forms of capital. In *The sociology of economic life* (pp. 78-92). Routledge.

Boury-Brisset, A.-C. (2003). Ontology-based approach for information fusion. Proceedings of the sixth international conference on information fusion,

Boyle, E. A., Hainey, T., Connolly, T. M., Gray, G., Earp, J., Ott, M., Lim, T., Ninaus, M., Ribeiro, C., & Pereira, J. (2016). An update to the systematic literature review of empirical evidence of the impacts and outcomes of computer games and serious games. *Computers & Education*, *94*, 178-192. https://ac.els-cdn.com/S0360131515300750/1-s2.0-S0360131515300750-main.pdf?_tid=442b03de-8720-4927-a48c-4a5f15c8b5fc&acdnat=1528879493_e65d8c590334d1f06a192bcaef4248dd

Brabham, D. C. (2012). Motivations for participation in a crowdsourcing application to improve public engagement in transit planning. *Journal of Applied Communication Research*, *40*(3), 307-328. https://www.tandfonline.com/doi/pdf/10.1080/00909882.2012.693940?needAccess=true

Braganza, A. (2004). Rethinking the data–information–knowledge hierarchy: towards a case-based model. *International Journal of Information Management*, *24*(4), 347-356.

Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom research into edX's first MOOC. *Research & Practice in Assessment*, *8*, 13-25.

Brickley, D., Burgess, M., & Noy, N. (2019). Google Dataset Search: Building a search engine for datasets in an open Web ecosystem. The World Wide Web Conference, San Francisco USA.

Brooker, A., Corrin, L., De Barba, P., Lodge, J., & Kennedy, G. (2018). A tale of two MOOCs: How student motivation and participation predict learning outcomes in different MOOCs. *Australasian Journal of Educational Technology*, *34*(1).

Brown, D. C. (2021). *Digital Nudges for Encouraging Developer Behaviors* North Carolina State University].

Brownell, S. E., Price, J. V., & Steinman, L. (2013). Science communication to the general public: why we need to teach undergraduate and graduate students this skill as part of their formal scientific training. *Journal of undergraduate neuroscience education*, *12*(1), E6.

Budescu, D. V., Por, H.-H., & Broomell, S. B. (2012). Effective communication of uncertainty in the IPCC reports. *Climatic Change*, *113*(2), 181-200. https://doi.org/10.1007/s10584-011-0330-3

Burd, E. L., Smith, S. P., & Reisman, S. (2015). Exploring business models for MOOCs in higher education. *Innovative Higher Education*, *40*(1), 37-49. https://link.springer.com/content/pdf/10.1007%2Fs10755-014-9297-0.pdf

Burel, G., He, Y., & Alani, H. (2012, 2012//). Automatic Identification of Best Answers in Online Enquiry Communities. The Semantic Web: Research and Applications, Berlin, Heidelberg.

Burtch, G., He, Q., Hong, Y., & Lee, D. (2021). How do peer awards motivate creative content? Experimental evidence from Reddit. *Management Science*.

Burtch, G., Hong, Y., Bapna, R., & Griskevicius, V. (2018). Stimulating online reviews by combining financial incentives and social norms. *Management Science*, *64*(5), 2065-2082.

Butler, B. S. (2001). Membership size, communication activity, and sustainability: A resource-based model of online social structures. *Information Systems Research*, *12*(4), 346-362.

Bylieva, D., Bekirogullari, Z., Lobatyuk, V., & Nam, T. (2020). Analysis of the consequences of the transition to online learning on the example of MOOC philosophy during the COVID-19 pandemic. *Humanities & Social Sciences Reviews*, *8*(4), 1083-1093.

Cabrera, A., Collins, W. C., & Salgado, J. F. (2006). Determinants of individual engagement in knowledge sharing. *The International Journal of Human Resource Management*, *17*(2), 245-264. https://www.tandfonline.com/doi/pdf/10.1080/09585190500404614?needAccess=true

Cacciatore, M. A., Scheufele, D. A., & Iyengar, S. (2016). The end of framing as we know it… and the future of media effects. *Mass communication and society*, *19*(1), 7-23.

Cai, S., Luo, Q., Fu, X., & Ding, G. (2018). Paying for Live Broadcast: Predicting Internet Knowledge Product Sharing.

Cai, Z., Liu, H., Huang, Q., & Liang, L. (2019). Developing organizational agility in product innovation: the roles of IT capability, KM capability, and innovative climate. *R&D Management*, *49*(4), 421-438. https://doi.org/10.1111/radm.12305

Campanelli, M. (2006). *Survey: Online Transaction Issues Can Have Negative Effect* (Insight on Profitable Data-Driven Marketing Strategies, Issue. http://www.dmnews.com/marketing-strategy/survey-online-transaction-issues-can-have-negative-effect/article/92820/

Campbell, D. T., & Riecken, H. (1968). Quasi-experimental design. *International encyclopedia of the social sciences*, *5*(3), 259-263.

Cao, T., Tang, T., & Chau, C. (2012). Text clustering with named entities: a model, experimentation and realization. In *Data mining: Foundations and intelligent paradigms* (pp. 267-287). Springer. https://doi.org/10.1007/978-3-642-23166-7_10

Carnahan, D., Hao, Q., & Yan, X. (2019). Framing methodology: A critical review. *Oxford Research Encyclopedia of Politics*.

Carneiro, H. A., & Mylonakis, E. (2009). Google trends: a web-based tool for real-time surveillance of disease outbreaks. *Clinical Infectious Diseases*, *49*(10), 1557-1564. https://doi.org/10.1086/630200

Carneiro, P. M., & Heckman, J. J. (2003). Human capital policy. *NBER WORKING PAPER SERIES.*

Carrillo, F. J. (2016). Knowledge markets: a typology and an overview. *International Journal of Knowledge-Based Development*, *7*(3), 264-289.

Carrillo, F. J., Edvardsson, B., Reynoso, J., & Maravillo, E. (2019). Alignment of resources, actors and contexts for value creation: Bringing knowledge management into service-dominant logic. *International Journal of Quality and Service Sciences*.

Carter, M. (1981). *An economic appraisal of management information* University of Keele].

Catersteel, A., Rajaeian, M. M., Toleman, M., & Troup, D. (2017). The phenomenon of P3 community for IT support: a crowd-support case study. The 10th International Conference on Information Resources Management, Santiago, Chile.

Cechanowicz, J., Gutwin, C., Brownell, B., & Goodfellow, L. (2013). Effects of gamification on participation and data quality in a real-world market research domain. Proceedings of the First International Conference on Gameful Design, Research, and Applications,

Centobelli, P., Cerchione, R., & Esposito, E. (2018). Aligning enterprise knowledge and knowledge management systems to improve efficiency and effectiveness performance: A three-dimensional Fuzzy-based decision support system. *Expert Systems with Applications*, *91*, 107-126. https://doi.org/10.1016/j.eswa.2017.08.032

Chang, H.-J., Eckman, M., & Yan, R.-N. (2011). Application of the Stimulus-Organism-Response model to the retail environment: the role of hedonic motivation in impulse buying behavior. *The International Review of Retail, Distribution and Consumer Research*, *21*(3), 233-249.

Chang, H. H., & Chuang, S.-S. (2011). Social capital and individual motivations on knowledge sharing: Participant involvement as a moderator. *Information & Management*, *48*(1), 9-18.

Charband, Y., & Navimipour, N. J. (2016). Online knowledge sharing mechanisms: a systematic review of the state of the art literature and recommendations for future research. *Information Systems Frontiers*, *18*(6), 1131-1151. https://link.springer.com/content/pdf/10.1007%2Fs10796-016-9628-z.pdf

Cheema, A., & Bagchi, R. (2010). The Effect of Goal Visualization on Goal Pursuit: Implications for Individuals and Managers. *Journal of Marketing, Forthcoming*.

Chen, B., & Wang, S.-s. (2008). The Model of Knowledge Pricing Decision Based on the Distance of Knowledge and Its Application. *Granular Computing*, *5*, 007. https://doi.org/10.1007/s41066-021-00309-8

Chen, C.-J., & Hung, S.-W. (2010). To give or to receive? Factors influencing members' knowledge sharing and community promotion in professional virtual communities. *Information & Management*, *47*(4), 226-236. https://ac.els-cdn.com/S0378720610000364/1-s2.0-S0378720610000364-main.pdf?_tid=1e608031-7e4d-466e-9303-f3dd5b018de3&acdnat=1528879397_299e45ffe86bb185bb0819e88e451694

Chen, K.-J., & Cheung, H. L. (2019). Unlocking the power of ephemeral content: The roles of motivations, gratification, need for closure, and engagement. *Computers in Human Behavior*, *97*, 67-74.

Chen, L., Baird, A., & Straub, D. (2019). Why do participants continue to contribute? Evaluation of usefulness voting and commenting motivational affordances within an online knowledge community. *Decision Support Systems*, *118*, 21-32.

Chen, L., Baird, A., & Straub, D. (2022). The impact of hierarchical privilege levels and non-hierarchical incentives on continued contribution in online Q&A communities: a motivational model of gamification goals. *Decision Support Systems*, *153*, 113667.

Chen, M.-Y., & Chen, A.-P. (2005). Integrating option model and knowledge management performance measures: an empirical study. *Journal of Information Science*, *31*(5), 381-393. http://journals.sagepub.com/doi/pdf/10.1177/0165551505055402

Chen, W., Wei, X., & Zhu, K. (2017). Engaging voluntary contributions in online communities: A hidden Markov model. *MIS Quarterly*, *42*(1), 83-100.

Chen, X., & Sin, S. C. J. (2013). 'Misinformation? What of it? 'Motivations and individual differences in misinformation sharing on social media. *Proceedings of the Association for Information Science and Technology*, *50*(1), 1-4.

Chen, Y., Ho, T. H., & Kim, Y. M. (2010). Knowledge market design: A field experiment at Google Answers. *Journal of Public Economic Theory*, *12*(4), 641-664. https://doi.org/10.1111/j.1467-9779.2010.01468.x

Cheney, C. (2017). *The road to real results for online learning in developing countries*. Devex. Retrieved 10th Feb. from https://www.devex.com/news/the-road-to-real-results-for-online-learning-in-developing-countries-89884

Cheng, J. (2019). *How Does a Gamification Design Influence Students' Interaction in an Online Course?* (Publication Number 27669199) [Ph.D., Syracuse University]. ProQuest One Academic; Social Science Premium Collection. Ann Arbor. https://surface.syr.edu/etd/1115/

Cheng, R., & Vassileva, J. (2005). User motivation and persuasion strategy for peer-to-peer communities. Proceedings of the 38th Annual Hawaii International Conference on, Cheng, X., Zhu, S., Su, S., & Chen, G. (2017). A multi-objective optimization approach for question routing in community question answering services. *IEEE Transactions on Knowledge and Data Engineering*, *29*(9), 1779-1792.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, *295*(2), 295-336.

Chiu, C.-M., Hsu, M.-H., & Wang, E. T. (2006). Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories. *Decision Support Systems*, *42*(3), 1872-1888. https://doi.org/10.1016/j.dss.2006.04.001

Chow, W. S., & Chan, L. S. (2008). Social network, social trust and shared goals in organizational knowledge sharing. *Information & Management*, *45*(7), 458-465.

Chu, T.-H., & Robey, D. (2008). Explaining changes in learning and work practice following the adoption of online learning: a human agency perspective. *European Journal of Information Systems*, *17*(1), 79-98. https://www.tandfonline.com/doi/full/10.1057/palgrave.ejis.3000731

Chua, A. Y. K., Goh, D. H.-L., & Lee, C. S. (2012). Mobile content contribution and retrieval: An exploratory study using the uses and gratifications paradigm. *Information Processing & Management*, *48*(1), 13-22. https://doi.org/10.1016/j.ipm.2011.04.002

Chuang, I., & Ho, A. D. (2016). HarvardX and MITx: Four Years of Open Online Courses--Fall 2012-Summer 2016.

Chumg, H. F., Shin, J. W., Chiang, H. Y., & Ho, M. T. (2022). What Drives Working Habits for Sharing Knowledge in Virtual Teams? An Organizational Embeddedness Perspective. *SAGE Open*, *12*(1), 21582440221079924.

Churchill, D. (2017). *Digital resources for learning*. Springer.

Claussen, S., & Osborne, J. (2013). Bourdieu's notion of cultural capital and its implications for the science curriculum. *Science Education*, *97*(1), 58-79.

Cohen, D., & Soto, M. (2007). Growth and human capital: good data, good results. *Journal of economic growth*, *12*(1), 51-76.

Cohen, J. A. (2011). *Intangible assets: valuation and economic benefit* (Vol. 273). John Wiley & Sons.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 128-152.

Cohn, M. (2004). *User stories applied: For agile software development*. Addison-Wesley Professional.

Compeau, D., Marcolin, B., Kelley, H., & Higgins, C. (2012). Generalizability of Information Systems Research Using Student Subjects-A Reflection on Our Practices and Recommendations for Future Research [Article]. *Information Systems Research*, *23*(4), 1093-1109. https://doi.org/10.1287/isre.1120.0423

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of management*, *37*(1), 39-67.

Cook, C. N., Hockings, M., & Carter, R. (2010). Conservation in the dark? The information used to support management decisions. *Frontiers in Ecology and the Environment*, *8*(4), 181-186. https://esajournals.onlinelibrary.wiley.com/doi/pdf/10.1890/090020

Cook, S., Conrad, C., Fowlkes, A. L., & Mohebbi, M. H. (2011). Assessing Google flu trends performance in the United States during the 2009 influenza virus A (H1N1) pandemic. *PloS one*, *6*(8). https://doi.org/10.1371/journal.pone.0023610

Cook, T. D., Campbell, D. T., & Day, A. (1979). *Quasi-experimentation: Design & analysis issues for field settings* (Vol. 351). Houghton Mifflin Boston.

Coon, D., & Mitterer, J. O. (2012). *Introduction to psychology: Gateways to mind and behavior with concept maps and reviews*. Cengage Learning.

Cooper, D. R., Schindler, P. S., & Sun, J. (2006). *Business research methods* (Vol. 9). McGraw-Hill New York.

Council, D. (2005). *The 'double diamond' design process model* (Design Council, Issue. https://www.designcouncil.org.uk/sites/default/files/asset/document/ElevenLessons_Design_Council%20(2).pdf

Courcoubetis, C., & Weber, R. (2003). Cost-based Pricing. *Wiley-Interscience Series in Systems and Optimization*, 163.

Cowan, R., David, P. A., & Foray, D. (2000). The explicit economics of knowledge codification and tacitness Information economics. *Industrial and Corporate Change*, *9*(2), 211-253. https://doi.org/10.1093/icc/9.2.211

Creswell, J. W. (2014). The selection of a research approach. *Research design: Qualitative, quantitative, and mixed methods approaches*, *2014*, 3-24.

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Creswell, J. W., & Poth, C. N. (2016). *Qualitative inquiry and research design: Choosing among five approaches*. Sage publications.

Crotty, M. J. (1998). The foundations of social research: Meaning and perspective in the research process. *The foundations of social research*, 1-256.

CSIRO. (2019). *Data Access Portal*. Retrieved 19th March from https://data.csiro.au/collections/

Cui, Y., & Wise, A. F. (2015). Identifying content-related threads in MOOC discussion forums. Proceedings of the Second (2015) ACM Conference on Learning@ Scale,

Curty, R. G. (2016). Factors Influencing Research Data Reuse in the Social Sciences: An Exploratory Study. *International Journal of Digital Curation*, *11*(1), 96-117. https://doi.org/10.2218/ijdc.v11i1.401

Curty, R. G., & Qin, J. (2014). Towards a model for research data reuse behavior. *Proceedings of the American Society for Information Science and Technology*, *51*(1), 1-4. https://doi.org/10.1002/meet.2014.14505101072

Custers, R., & Aarts, H. (2005). Positive affect as implicit motivator: on the nonconscious operation of behavioral goals. *Journal of Personality and Social Psychology*, *89*(2), 129.

Cusumano, M. A. (2013). Are the costs of 'free' too high in online education? *Communications of the ACM*, *56*(4), 26-28.

Dakova, J., Antunes, P., & Chiu, Y. T. (2018). A Pluralistic Approach to Information Valuation. *Proceeding in the 22nd Pacific Asia Conference on Information Systems,* Yokohama, Japan.

Daradoumis, T., Bassi, R., Xhafa, F., & Caballé, S. (2013). A review on massive e-learning (MOOC), *Proceeding in the Eighth International Conference on P2P, Parallel, Grid, Cloud and Internet Computing.* Compiegne, France. https://doi.org/10.1109/3PGCIC.2013.37

Davenport, T. H., & Prusak, L. (1998). *Working knowledge: How organizations manage what they know*. Harvard Business Press. https://doi.org/10.1145/348772.348775

Davies, H. (2017). Chinese culture, guanxi and their consequences. In *Understanding a Changing China* (pp. 52-68). Routledge.

Davlembayeva, D., Papagiannidis, S., & Alamanos, E. (2021). Sharing economy platforms: An equity theory perspective on reciprocity and commitment. *Journal of Business Research*, *127*, 151-166.

Dawson, D. D. (2012). Open science and crowd science: Selected sites and resources.

Dayasindhu, N. (2002). Embeddedness, knowledge transfer, industry clusters and global competitiveness: a case study of the Indian software industry. *Technovation*, *22*(9), 551-560.

Deci, E. L., Koestner, R., & Ryan, R. M. (1999). A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychological bulletin*, *125*(6), 627.

Deci, E. L., & Ryan, R. M. (2008). Self-determination theory: A macro theory of human motivation, development, and health. *Canadian Psychology/Psychologie Canadienne*, *49*(3), 182.

Deci, E. L., & Ryan, R. M. (2013). *Intrinsic motivation and self-determination in human behavior*. Springer Science & Business Media.

Denzin, N. K., & Lincoln, Y. S. (2011). *The Sage handbook of qualitative research*. sage.

Desouza, K. C., & Awazu, Y. (2003). Constructing internal knowledge markets: considerations from mini cases. *International Journal of Information Management*, *23*(4), 345-353. https://doi.org/10.1016/S0268-4012(03)00056-2

Desouza, K. C., Awazu, Y., & Wan, Y. (2006). Factors governing the consumption of explicit knowledge. *Journal of the Association for Information Science and Technology*, *57*(1), 36-43. https://doi.org/10.1002/asi.20250

Desouza, K. C., Awazu, Y., Yamakawa, S., & Umezawa, M. (2005). Facilitating knowledge management through market mechanism. *Knowledge and process management*, *12*(2), 99-107. https://onlinelibrary.wiley.com/doi/pdf/10.1002/kpm.226

Dev, H., Geigle, C., Hu, Q., Zheng, J., & Sundaram, H. (2017). Size Does Matter: Why Knowledge Markets Can Fail at Scale! *Social Media Sustainability*. https://doi.org/10.1145/3178876.3186037

Dev, H., Geigle, C., Hu, Q., Zheng, J., & Sundaram, H. (2018). The size conundrum: why online knowledge markets can fail at scale. Proceedings of the 2018 World Wide Web Conference,

Di Vincenzo, F., Mascia, D., Björk, J., & Magnusson, M. (2021). Attention to ideas! Exploring idea survival in internal crowdsourcing. *European Journal of Innovation Management*, *24*(2), 213-234. https://doi.org/10.1108/EJIM-03-2019-0073

Diafas, I., Barkmann, J., & Mburu, J. (2017). Measurement of Bequest Value Using a Non-monetary Payment in a Choice Experiment—The Case of Improving Forest Ecosystem Services for the Benefit of Local Communities in Rural Kenya. *Ecological Economics*, *140*(Supplement C), 157-165. https://doi.org/10.1016/j.ecolecon.2017.05.006

Diamond, P. A., Mortensen, D. T., & Pissarides, C. A. (2010). Markets with search frictions. *Scientific Background on the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel*.

Dieckmann, N. F., Mauro, R., & Slovic, P. (2010). The effects of presenting imprecise probabilities in intelligence forecasts. *Risk Anal*, *30*(6), 987-1001. https://doi.org/10.1111/j.1539-6924.2010.01384.x

Diehr, G., & Gueldenberg, S. (2017). Knowledge utilisation: an empirical review on processes and factors of knowledge utilisation. *Global Business and Economics Review*, *19*(4), 401-419.

Dignum, V., & Dignum, F. (2003). The knowledge market: agent-mediated knowledge sharing. *Proceedings of the International Central and Eastern European Conference on Multi-Agent Systems*, 168-179. Springer, Berlin, Heidelberg.

Ding, G., Liu, H., Huang, Q., & Gu, J. (2017). Moderating effects of guanxi and face on the relationship between psychological motivation and knowledge-sharing in China. *Journal of Knowledge Management*, *21*(5), 1077-1097. https://doi.org/10.1108/JKM-10-2016-0439

Dolan, R., Conduit, J., Fahy, J., & Goodman, S. (2016). Social media engagement behaviour: a uses and gratifications perspective. *Journal of Strategic Marketing*, *24*(3-4), 261-277. https://doi.org/10.1080/0965254X.2015.1095222

Dolan, R., Conduit, J., Frethey-Bentham, C., Fahy, J., & Goodman, S. (2019). Social media engagement behavior: A framework for engaging customers through social media content. *European Journal of Marketing*, *53*(10), 2213-2243. https://doi.org/10.1108/EJM-03-2017-0182

Dong, J., Lai, X., & Zhao, D. (2022). How incentive affects knowledge transfer performance in corporate user community: The mediating roles of users' transfer willingness and ability. *Managerial and Decision Economics, 43*(6), 2249-2260. https://doi.org/10.1002/mde.3522

Dong, X., Gabrilovich, E., Heitz, G., Horn, W., Lao, N., Murphy, K., Strohmann, T., Sun, S., & Zhang, W. (2014). Knowledge vault: A web-scale approach to probabilistic knowledge fusion. Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining,

Douglas, S. P., & Craig, C. S. (2007). Collaborative and iterative translation: An alternative approach to back translation. *Journal of International Marketing*, *15*(1), 30-43. https://doi.org/10.1509/jimk.15.1.030

DuBay, W. H. (2007). *Smart Language: Readers, Readability, and the Grading of Text* (Vol. 5). ERIC.

Duffie, D. (2010). *Dynamic asset pricing theory*. Princeton University Press.

Dunning, A., Smaele, d. M., & Jasmin, B. (2017). Are the FAIR Data Principles fair? *International Journal of Digital Curation*, *12*(2), 177-189. https://doi.org/10.2218/ijdc.v12i2.567

Dushnitsky, G., & Klueter, T. (2011). Is there an eBay for ideas? Insights from online knowledge marketplaces. *European Management Review*, *8*(1), 17-32. https://doi.org/10.1111/j.1740-4762.2010.01002.x

Edelman, B. (2004). Earnings and ratings at Google Answers. *Economic Inquiry*, *50*(2), 309-320. https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1465-7295.2011.00414.x

Eisenbardt, M. (2020). Incentives as a trigger for consumer knowledge sharing with enterprises and public sector organizations. *Proceedings of the 21st European Conference on Knowledge*

Management ECKM, Academic Conferences International Limited. https://doi.org/10.34190/EKM.20.133

El-Den, J. (2007). Tacit knowledge transfer among geographically distributed group members: An experimental analysis. *Proceedings of the 8th European Conference on Knowledge Management: ECKM*, Academic Conferences Limited.

Empson, L. (2001). Fear of exploitation and fear of contamination: Impediments to knowledge transfer in mergers between professional service firms. *Human Relations*, *54*(7), 839-862. http://journals.sagepub.com/doi/pdf/10.1177/0018726701547003

Enders, A., Hungenberg, H., Denker, H.-P., & Mauch, S. (2008). The long tail of social networking.: Revenue models of social networking sites. *European Management Journal*, *26*(3), 199-211. https://doi.org/10.1016/j.emj.2008.02.002

Engle, D., Mankoff, C., & Carbrey, J. (2015). Coursera's introductory human physiology course: Factors that characterize successful completion of a MOOC. *International Review of Research in Open and Distributed Learning*, *16*(2), 46-68.

Ergün, E., & Avcı, Ü. (2018). Knowledge Sharing Self-Efficacy, Motivation and Sense of Community as Predictors of Knowledge Receiving and Giving Behaviors. *Journal of Educational Technology & Society*, *21*(3), 60-73. http://www.jstor.org.virtual.anu.edu.au/stable/26458507

Estabrooks, C. A., Derksen, L., Winther, C., Lavis, J. N., Scott, S. D., Wallin, L., & Profetto-McGrath, J. (2008). The intellectual structure and substance of the knowledge utilization field: A longitudinal author co-citation analysis, 1945 to 2004. *Implementation Science*, *3*(1), 1-22.

Faems, D., Janssens, M., & Van Looy, B. (2007). The initiation and evolution of interfirm knowledge transfer in R&D relationships. *Organization Studies*, *28*(11), 1699-1728. https://doi.org/10.1177/0170840606082222

Fang, J., Chen, L., Wang, X., & George, B. (2018). Not all posts are treated equal: An empirical investigation of post replying behavior in an online travel community. *Information & Management*, *55*(7), 890-900. https://doi.org/10.1016/j.im.2018.04.003

Fang, S. C., Yang, C.-W., & Hsu, W. Y. (2013). Inter-organizational knowledge transfer: the perspective of knowledge governance. *Journal of Knowledge Management*. 10.1108/JKM-04-2013-0138. https://doi.org/10.1108/JKM-04-2013-0138

Faniel, I., Kansa, E., Whitcher Kansa, S., Barrera-Gomez, J., & Yakel, E. (2013). The challenges of digging data: a study of context in archaeological data reuse. *Proceedings of the 13th ACM/IEEE-CS Joint Conference on Digital libraries*, Indianapolis USA. https://doi.org/10.1145/2467696.2467712

Faraj, S., Jarvenpaa, S. L., & Majchrzak, A. (2011). Knowledge collaboration in online communities. *Organization Science*, *22*(5), 1224-1239.

Fasbender, U., Gerpott, F. H., & Unger, D. (2021). Give and take? Knowledge exchange between older and younger employees as a function of generativity and development striving. *Journal of knowledge management*. https://doi.org/10.1287/orsc.1100.0614

Feltham, G. A. (1968). The value of information. *The Accounting Review*, *43*(4), 684-696.

Fen, L., Zhigang, Z., Lutao, Z., Xiongfeng, Z., & Meiyu, X. (2015). Multi-stage game of knowledge pricing. *Open Automation and Control Systems Journal*, *7*(1), 421-425. https://doi.org/10.2174/1874444301507010421

Feng, E. (2017). Chinese tech apps trade knowledge for cash. *Financial Times*. https://www.ft.com/content/add21080-0ace-11e7-97d1-5e720a26771b

Feng, X., Hui, K., Deng, X., & Jiang, G. (2021). Understanding how the semantic features of contents influence the diffusion of government microblogs: Moderating role of content topics. *Information & Management*, *58*(8), 103547. https://doi.org/10.1016/j.im.2021.103547

Feng, Y., & Ye, H. J. (2016). Why do you return the favor in online knowledge communities? A study of the motivations of reciprocity. *Computers in Human Behavior*, *63*, 342-349.

Ferschke, O., Yang, D., Tomar, G., & Rosé, C. P. (2015). Positive Impact of Collaborative Chat Participation in an edX MOOC. *Proceedings of the 25th International Conference on Artificial Intelligence in Education*, Springer, Cham. http://dx.doi.org/10.1007/978-3-319-19773-9_12

Feser, D., & Proeger, T. (2017). Asymmetric information as a barrier to knowledge spillovers in expert markets. *International Entrepreneurship and Management Journal*, *13*(1), 211-232. http://dx.doi.org/10.1007/s11365-016-0404-9

Field, A., Bhat, G., & Tsvetkov, Y. (2019). Contextual affective analysis: A case study of people portrayals in online# metoo stories. *Proceedings of the International AAAI Conference on Web and Social Media,* Münich, Germany.

Fiksel, J. (2015). *Resilient by design: Creating businesses that adapt and flourish in a changing world*. Island Press.

Fink, L., Rosenfeld, L., & Ravid, G. (2018). Longer online reviews are not necessarily better. *International Journal of Information Management*, *39*, 30-37. https://doi.org/10.1016/j.ijinfomgt.2017.11.002

Fischer, C. (2021). Incentives Can't Buy Me Knowledge: The Missing Effects of Appreciation and Aligned Performance Appraisals on Knowledge Sharing of Public Employees. *Review of Public Personnel Administration*, *Preprint*, 1-22. https://doi.org/10.1177/0734371X20986839

Foa, U. G., Converse Jr, J. E., Törnblom, K. Y., & Foa, E. B. (1993). *Resource theory: Explorations and applications*. Academic Press.

Ford, D. P., & Chan, Y. E. (2003). Knowledge sharing in a multi-cultural setting: a case study. *KNOWLEDGE MANAGEMENT RESEARCH & PRACTICE*, *1*(1), 11-27. https://www.tandfonline.com/doi/abs/10.1057/palgrave.kmrp.8499999

Franke, N., Von Hippel, E., & Schreier, M. (2006). Finding commercially attractive user innovations: A test of lead-user theory. *Journal of Product Innovation Management*, *23*(4), 301-315.

Frederick, S., Loewenstein, G., & O'Donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, *40*(2), 351-401. https://pubs.aeaweb.org/doi/pdfplus/10.1257/002205102320161311

Frey, B. S., & Jegen, R. (2001). Motivation crowding theory. *Journal of Economic Surveys*, *15*(5), 589-611. https://onlinelibrary.wiley.com/doi/pdf/10.1111/1467-6419.00150

Fu, H., & Oh, S. (2019). Quality assessment of answers with user-identified criteria and data-driven features in social Q&A. *Information Processing & Management*, *56*(1), 14-28.

Fu, H., Wu, S., & Oh, S. (2015). Evaluating answer quality across knowledge domains: Using textual and non-textual features in social Q&A. *Proceedings of the Association for Information Science and Technology*, *52*(1), 1-5.

Furnham, A. (1984). Many sides of the coin: The psychology of money usage. *Personality and individual Differences*, *5*(5), 501-509. https://doi.org/10.1016/0191-8869(84)90025-4

Gaebel, M. (2014). *MOOCs: Massive Open Online Courses*.

Galatin, M., & Leiter, R. D. (2012). *Economics of information* (Vol. 3). Springer Science & Business Media.

Galikyan, I., Admiraal, W., & Kester, L. (2021). MOOC discussion forums: The interplay of the cognitive and the social. *Computers & Education*, *165*, 104133. https://doi.org/10.1016/j.compedu.2021.104133

Gallagher, R., Falster, D., & Maitner, B. (2020). Principles for accelerating trait-based science across the Tree of Life. *Nature Ecology and Evolution, 4*(3), 294–303. https://doi.org/10.1038/s41559-020-1109-6

Gallagher, R. V., Falster, D. S., Maitner, B. S., Salguero-Gómez, R., Vandvik, V., Pearse, W. D., Schneider, F. D., Kattge, J., Poelen, J. H., & Madin, J. S. (2020). Open Science principles for accelerating trait-based science across the Tree of Life. *Nature Ecology & Evolution*, *4*(3), 294-303.

Gans, J. S., Murray, F. E., & Stern, S. (2017). Contracting over the disclosure of scientific knowledge: Intellectual property and academic publication. *Research policy*, *46*(4), 820-835. https://doi.org/10.1016/j.respol.2017.02.005

Gans, J. S., & Stern, S. (2010). Is there a market for ideas? *Industrial and Corporate Change*, *19*(3), 805-837. https://doi.org/10.1093/icc/dtq023

Gao, X., Guan, J., & Rousseau, R. (2011). Mapping collaborative knowledge production in China using patent co-inventorships. *Scientometrics*, *88*(2), 343-362. https://doi.org/10.1007/s11192-011-0404-z

García-Molina, S., Alario-Hoyos, C., Moreno-Marcos, P. M., Muñoz-Merino, P. J., Estévez-Ayres, I., & Delgado Kloos, C. (2021). An algorithm and a tool for the automatic grading of MOOC learners from their contributions in the discussion forum. *Applied Sciences*, *11*(1), 95.

Garnefeld, I., Iseke, A., & Krebs, A. (2012). Explicit incentives in online communities: boon or bane? *International Journal of Electronic Commerce*, *17*(1), 11-38.

Garud, R., & Kumaraswamy, A. (2005). Vicious and virtuous circles in the management of knowledge: The case of Infosys Technologies. *MIS Quarterly*, 9-33.

Gassmann, O., Frankenberger, K., & Csik, M. (2014). *The business model navigator: 55 models that will revolutionise your business*. Pearson UK.

Gaur, A. S., Ma, H., & Ge, B. (2019). MNC strategy, knowledge transfer context, and knowledge flow in MNEs. *Journal of Knowledge Management*, *23*(9), 1885-1900. https://doi.org/10.1108/JKM-08-2018-0476

Gautier, L., De Allegri, M., & Ridde, V. (2021). Transnational networks' contribution to health policy diffusion: a mixed method study of the performance-based financing community of practice in Africa. *International Journal of Health Policy and Management*, *10*(6), 310-323. https://dx.doi.org/10.34172/ijhpm.2020.57

Gazan, R. (2006). Specialists and synthesists in a question answering community. *Proceedings of the Association for Information Science and Technology*, *43*(1), 1-10.

Gera, R. (2012). Bridging the gap in knowledge transfer between academia and practitioners. *International Journal of Educational Management* *26*(3), 252-273. https://doi.org/10.1108/09513541211213336

Gerdenitsch, C., Sellitsch, D., Besser, M., Burger, S., Stegmann, C., Tscheligi, M., & Kriglstein, S. (2020). Work gamification: Effects on enjoyment, productivity and the role of leadership. *Electronic Commerce Research and Applications*, *43*, 100994-101005. https://doi.org/10.1016/j.elerap.2020.100994

Ghasemkhani, H., Kannan, K. N., & Khern-am-nuai, W. (2016). Extrinsic versus Intrinsic Rewards to Participate in a Crowd Context: An Analysis of a Review Platform.

Ghose, A. (2009). Internet exchanges for used goods: An empirical analysis of trade patterns and adverse selection. *MIS Quarterly*, 263-291.

Ghose, A., & Ipeirotis, P. G. (2011). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. *IEEE Transactions on Knowledge and Data Engineering*, *23*(10), 1498-1512. https://ieeexplore.ieee.org/ielx5/69/5982126/05590249.pdf?tp=&arnumber=5590249&isnumber=5982126

Gibson, G., Timlin, A., Curran, S., & Wattis, J. (2004). The scope for qualitative methods in research and clinical trials in dementia. *Age and Ageing*, *33*(4), 422-426.

Gibson, J. J. (1977). The theory of affordances. *The Ecological Approach to Visual Perception: Classic Edition*, 67-82. Psychology Press.

Gilbert, S. (2016). Learning in a Twitter-based community of practice: an exploration of knowledge exchange as a motivation for participation in# hcsmca. *Information, Communication & Society*, *19*(9), 1214-1232.

Gillani, N., & Eynon, R. (2014). Communication patterns in massively open online courses. *The Internet and Higher Education*, *23*, 18-26.

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., & Brilliant, L. (2009). Detecting influenza epidemics using search engine query data. *Nature*, *457*(7232), 1012–1014. https://doi.org/10.1038/nature07634

GMAC. (2018). *Analytical Writing Assessment Section*. Graduate Management Admission Council. Retrieved 16th Oct from https://www.mba.com/exams/gmat/about-the-gmat-exam/gmat-exam-structure/analytical-writing-assessment

Gneezy, U., Meier, S., & Rey-Biel, P. (2011). When and why incentives (don't) work to modify behavior. *Journal of Economic Perspectives*, *25*(4), 191-210.

Gode, D. K., & Sunder, S. (1993). Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality. *Journal of Political Economy*, *101*(1), 119-137.

Goes, P. B., Guo, C., & Lin, M. (2016). Do incentive hierarchies induce user effort? Evidence from an online knowledge exchange. *Information Systems Research*, *27*(3), 497-516.

Goffman, E. (1974). *Frame analysis: An essay on the organization of experience*. Harvard University Press.

Goh, S. C. (2002). Managing effective knowledge transfer: an integrative framework and some practice implications. *Journal of Knowledge Management*, *6*(1), 23-30. https://www.emeraldinsight.com/doi/abs/10.1108/13673270210417664

Goldberg, L. R., Johnson, J. A., Eber, H. W., Hogan, R., Ashton, M. C., Cloninger, C. R., & Gough, H. G. (2006). The international personality item pool and the future of public-domain personality measures. *Journal of Research in Personality*, *40*(1), 84-96. https://doi.org/10.1016/j.jrp.2005.08.007

Goswami, A. K., & Agrawal, R. K. (2019). Building intellectual structure of knowledge sharing: Very Informal Newsletter on Library Automation. *VINE Journal of Information and Knowledge Management Systems*, *50*(1), 136-162. https://dx.doi.org/10.1108/VJIKMS-03-2019-0036

Goyal, A., Gupta, V., & Kumar, M. (2018). Recent named entity recognition and classification techniques: a systematic review. *Computer Science Review*, *29*, 21-43.

Graa, A., & Dani, e. K. M. (2012). Application of stimulus & response model to impulse buying behavior of Algerian consumers. *Serbian Journal of Management*, *7*(1), 53-64.

Graham, L., & Wright, S. (2010). Information, heterogeneity and market incompleteness. *Journal of Monetary Economics*, *57*(2), 164-174. https://doi.org/10.1016/j.jmoneco.2009.12.005

Graziano, A. M., & Raulin, M. L. (1993). *Research methods: A process of inquiry*. Harper Collins College Publishers.

Greer, J. G. (2013). *The Influence of Community Commitment on Knowledge Management in Online Communities of Practice* Dakota State University.

Gregg, D. G., Kulkarni, U. R., & Vinzé, A. S. (2001). Understanding the philosophical underpinnings of software engineering research in information systems. *Information Systems Frontiers*, *3*(2), 169-183. https://doi.org/10.1023/A:1011491322406

Gregory, K., Cousijn, H., Groth, P., Scharnhorst, A., & Wyatt, S. (2018). Understanding data retrieval practices: A social informatics perspective. *Journal of Information Science*, *46*(4), 459-475. https://doi.org/10.1177/0165551519837182

Gregory, K., Groth, P. T., Cousijn, H., Scharnhorst, A., & Wyatt, S. (2019). Searching Data: A Review of Observational Data Retrieval Practices in Selected Disciplines. *Journal of the Association for Information Science and Technology*, *70*(5), 419-432. https://doi.org/10.1002/asi.24165

Groff, T., & Jones, T. (2012). *Introduction to knowledge management*. Routledge.

Gu, J., & Zhou, Y. (2006). Ontology fusion with complex mapping patterns. *Proceeding of Knowledge-Based Intelligent Information and Engineering Systems, 4251, 738–745.* Springer, Berlin, Heidelberg. https://doi.org/10.1007/11892960_89

Guan, T., Wang, L., Jin, J., & Song, X. (2018). Knowledge contribution behavior in online Q&A communities: An empirical investigation. *Computers in Human Behavior*, *81*, 137-147. https://doi.org/10.1016/j.chb.2017.12.023

Guba, E. G. (1990). The paradigm dialog. *Proceeding of Alternative Paradigms Conference,* San Francisco, US.

Guo, W., Liang, R.-Y., Wang, L., & Peng, W. (2017). Exploring sustained participation in firm-hosted communities in China: the effects of social capital and active degree. *Behaviour & Information Technology*, *36*(3), 223-242.

Guo, Y., Lu, Z., Kuang, H., & Wang, C. (2020). Information avoidance behavior on social network sites: Information irrelevance, overload, and the moderating role of time pressure. *International Journal of Information Management*, *52*, 102067. https://doi.org/10.1016/j.ijinfomgt.2020.102067

Gupta, A. K., & Govindarajan, V. (2000). Knowledge management's social dimension: Lessons from Nucor Steel. *MIT Sloan Management Review*, *42*(1), 71.

Hafeez, K., Alghatas, F. M., Foroudi, P., Nguyen, B., & Gupta, S. (2019). Knowledge sharing by entrepreneurs in a virtual community of practice (VCoP). *Information Technology & People*, *32*(2), 405-429. https://doi.org/10.1108/ITP-09-2016-0202

Hajkowicz, S., Reeson, A., Rudd, L., Bratanova, A., Hodgers, L., Mason, C., & Boughen, N. (2016). Tomorrow's digitally enabled workforce: Megatrends and scenarios for jobs and employment in Australia over the coming twenty years.

Hamari, J. (2015). Gamification-motivations & effects. *School of Business*, *PhD*, 1-123. https://aaltodoc.aalto.fi/bitstream/handle/123456789/15037/isbn9789526060569.pdf?sequence=1&isAllowed=y

Hamari, J. (2017). Do badges increase user activity? A field experiment on the effects of gamification. *Computers in Human Behavior, 71*, 469-478.

Han, S., Min, J., & Lee, H. (2015). Antecedents of social presence and gratification of social connection needs in SNS: a study of Twitter users and their mobile and non-mobile usage. *International Journal of Information Management*, *35*(4), 459-471.

Hancock, B., Ockleford, E., & Windridge, K. (2001). *An introduction to qualitative research*. Trent focus group London.

Hansen, L. P. (2017). Uncertainty in Economic Analysis and the Economic Analysis of Uncertainty. *KNOW: A Journal on the Formation of Knowledge*, *1*(1). https://doi.org/10.1086/692519

Hansen, M. T. (2002). Knowledge networks: Explaining effective knowledge sharing in multiunit companies. *Organization Science*, *13*(3), 232-248. https://doi.org/10.1287/orsc.13.3.232.2771

Hanson, R. (2003). Combinatorial information market design. *Information Systems Frontiers*, *5*(1), 107-119.

Harper, F. M. (2007). Encouraging Contributions to Online Communities with Personalization and Incentives. *Proceeding of the International Conference on User Modeling,* Corfu, Greece.

Hartig, O., & Zhao, J. (2009). Using web data provenance for quality assessment.

Hassan, L., Dias, A., & Hamari, J. (2019). How motivational feedback increases user's benefits and continued use: A study on gamification, quantified-self and social networking. *International Journal of Information Management*, *46*, 151-162.

Hau, Y. S., Kim, B., Lee, H., & Kim, Y.-G. (2013). The effects of individual motivations and social capital on employees' tacit and explicit knowledge sharing intentions. *International Journal of Information Management*, *33*(2), 356-366.

Hayaeian, S., Hesarzadeh, R., & Abbaszadeh, M. R. (2021). The impact of knowledge management strategies on the relationship between intellectual capital and innovation: evidence from SMEs. *Journal of Intellectual Capital*.

Hayek, F. A. (1945). The use of knowledge in society. *The American economic review*, 519-530.

Hayes, G. R. (2011). The relationship of action research to human-computer interaction. *Proceeding of the ACM Transactions on Computer-Human Interaction (TOCHI)*, *18*(3), 15.

He, C., Ma, P., Zhou, L., & Wu, J. (2018). Is participating in MOOC forums important for students? A data-driven study from the perspective of the supernetwork. *Journal of Data and Information Science*, *3*(2), 62-77.

He, W., & Wei, K.-K. (2009). What drives continued knowledge sharing? An investigation of knowledge-contribution and-seeking beliefs. *Decision Support Systems*, *46*(4), 826-838.

Heidorn, P. B. (2008). Shedding light on the dark data in the long tail of science. *Library Trends*, *57*(2), 280-299. https://doi.org/10.1353/lib.0.0036

Helbing, D. (2019). Societal, economic, ethical and legal challenges of the digital revolution: from big data to deep learning, artificial intelligence, and manipulative technologies. In *Towards digital enlightenment* (pp. 47-72). Springer.

Hermans, F., Sartas, M., Van Schagen, B., van Asten, P., & Schut, M. (2017). Social network analysis of multi-stakeholder platforms in agricultural research for development: Opportunities and constraints for innovation and scaling. *PloS one*, *12*(2), e0169634.

Hinze, V. K., Uslu, O., Antono, J. E., Wilke, M., & Pooresmaeili, A. (2021). The effect of subliminal incentives on goal-directed eye movements. *Journal of neurophysiology*, *126*(6), 2014-2026.

Hirschberg, J., & Manning, C. D. (2015). Advances in natural language processing. *Science*, *349*(6245), 261-266.

Hirshleifer, J. (1973). Where are we in the theory of information? *The American economic review*, *63*(2), 31-39.

Hirshleifer, J., Glazer, A., & Hirshleifer, D. (2005). *Price theory and applications: decisions, markets, and information*. Cambridge University Press.

Hobbiss, M., Sims, S., & Allen, R. (2021). Habit formation limits growth in teacher effectiveness: A review of converging evidence from neuroscience and social science. *Review of Education*, *9*(1), 3-23.

Homans, G. C. (1958). Social behavior as exchange. *American journal of Sociology*, *63*(6), 597-606.

Housel, T. J., & Nelson, S. K. (2005). Knowledge valuation analysis: Applications for organizational intellectual capital. *Journal of Intellectual Capital*, *6*(4), 544-557. https://www.emeraldinsight.com/doi/abs/10.1108/14691930510628816

Hox, J. J., & Boeije, H. R. (2005). Data collection, primary versus secondary.

Hsieh, G., & Counts, S. (2009). mimir: a market-based real-time question and answer service. CHI,

Hsieh, G., Kraut, R. E., & Hudson, S. E. (2010). Why pay?: exploring how financial incentives are used for question & answer. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,* New York, US.

Hsu, M.-H., Ju, T. L., Yen, C.-H., & Chang, C.-M. (2007). Knowledge sharing behavior in virtual communities: The relationship between trust, self-efficacy, and outcome expectations. *International Journal of Human-Computer Studies*, *65*(2), 153-169.

Hu, Y. (2015). Measuring the performance of knowledge resources using a value perspective: integrating BSC and ANP. *Journal of knowledge management*, *19*(6), 1250-1272. https://doi.org/10.1108/JKM-10-2014-0431

Huang, H. C., Cheng, T., Huang, W. F., & Teng, C. I. (2018). Impact of online gamers' personality traits on interdependence, network convergence, and continuance intention: Perspective of social exchange theory. *International Journal of Information Management*, *38*(1), 232-242.

Huang, N., Burtch, G., Gu, B., Hong, Y., Liang, C., Wang, K., Fu, D., & Yang, B. (2019). Motivating User-Generated Content with Performance Feedback: Evidence from Randomized Field Experiments. *Management Science*, *65*(1), 327-345. https://doi.org/10.1287/mnsc.2017.2944

Huang, N., Chen, P., Hong, Y., & Wu, S. (2018). Digital nudging for online social sharing: Evidence from a randomized field experiment. *Proceedings in the 51st Hawaii International Conference on System Sciences*, Hawaii, USA.

Huang, N., Gu, B., Burtch, G., Hong, Y., Chen, L., Wang, K., Fu, D., Yang, B., & Lan, W. (2017). Designing Effective performance feedback notification systems to stimulate content contribution: evidence from a crowdsourcing recipe platform. *Proceedings in the 50th Hawaii International Conference on System Sciences,* Hawaii, USA.

Huang, P., Tafti, A., & Mithas, S. (2018). The secret to successful knowledge seeding. *MIT Sloan Management Review*, *59*(3), 10-13.

Huang, P., Tafti, A. R., & Mithas, S. (2017). Platform sponsor's investments and user contributions in knowledge communities: The role of knowledge seeding. *MIS Quart*erly, *42*(1), 213–240. https://doi.org/10.25300/MISQ/2018/13490

Huang, Q., Davison, R. M., & Gu, J. (2008). Impact of personal and cultural factors on knowledge sharing in China. *Asia Pacific Journal of Management*, *25*(3), 451-471.

Hui, X., Liu, M., & Chan, T. (2020). Targeted Incentives, Broad Impacts: Evidence from an E-commerce Platform. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3709380

Hung, S.-Y., Durcikova, A., Lai, H.-M., & Lin, W.-M. (2011). The influence of intrinsic and extrinsic motivation on individuals' knowledge sharing behavior. *International journal of human-computer studies*, *69*(6), 415-427. https://doi.org/10.1016/j.ijhcs.2011.02.004

Huosong, X., Qingdi, W., & Zhang, Z. (2019). Knowledge heterogeneity in university-industry knowledge transfer: A case analysis of Xu's Ruyi textile. *Knowledge Management Research & Practice*, *17*(4), 486-498.

Huseman, R. C., Hatfield, J. D., & Miles, E. W. (1987). A new perspective on equity theory: The equity sensitivity construct. *Academy of Management Review*, *12*(2), 222-234.

Ihrig, M., & MacMillan, I. (2015). Managing your mission-critical knowledge. *Harvard Business Review*, *93*(93), 80-87.

Ilmola, L., & Kuusi, O. (2006). Filters of weak signals hinder foresight: Monitoring weak signals efficiently in corporate decision-making. *Futures*, *38*(8), 908-924.

Impey, C., & Formanek, M. (2021). MOOCS and 100 Days of COVID: Enrolment surges in massive open online astronomy classes during the coronavirus pandemic. *Social Sciences & Humanities Open*, *4*(1), 100177. https://doi.org/10.1016/j.ssaho.2021.100177

Inkpen, A. C., & Tsang, E. W. (2005). Social capital, networks, and knowledge transfer. *Academy of Management Review*, *30*(1), 146-165.

Ipe, M. (2003). Knowledge sharing in organizations: A conceptual framework. *Human Resource Development Review*, *2*(4), 337-359. http://journals.sagepub.com/doi/pdf/10.1177/1534484303257985

Israel, M., & Hay, I. (2006). *Research ethics for social scientists*. Sage.

Issing, O. (2002, 5 December). *Why stable prices and stable markets are important and how they fit together* First Conference of the Monetary Stability Foundation, Frankfurt/Main. https://www.ecb.europa.eu/press/key/date/2002/html/sp021205.en.html

Jabr, W., Mookerjee, R., Tan, Y., & Mookerjee, V. (2013). Leveraging philanthropic behavior for customer support: the case of user support forums. *MIS Quarterly*, *38*(1), 187-208 https://doi.org/10.25300/MISQ/2014/38.1.09

Jan, S. T., Wang, C., Zhang, Q., & Wang, G. (2017). Towards monetary incentives in social Q&A services. *arXiv preprint arXiv:1703.01333*.

Jan, S. T., Wang, C., Zhang, Q., & Wang, G. (2018). Pay-per-Question: Towards Targeted Q&A with Payments. *Proceedings of the 2018 ACM Conference on Supporting Groupwork*, Chicago, USA.

Janssen, M., & Mendys-Kamphorst, E. (2004). The price of a price: On the crowding out and in of social norms. *Journal of Economic Behavior & Organization*, *55*, 377-395. https://doi.org/10.1016/j.jebo.2002.11.004

Jarvenpaa, S. L., & Staples, D. S. (2000). The use of collaborative electronic media for information sharing: an exploratory study of determinants. *The Journal of Strategic Information Systems*, *9*(2), 129-154. https://doi.org/10.1016/S0963-8687(00)00042-1

Jeon, G. Y., Kim, Y.-M., & Chen, Y. (2010). Re-examining price as a predictor of answer quality in an online Q&A site. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Atlanta, US.

Jeon, G. Y., & Rieh, S. Y. (2013). The value of social search: Seeking collective personal experience in social Q&A. *Proceedings of the Association for Information Science and Technology*, *50*(1), 1-10. https://doi.org/10.1002/meet.14505001067

Jeon, J., Croft, W. B., Lee, J. H., & Park, S. (2006). A framework to predict the quality of answers with non-textual features. *Proceedings of the 29th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval,* Seattle, USA.

Jeong, D.-Y., & Kim, S.-M. (2014). The Relationship between Price Perceptions and Price Acceptability of Digital Information Goods. *Advanced Science and Technology Letters*, *70*.

Jeong, S.-K., Ahn, J.-C., & Rhee, B.-H. (2013). Knowledge transfer activation analysis: knowledge trade perspective. *Journal of Computer Information Systems*, *53*(3), 47-55. https://doi.org/10.1080/08874417.2013.11645631

Jeong, S. W., Ha, S., & Lee, K.-H. (2016). Impacts of community commitment on brand equity creation in company-initiated online brand communities. *Fashion, Industry and Education*, *14*(1), 31-39.

Jeppesen, L. B., & Lakhani, K. R. (2010). Marginality and problem-solving effectiveness in broadcast search. *Organization Science*, *21*(5), 1016-1033.

Jia, Y., Song, Z., Bai, X., & Xu, W. (2017). Towards Economic Models for MOOC Pricing Strategy Design. *Proceedings of the International Conference on Database Systems for Advanced Applications,* Suzhou, China.

Jin, B., Park, J. Y., & Kim, H.-S. (2010). What makes online community members commit? A social exchange perspective. *Behaviour & Information Technology*, *29*(6), 587-599.

Jing, B. (2000). *Versioning information goods with network externalities. Proceedings of the 21st International Conference on Information Systems*, Brisbane, Queensland, Australia.

Jo, S.-J., & Jeon, J.-H. (2010). An Integrated Framework of Knowledge Transactions in Firms: Resource-based, Transactional and Social Exchange Approaches. *Journal of Agricultural*

Education and Human Resource Development 42(1), 131-153. https://doi.org/10.23840/agehrd.2010.42.1.131

Jones, Q., & Rafaeli, S. (1999). User population and user contributions to virtual publics: A systems model. *Proceedings of the International ACM SIGGROUP Conference on Supporting Group Work*, Phoenix, US.

Jung, J., Bapna, R., Gupta, A., & Sen, S. (2021). Impact of Incentive Mechanism in Online Referral Programs: Evidence from Randomized Field Experiments. *Journal of Management Information Systems*, *38*(1), 59-81.

Kafentzis, K., Apostolou, D., Mentzas, G., & Georgolios, P. (2002). A Framework for analysis and a review of knowledge asset marketplaces. *Lecture Notes in Computer Science*, 301-313.

Kafentzis, K., Mentzas, G., Apostolou, D., & Georgolios, P. (2004). Knowledge marketplaces: strategic issues and business models. *Journal of Knowledge Management*, *8*(1), 130-146. https://www.emeraldinsight.com/doi/abs/10.1108/13673270410523961

Kang, M. (2022). Motivational affordances and survival of new askers on social Q&A sites: The case of Stack Exchange network. *Journal of the Association for Information Science and Technology*, *73*(1), 90-103. https://doi.org/10.1002/asi.24548

Kankanhalli, A., Tan, B. C., & Wei, K.-K. (2005). Contributing knowledge to electronic knowledge repositories: an empirical investigation. *MIS Quarterly*, 113-143.

Kaplan, A. M., & Haenlein, M. (2016). Higher education and the digital revolution: About MOOCs, SPOCs, social media, and the Cookie Monster. *Business Horizons*, *59*(4), 441-450. https://doi.org/10.1016/j.bushor.2016.03.008

Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., & Nerur, S. (2018). Advances in social media research: Past, present and future. *Information Systems Frontiers*, *20*(3), 531-558.

Kayes, I., Kourtellis, N., Quercia, D., Iamnitchi, A., & Bonchi, F. (2015). The social world of content abusers in community question answering. Proceedings of the 24th International Conference on World Wide Web, Florence, Italy.

Ke, W., & Zhang, P. (2010). The effects of extrinsic motivations and satisfaction in open-source software development. *Journal of the Association for Information Systems*, *11*(12), 784.

Kelly, S. (2016). *Natural language processing, in javascript*. Retrieved 12.21 from https://github.com/nlp-compromise/compromise

Keren, G., & Roelofsma, P. (1995). Immediacy and certainty in intertemporal choice. *Organizational behavior and human decision processes*, *63*(3), 287-297.

Keren, G., & Wu, G. (2015). *The Wiley-Blackwell handbook of judgment and decision making*. Wiley Online Library.

Kettles, D., St Louis, R. D., & Steinbart, P. J. (2017). An experimental investigation of the individual and joint effects of financial and non-financial incentives on knowledge sharing using enterprise social media. *Communications of the Association for Information Systems*, *41*(1), 27. http://dx.doi.org/10.17705/1CAIS.04127

Khansa, L., Ma, X., Liginlal, D., & Kim, S. S. (2015). Understanding members' active participation in online question-and-answer communities: A theory and empirical analysis. *Journal of Management Information Systems*, *32*(2), 162-203.

Khare, A. (2014). Money Attitudes, Materialism, and Compulsiveness: Scale Development and Validation. *Journal of Global Marketing*, *27*(1), 30-45. https://doi.org/10.1080/08911762.2013.850140

Kim, J., Lee, C., & Elias, T. (2015). Factors affecting information sharing in social networking sites amongst university students: Application of the knowledge-sharing model to social networking sites. *Online Information Review*, *39*(3), 290-309. https://doi.org/10.1108/OIR-01-2015-0022

Kim, P. (2014). *Massive open online courses: The MOOC revolution*. Routledge.

Kim, S., Malhotra, N., & Narasimhan, S. (2005). Two Competing Perspectives on Automatic Use: A Theoretical and Empirical Comparison. Information Systems Research. *Information Systems Research*, *16*(4), 418-432. http://dx.doi.org/10.1287/isre.1050.0070

Kim, S. S., & Son, J.-Y. (2009). Out of dedication or constraint? A dual model of post-adoption phenomena and its empirical test in the context of online services. *MIS Quarterly*, 49-70.

Kim, Y. (2017). Fostering scientists' data sharing behaviors via data repositories, journal supplements, and personal communication methods. *Information Processing & Management*, *53*(4), 871-885. https://doi.org/10.1016/j.ipm.2017.03.003

Kinsman, T., Wessel, M., Gerosa, M. A., & Treude, C. (2021). How do software developers use GitHub Actions to automate their workflows? *Proceedings of the 2021 IEEE/ACM 18th International Conference on Mining Software Repositories (MSR),* Madrid, Spain. https://doi.org/10.1109/MSR52588.2021

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: analyzing learner subpopulations in massive open online courses. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge,* Leuven, Belgium.

Kizilcec, R. F., Schneider, E., Cohen, G. L., & McFarland, D. A. (2014). Encouraging forum participation in online courses with collectivist, individualist and neutral motivational framings. *Proceedings of the 2014 European MOOC Stakeholder Summit*, Lausanne, Switzerland

Klain, T. J., Lusk, J. L., Tonsor, G. T., & Schroeder, T. C. (2014). An experimental approach to valuing information. *Agricultural economics*, *45*(5), 635-648. https://onlinelibrary.wiley.com/doi/pdf/10.1111/agec.12112

Klenow, P. J., & Rodriguez-Clare, A. (1997). The neoclassical revival in growth economics: Has it gone too far? *NBER Macroeconomics Annual*, *12*, 73-103.

Klenow, P. J., & Rodriguez-Clare, A. (2005). Externalities and growth. *Handbook of Economic Growth*, *1*, 817-861. https://doi.org/10.1016/S1574-0684(05)01011-7

Kohn, A. (1993). Why Incentive Plans Cannot Work. *Harvard Business Review*, *71*(5), 54-62.

Koivisto, J., & Hamari, J. (2019). The rise of motivational information systems: A review of gamification research. *International Journal of Information Management*, *45*, 191-210.

Kollock, P. (1999). The economies of online cooperation. *Communities in cyberspace*, *220*.

Kolowich, S. (2013). *How EdX plans to earn, and share, revenue from its free online courses*.

Krashen, S. D. (2003). *Explorations in language acquisition and use*. Heinemann Portsmouth, NH.

Kraut, R., Mukhopadhyay, T., Szczypula, J., Kiesler, S., & Scherlis, B. (1999). Information and communication: Alternative uses of the Internet in households. *Information Systems Research*, *10*(4), 287-303. https://doi.org/10.1287/isre.10.4.287

Kuang, L., Huang, N., Hong, Y., & Yan, Z. (2019). Spillover effects of financial incentives on non-incentivized user engagement: Evidence from an online knowledge exchange platform. *Journal* *of Management Information Systems*, *36*(1), 289-320. https://doi.org/10.1080/07421222.2018.1550564

Kuem, J., Khansa, L., & Kim, S. S. (2020). Prominence and engagement: Different mechanisms regulating continuance and contribution in online communities. *Journal of Management Information Systems*, *37*(1), 162-190. https://doi.org/10.1080/07421222.2019.1705510

Kuo, F. Y., & Young, M. L. (2008). Predicting knowledge sharing practices through intention: A test of competing models. *Computers in Human Behavior*, *24*(6), 2697-2722.

Kuo, Y. F., Lin, C. S., & Wu, C. H. (2020). Why do people intend to back crowdfunding projects? a perspective on social cognitive theory. *Journal of Electronic Commerce Research*, *21*(3), 180-196.

Kwok, S. H., & Gao, S. (2005). Attitude towards knowledge sharing behavior. *Journal of Computer Information Systems*, *46*(2), 45-51.

Lai, H.-M., & Hsieh, P. J. (2021). The Effect of System Quality, Knowledge Quality, and Knowledge-Contribution Signals on Members' Knowledge Contribution and-Seeking Behaviors in Professional Virtual Communities. *Proceeding of the International Conference on Knowledge Management in Organizations*, Kaohsiung, Taiwan.

Lalingkar, A., Arulchelvan, P., Lonkar, A., Mishra, P., Mandyam, S., & Srinivasa, S. (2022). Discussion Forum Analyzer: A tool for finding the quality of affirmation and identifying points of intervention in an academic discussion forum. *Proceedings of the 5th Joint International Conference on Data Science & Management of Data*, Bangalore, India.

Lalingkar, A., Mishra, P., Mandyam, S., Pattanaik, J., & Srinivasa, S. (2020). Building a Model for finding Quality of Affirmation in a Discussion Forum. *Proceedings of the 2020 IEEE 20th International Conference on Advanced Learning Technologies*, Tartu, Estonia.

Lamb, B. (2004). Wide open spaces: Wikis, ready or not. *EDUCAUSE Review*, *39*(5), 36-48.

Lang, K. R., Shang, R. D., & Vragov, R. (2009). Designing markets for co-production of digital culture goods. *Decision Support Systems*, *48*(1), 33-45. https://doi.org/10.1016/j.dss.2009.05.010

Langinier, C., & Moschini, G. (2002). The economics of patents. *Intellectual Property Rights in Animal Breeding and Genetics, ed. Max F. Rothschild and Scott Newman*, 31-50.

Laplante-Lévesque, A., & Thorén, E. S. (2015). Readability of Internet information on hearing: Systematic literature review. *American Journal of Audiology*, *24*(3), 284-288. https://doi.org/10.1044/2015_aja-14-0091

Latsis, J., De Larquier, G., & Besis, F. (2010). Are conventions solutions to uncertainty? Contrasting visions of social coordination. *Journal of Post Keynesian Economics*, *32*(4), 535-558.

Lawler, E. E. (1994). From job-based to competency-based organizations. *Journal of Organizational Behaviour*, *15*(1), 3-15.

Lawrence, D. B. (1979). *The quantification of the value of information in decision making,* Iowa State University.

Lawrence, M. (2018). *DAP statistics*. Retrieved 17 April from https://confluence.csiro.au/display/daphelp/Home

Lawson, T. (1985). Uncertainty and Economic Analysis. *The Economic Journal*, *95*(380), 909-927. https://doi.org/10.2307/2233256

Lazer, D., Kennedy, R., King, G., & Vespignani, A. (2014). The parable of Google Flu: traps in big data analysis. *Science*, *343*(6176), 1203-1205.

Lee, A. S. (1991). Integrating positivist and interpretive approaches to organizational research. *Organization Science*, *2*(4), 342-365.

Lee, C. S., Goh, D. H. L., Chua, A. Y., & Ang, R. P. (2010). Indagator: Investigating perceived gratifications of an application that blends mobile content sharing with gameplay. *Journal of the American Society for Information Science and Technology*, *61*(6), 1244-1257. https://doi.org/10.1002/asi.21305

Lee, D.-J., & Ahn, J.-H. (2007). Reward systems for intra-organizational knowledge sharing. *European Journal of Operational Research*, *180*(2), 938-956. https://doi.org/10.1016/j.ejor.2006.03.052

Lee, G. K., & Cole, R. E. (2003). From a firm-based to a community-based model of knowledge creation: The case of the Linux kernel development. *Organization Science*, *14*(6), 633-649.

Lee, K. C., Lee, S., & Kang, I. W. (2005). KMPI: measuring knowledge management performance. *Information & Management*, *42*(3), 469-482. https://doi.org/10.1016/j.im.2004.02.003

Lee, S.-G., Trimi, S., & Yang, C.-G. (2018). Perceived usefulness factors of online reviews: a study of Amazon. com. *Journal of Computer Information Systems*, *58*(4), 344-352.

Lee, S., Trimi, S., & Yang, C. (2018). Perceived usefulness factors of online reviews: a study of Amazon. com. *Journal of Computer Information Systems*, *58*(4), 344-352.

Lee, U., Kim, J., Yi, E., Sung, J., & Gerla, M. (2013). *Analyzing crowd workers in mobile pay-for-answer q&a. Proceedings of the SIGCHI Conference on Human Factors in Computing* Systems, Paris, France. https://dl.acm.org/citation.cfm?id=2470730

Lee, Y. W., Strong, D. M., Kahn, B. K., & Wang, R. Y. (2002). AIMQ: a methodology for information quality assessment. *Information & Management*, *40*(2), 133-146. https://doi.org/10.1016/S0378-7206(02)00043-5

Lemley, M. A., & Myhrvold, N. (2007). How to make a patent market. *Hofstra Law Review*, *36*(2), 257-259.

Levy, Y., & Ellis, T. J. (2006). A systems approach to conduct an effective literature review in support of information systems research. *Informing Science*, *9*.

Lew, R., Frankenberg-Garcia, A., Rees, G. P., Roberts, J. C., & Sharma, N. (2018). ColloCaid: A Real-time Tool to Help Academic Writers with English Collocations. *Proceedings of the 18th EURALEX International Congress,* Ljubljana, Slovenia.

Lewin, T. (2013). Master's degree is new frontier of study online. *The New York Times*.

Li, C., & Xing, W. (2021). Natural language generation using deep learning to support MOOC learners. *International Journal of Artificial Intelligence in Education*, *31*(2), 186-214.

Li, F., & Du, T. C. (2011). Who is talking? An ontology-based opinion leader identification framework for word-of-mouth marketing in online social blogs. *Decision Support Systems*, *51*(1), 190-197.

Li, J., Tang, J., Jiang, L., Yen, D. C., & Liu, X. (2019). Economic success of physicians in the online consultation market: a signaling theory perspective. *International Journal of Electronic Commerce*, *23*(2), 244-271. https://doi.org/10.1080/10864415.2018.1564552

Li, L. H., Hsu, R. W., Tsai, W. C., & Lo, T. W. (2012). Analytical Study of Hotel Service Quality and Customer Satisfaction - A Case Study of Ctrip Website. *International Journal of Advancements in Computing Technology*, *4*(22), 796. http://dx.doi.org/10.5539/ass.v11n10p73

Li, S., Su, Y., & Sun, Y. (2010). The effect of pseudo-immediacy on intertemporal choices. *Journal of Risk Research*, *13*(6), 781-787.

Li, W., Wu, W.-j., Wang, H.-m., Cheng, X.-q., Chen, H.-j., Zhou, Z.-h., & Ding, R. (2017). Crowd intelligence in AI 2.0 era. *Frontiers of Information Technology & Electronic Engineering*, *18*(1), 15-43. https://doi.org/10.1631/FITEE.1601859

Lichtenstein, S., Parker, C. M., & Hunter, A. (2007). Dynamic knowledge integration in socio-technical networks: An interpretive study of intranet use for knowledge integration. *Journal of Information & Knowledge Management*, *6*(02), 91-103. http://dx.doi.org/10.1142/S021964920700172X

Lin, H. C., & Chang, C. M. (2018). What motivates health information exchange in social media? The roles of the social cognitive theory and perceived interactivity. *Information & Management*, *55*(6), 771-780. https://doi.org/10.1016/j.im.2018.03.006

Lin, H. F. (2007). Effects of extrinsic and intrinsic motivation on employee knowledge sharing intentions. *Journal of Information Science*, *33*(2), 135-149. https://doi.org/10.1016/j.im.2004.02.003

Lin, N. (2002). *Social capital: A theory of social structure and action* (Vol. 19). Cambridge university press.

Lin, T. C., & Huang, C. C. (2010). Withholding effort in knowledge contribution: The role of social exchange and social cognitive on project teams. *Information & Management*, *47*(3), 188-196.

Lincoln, Y. S., Lynham, S. A., & Guba, E. G. (2011). Paradigmatic controversies, contradictions, and emerging confluences, revisited. *The Sage handbook of qualitative research*, *4*(2), 97-128.

Ling, K., Beenen, G., Ludford, P., Wang, X., Chang, K., Li, X., Cosley, D., Frankowski, D., Terveen, L., Rashid, A. M., Resnick, P., & Kraut, R. (2005). Using Social Psychology to Motivate Contributions to Online Communities. *Journal of Computer-Mediated Communication*, *10*(4), 00-00. https://doi.org/10.1111/j.1083-6101.2005.tb00273.x

Liu, B. (2007). *Web data mining: exploring hyperlinks, contents, and usage data*. Springer Science & Business Media.

Liu, C. C., Liang, T. P., Rajagopalan, B., & Sambamurthy, V. (2011). The crowding effect of rewards on knowledge-sharing behavior in virtual communities. *Proceedings of the 15th Pacific Asia Conference on Information Systems*, Brisbane, Australia.

Liu, H., & Li, G. (2017). To gain or not to lose? The effect of monetary reward on motivation and knowledge contribution. *Journal of Knowledge Management*, *21*(2), 397-415. https://doi.org/10.1108/JKM-03-2016-0100

Liu, H., Zhang, J., Liu, R., & Li, G. (2014). A model for consumer knowledge contribution behavior: the roles of host firm management practices, technology effectiveness, and social capital. *Information Technology and Management*, *15*(4), 255-270.

Liu, J., & Ye, Q. (2016). *How Price Affect Online Purchase Behavior in Online Healthcare Consulting? Perceived Quality as a Mediator*. https://doi.org/10.1007/978-3-319-29175-8_18

Liu, J., Zhang, Z., Qi, J., Wu, H., & Chen, M. (2019). Understanding the impact of opinion leaders' characteristics on online group knowledge-sharing engagement from in-group and out-group perspectives: evidence from a Chinese online knowledge-sharing community. *Sustainability*, *11*(16), 4461-4489. https://doi.org/10.3390/su11164461

Liu, L., Jiang, J., Ren, S., & Hu, L. (2021). Why Audiences Donate Money to Content Creators? A Uses and Gratifications Perspective. HCI International 2021 - Late Breaking Posters, Cham.

Liu, X., Min, Q., & Han, S. (2020). Understanding users' continuous content contribution behaviours on microblogs: an integrated perspective of uses and gratification theory and social influence theory. *Behaviour & Information Technology*, *39*(5), 525-543. https://doi.org/10.1080/0144929X.2019.1603326

Liu, Z., Zhao, Y., Chen, S., Song, S., Hansen, P., & Zhu, Q. (2021). Exploring askers' switching from free to paid social Q&A services: A perspective on the push-pull-mooring framework. *Information Processing & Management*, *58*(1), 102396. https://doi.org/10.1016/j.ipm.2020.102396

Locke, E. A. (1997). Self-efficacy: The exercise of control. *Personnel psychology*, *50*(3), 801.

Lombardi, R., Manfredi, S., Nappo, F., & Russo, G. (2016). Economic valuation of structural capital through static and dynamic approaches: first evidence. *Journal for International Business and Entrepreneurship Development*, *9*(2), 135-151. https://dx.doi.org/10.1504/JIBED.2016.077716

Lombardi, S., Cavaliere, V., Giustiniano, L., & Cipollini, F. (2020). What money cannot buy: The detrimental effect of rewards on knowledge sharing. *European Management Review*, *17*(1), 153-170. https://doi.org/10.1111/emre.12346

Lou, J., Fang, Y., Lim, K. H., & Peng, J. Z. (2013). Contributing high quantity and quality knowledge to online Q&A communities. *Journal of the American Society for Information Science and Technology*, *64*(2), 356-371. https://doi.org/10.1002/asi.22750

Lu, Y., Ou, C., & Angelopoulos, S. (2018). Exploring the effect of monetary incentives on user behavior in Online Sharing Platforms. *Proceedings of the 51st Hawaii International Conference on System Sciences*, Hawaii, USA.

Lueg, C. (2003). *From Usenet to CoWebs: interacting with social information spaces*. Springer Science & Business Media.

Lukashov, D. (2011). *Knowledge Markets for Competitive Information*.

Luo, Y., Soman, D., & Zhao, J. (2021). *A meta-analytic cognitive framework of nudge and sludge* University of British Columbia, Toronto.

Ma, C., Ganegoda, D. B., Chen, Z. X., Jiang, X., & Dong, C. (2020). Effects of perceived overqualification on career distress and career planning: Mediating role of career identity and moderating role of leader humility. *Human Resource Management*, *59*(6), 521-536. https://doi.org/10.1002/hrm.22009

Ma, M., & Agarwal, R. (2007). Through a Glass Darkly: Information Technology Design, Identity Verification, and Knowledge Contribution in Online Communities. *Information Systems Research*, *18*(1), 42-67. https://doi.org/10.1287/isre.1070.0113

Machlup, F. (1962). *The production and distribution of knowledge in the United States* (Vol. 278). Princeton university press.

Machlup, F. (2014). *Knowledge: Its Creation, Distribution and Economic Significance, Volume III: The Economics of Information and Human Capital* (Vol. 3). Princeton University Press.

Mackness, J., Mak, S., & Williams, R. (2010). The ideals and reality of participating in a MOOC. *Proceedings of the 7th International Conference on Networked Learning*, Lancaster, UK.

Malgonde, O., Zhang, H., Padmanabhan, B., & Limayem, M. (2020). Taming complexity in search matching: Two-sided recommender systems on digital platforms. *MIS Quarterly*, *44*(1).

Mallasi, H., & Ainin, S. (2015). Investigating knowledge sharing behaviour in academic environment. *Journal of Organizational Knowledge Management*, *2015*, 1-19. https://doi.org/10.5171/2015.643253

Malone, T. W., Laubacher, R., & Dellarocas, C. (2009). Harnessing crowds: Mapping the genome of collective intelligence.

Mankiw, N. G. (2014). *Principles of macroeconomics*. Cengage Learning.

Manning, J., & Sanders, M. (2013). How widely used are MOOC forums. *A first look. Signals: Thoughts on Online Learning*.

Markonis, D., Holzer, M., Dungs, S., Vargas, A., Langs, G., Kriewel, S., & Müller, H. (2012). A survey on visual information search behavior and requirements of radiologists. *Methods of Information in Medicine*, *51*(06), 539-548. https://doi.org/10.3414/ME11-02-0025

Marr, B. (2005). Perspective on intellectual capital: Multidisciplinary Insights into management, measurement, and reporting. *Perspectives on Intellectual Capital: Multidisciplinary/Insights into Management, Measurement and Reporting*.

Mårtensson, P., & Lee, A. S. (2004). Dialogical action research at omega corporation. *MIS Quarterly*, 507-536.

Matschke, C., Moskaliuk, J., & Cress, U. (2012). Knowledge exchange using Web 2.0 technologies in NGOs. *Journal of knowledge management*.

Matson, E., Patiath, P., & Shavers, T. (2003). Stimulating knowledge sharing: Strengthening your organization's internal knowledge market. *Organizational dynamics*, *32*(3), 275-285. https://doi.org/10.1016/S0090-2616(03)00030-5

McCain, R. (2006). Defining cultural and artistic goods. *Handbook of the Economics of Art and Culture*, *1*, 147-167. https://doi.org/10.1016/S1574-0676(06)01005-2

Melenhorst, M., Grootveld, M., van Setten, M., & Veenstra, M. (2008). Tag-based information retrieval of video content. *Proceedings of the 1st International Conference on Designing Interactive User Experiences for TV and Video*, California, USA.

Melody, W. H. (1985). The information society: Implications for economic institutions and market theory. *Journal of Economic Issues*, *19*(2), 523-539. https://www.tandfonline.com/doi/abs/10.1080/00213624.1985.11504392

Melody, W. H. (1987). Information: an emerging dimension of institutional analysis. *Journal of Economic Issues*, *21*(3), 1313-1339.

Menon, T., & Blount, S. (2003). The messenger bias: A relational model of knowledge valuation. *Research in Organizational Behavior*, *25*, 137-186. https://doi.org/10.1016/S0191-3085(03)25004-8

Merchant, A., Shah, D., Bhatia, G. S., Ghosh, A., & Kumaraguru, P. (2019). Signals matter: understanding popularity and impact of users on stack overflow. The World Wide Web Conference,

Mertens, D. M. (2008). *Transformative research and evaluation*. Guilford press.

Mertens, D. M. (2019). *Research and evaluation in education and psychology: Integrating diversity with quantitative, qualitative, and mixed methods*. Sage publications.

Mettler, T., & Winter, R. (2016). Are business users social? A design experiment exploring information sharing in enterprise social systems. *Journal of Information Technology*, *31*(2), 101-114. https://doi.org/10.1057/jit.2015.28

Miller, N. E. (1945). *Social learning and imitation*.

Milton, N. (2010). *The lessons learned handbook: Practical approaches to learning from experience*. Elsevier.

Minbaeva, D. B. (2008). HRM practices affecting extrinsic and intrinsic motivation of knowledge receivers and their effect on intra-MNC knowledge transfer. *International business review*, *17*(6), 703-713.

Mitchell, T. R. (1985). An evaluation of the validity of correlational research conducted in organizations. *Academy of Management Review*, *10*(2), 192-205.

Mitrovic, A., Gordon, M., Piotrkowicz, A., & Dimitrova, V. G. (2019). Investigating the Effect of Adding Nudges to Increase Engagement in Active Video Watching. *Proceedings of the 20th International Conference on Artificial Intelligence in Education*. Springer, Chicago, USA.

Mittal, A., Vigentini, L., Djatmiko, M., Prusty, G., Sharma, Y., & King, M. E. (2018). Mooc-o-bot: using cognitive technologies to extend knowledge support in moocs. *Proceedings of the 2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering*, Wollongong, Australia.

Mitton, C., Adair, C. E., McKenzie, E., Patten, S. B., & Perry, B. W. (2007). Knowledge transfer and exchange: review and synthesis of the literature. *The Milbank Quarterly*, *85*(4), 729-768.

Mizintseva, M., & Gerbina, T. (2018). Knowledge management: a tool for implementing the digital economy. *Scientific and Technical Information Processing*, *45*(1), 40-48.

Mochon, D., Schwartz, J., Maroba, J., Patel, D., & Ariely, D. (2016). Gain Without Pain: The Extended Effects of a Behavioral Health Intervention. *Management Science*, *63*(1), 58-72. https://doi.org/10.1287/mnsc.2015.2322

Moe, R. (2015). The brief & expansive history (and future) of the MOOC: Why two divergent models share the same name. *Current Issues in Emerging E-learning*, *2*(1), 2.

Mohammadhassan, N., Mitrovic, A., & Neshatian, K. (2022). Investigating the effect of nudges for improving comment quality in active video watching. *Computers & Education*, *176*, 104340. https://doi.org/10.1016/j.compedu.2021.104340

Molloy, J. C. (2011). The open knowledge foundation: open data means better science. *PLOS Biology*, *9*(12). https://doi.org/10.1371/journal.pbio.1001195

MoocLab. (2017). *State of the MOOC 2016: A Year of Massive Landscape Change For Massive Open Online Courses*. https://www.onlinecoursereport.com/state-of-the-mooc-2016-a-year-of-massive-landscape-change-for-massive-open-online-courses/

Moon, J.-W., & Kim, Y.-G. (2001). Extending the TAM for a World-Wide-Web context. *Information & Management*, *38*(4), 217-230.

Moon, J. Y., & Sproull, L. S. (2008). The Role of Feedback in Managing the Internet-Based Volunteer Work Force. *Information Systems Research*, *19*(4), 494-515.

Morell, C. (2015). *Udacity Nanodegree Reviews: Your Questions Answered*. https://blog.udacity.com/2015/03/udacity-nanodegree-reviews-your-questions-answered.html

Moreno-Marcos, P. M., Alario-Hoyos, C., Muñoz-Merino, P. J., Estévez-Ayres, I., & Kloos, C. D. (2018). Sentiment analysis in MOOCs: A case study. Proceedings of the 2018 IEEE Global Engineering Education Conference, Canary Islands, Spain.

Moretti, E. (2004). Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics*, *121*(1), 175-212. https://doi.org/10.1016/j.jeconom.2003.10.015

Moxley, J. (2015). Maintain a high verb-to-noun ratio. *Writing Commons*, *20*.

Muntinga, D. G., Moorman, M., & Smit, E. G. (2011). Introducing COBRAs. *International Journal of Advertising*, *30*(1), 13-46. https://doi.org/10.2501/IJA-30-1-013-046

Murray, F., & Stern, S. (2007). Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis. *Journal of Economic Behavior & Organization*, *63*(4), 648-687. https://doi.org/10.1016/j.jebo.2006.05.017

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review*, *23*(2), 242-266.

Nakash, M., & Bouhnik, D. (2023). Motivations for the initiation of knowledge management activities in times of routine and emergency. *Aslib Journal of Information Management.* https://doi.org/10.1108/AJIM-10-2022-0458

Nam, K., Ackerman, M., & Adamic, L. A. (2009). Questions in, knowledge in?: a study of Naver's question answering community. *Proceedings of the SIGCHI Conference on human factors in computing systems,* Boston, USA.

Nan, G., Wu, D., Li, M., & Tan, Y. (2016). Optimal Pricing of Information Goods under the Freemium Strategy in the Presence of Piracy and Network Effects. *SSRN Electronic Journal*. http://dx.doi.org/10.2139/ssrn.2798421

Nardi, B. (2006). Collaborative play in World of Warcraft. Web Congress, 2006. *Proceedings of the Fourth LA-Web'06,* Cholula, Mexico.

Nataf, E. (2018). *Education technology is a global opportunity*. https://techcrunch.com/2018/01/19/education-technology-is-a-global-opportunity/

Nelson, R. R. (2004). The market economy, and the scientific commons. *Research Policy*, *33*(3), 455-471. https://doi.org/10.1016/j.respol.2003.09.008

Neuman, L. W. (2007). Social Research Methods, 6/E. In. Pearson Education India.

Neuman, S. B., & McCormick, S. (1995). *Single-subject experimental research: Applications for Literacy*. ERIC.

Nguyen, T. (2015). The effectiveness of online learning: Beyond no significant difference and future horizons. *Journal of Online Learning and Teaching*, *11*(2), 309-319.

Nimark, K. (2008). Dynamic pricing and imperfect common knowledge. *Journal of Monetary Economics*, *55*(2), 365-382. https://doi.org/10.1016/j.jmoneco.2007.12.008

Niu, J. (2009). *Perceived Documentation Quality of Social Science Data.*

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science*, *5*(1), 14-37.

Nuvolari, A. (2004). Collective invention during the British Industrial Revolution: the case of the Cornish pumping engine. *Cambridge Journal of Economics*, *28*(3), 347-363. https://academic.oup.com/cje/article/28/3/347/1711845

Oh, H., Animesh, A., & Pinsonneault, A. (2016). Free Versus For-a-Fee. *MIS Quarterly*, *40*(1), 31-56.

Okoli, C., & Oh, W. (2007). Investigating recognition-based performance in an open content community: A social capital perspective. *Information & Management*, *44*(3), 240-252.

Olesk, A., Kaal, E., & Toom, K. (2019). The possibilities of Open Science for knowledge transfer in the science-policy interface. *Journal of Science Communication*, *18*(3), A03.

Onah, D., Sinclair, J. E., Boyatt, R., & Foss, J. (2014). Massive open online courses: learner participation. *Presented in the Proceeding of the 7th International Conference of Education, Research and Innovation*, Seville, Spain.

Onah, D., Sinclair, J. E., & Boyatt, R. (2014). Exploring the use of MOOC discussion forums. *Proceedings of London International Conference on Education*, London, UK.

Ortega-Arranz, A., Bote-Lorenzo, M. L., Asensio-Pérez, J. I., Martínez-Monés, A., Gómez-Sánchez, E., & Dimitriadis, Y. (2019). To reward and beyond: Analyzing the effect of reward-based strategies in a MOOC. *Computers & Education*, *142*, 103639. https://doi.org/10.1016/j.compedu.2019.103639

Ortiz, A., Chang, L., & Fang, Y. (2015). International student mobility trends 2015: An economic perspective. *World Education News & Reviews*.

Ortiz, M. A. A. (2011). Intellectual capital (intangible assets) valuation considering the context. *Journal of Business & Economics Research*, *4*(9).

Osterloh, M., & Frey, B. S. (2000). Motivation, knowledge transfer, and organizational forms. *Organization Science*, *11*(5), 538-550.

Otero-Cerdeira, L., Rodríguez-Martínez, F. J., & Gómez-Rodríguez, A. (2015). Ontology matching: A literature review. *Expert Systems with Applications*, *42*(2), 949-971. https://doi.org/10.1016/j.eswa.2014.08.032

Otto, B., Hüner, K. M., & Österle, H. (2009). Identification of Business Oriented Data Quality Metrics. *Proceedings of the 14th International Conference on Information Quality,* Lippstadt, Germany.

Overpeck, J. T., Meehl, G. A., Bony, S., & Easterling, D. R. (2011). Climate data challenges in the 21st century. *Science*, *331*(6018), 700-702.

Oye, N., Salleh, M., & Noorminshah, A. (2011). Knowledge sharing in workplace: Motivators and demotivators. *International Journal of Managing Information Technology, 3*(4).

Pan, D. (2018). Research on the influence factors of online health community doctors' service prices. *Proceedings of the 2018 Chinese Control and Decision Conference*, Shenyang, China.

Pan, S. L., & Pee, L. (2020). Usable, in-use, and useful research: A 3U framework for demonstrating practice impact. *Information Systems Journal*, *30*(2), 403-426. https://doi.org/10.1111/isj.12274

Pang, S., Bao, P., Hao, W., Kim, J., & Gu, W. (2020). Knowledge sharing platforms: An empirical study of the factors affecting continued use intention. *Sustainability*, *12*(6), 2341.

Papasavva, A., Zannettou, S., De Cristofaro, E., Stringhini, G., & Blackburn, J. (2020). Raiders of the lost kek: 3.5 years of augmented 4chan posts from the politically incorrect board. *Proceedings of the International AAAI Conference on Web and Social Media*. Atlanta, USA.

Pathak, V., Jena, B., & Kalra, S. (2013). Qualitative research. *Perspect Clin Res*, *4*(3), 192. https://doi.org/10.4103/2229-3485.115389

Patton, M. Q. (1990). *Qualitative evaluation and research methods*. SAGE Publications, inc.

Pauliuk, S. (2020). Making sustainability science a cumulative effort. *Nature Sustainability*, *3*(1), 2-4. https://doi.org/10.1038/s41893-019-0443-7

Pauliuk, S., & Heeren, N. (2020). ODYM—An open software framework for studying dynamic material systems: Principles, implementation, and data structures. *Journal of Industrial Ecology*, *24*(3), 446-458. https://doi.org/10.1111/jiec.12952

Peer, E., Egelman, S., Harbach, M., Malkin, N., Mathur, A., & Frik, A. (2020). Nudge me right: Personalizing online security nudges to people's decision-making styles. *Computers in Human Behavior*, *109*, 106347. https://doi.org/10.1016/j.chb.2020.106347

Pentland, B. T., Recker, J., Wolf, J. R., & Wyner, G. (2020). Bringing context inside process research with digital trace data. *Journal of the Association for Information Systems*, *21*(5), 1214-1236. http://dx.doi.org/10.17705/1jais.00635

Pérez-Nicolás, R. L., Alario-Hoyos, C., Estévez-Ayres, I., Moreno-Marcos, P. M., Muñoz-Merino, P. J., & Delgado Kloos, C. (2021). Evaluation of an Algorithm for Automatic Grading of Forum Messages in MOOC Discussion Forums. *Sustainability*, *13*(16), 9364.

Phang, C. W., Kankanhalli, A., & Sabherwal, R. (2009). Usability and sociability in online communities: A comparative study of knowledge seeking and contribution. *Journal of the association for information systems*, *10*(10), 2.

Phillips, D. C., Phillips, D. C., & Burbules, N. C. (2000). *Postpositivism and educational research*. Rowman & Littlefield.

Picardi, E. (2011). Pragmatism as anti-representationalism? In *New Perspectives on Pragmatism and Analytic Philosophy*, 129-144. Brill.

Pipek, V., Wulf, V., & Johri, A. (2012). Bridging artifacts and actors: Expertise sharing in organizational ecosystems. *Computer Supported Cooperative Work*, *21*(2), 261-282.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879. https://doi.org/10.1037/0021-9010.88.5.879

Polinsky, M. (2012). Headedness, again. *Theories of Everything. In Honor of Ed Keenan*.

Pollett, S., Wood, N., Boscardin, W. J., Bengtsson, H., Schwarcz, S., Harriman, K., Winter, K., & Rutherford, G. (2015). Validating the use of Google Trends to enhance pertussis surveillance in California. *PLOS Current*. https://doi.org/10.1371/currents.outbreaks.7119696b3e7523faa4543faac87c56c2

Poquet, O., Dowell, N., Brooks, C., & Dawson, S. (2018). Are MOOC forums changing? Proceedings of the 8th international conference on learning analytics and knowledge,

Porter, C. E. (2015). Virtual communities and social networks. *Communication and technology*, 161-179.

Powell, J. K. (2011). The Rise of the Knowledge Market. *Forbes*, 1-3. https://www.forbes.com/sites/jpmorganchase/2017/11/09/ben-simmons-easily-navigates-court-business-of-sports/#7876abd33058

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. *Scientific Reports*, *3*, 1684. https://doi.org/10.1038/srep01684

Priharsari, D., Abedin, B., & Mastio, E. (2020). Value co-creation in firm sponsored online communities. *Internet Research*, *30*(3), 763-788. https://doi.org/10.1108/INTR-05-2019-0205

Pu, J., Liu, Y., Chen, Y., Qiu, L., & Cheng, H. K. (2022). What questions are you inclined to answer? Effects of hierarchy in corporate Q&A communities. *Information Systems Research*, *33*(1), 244-264.

Qi, T., Wang, T., Ma, Y., & Zhou, X. (2019). Knowledge payment research: status quo and key issues. *International Journal of Crowd Science*, *3*(2), 117-137. https://doi.org/10.1108/IJCS-01-2019-0007

Qi, T., Wang, T., & Yan, J. (2021). The spillover effects of different monetary incentive levels on health experts' free knowledge contribution behavior. *Internet Research*, *31*(6), 2143-2166. https://doi.org/10.1108/INTR-08-2020-0445

Qiang, J. P., Chen, P., Ding, W., Xie, F., & Wu, X. (2016). Multi-document summarization using closed patterns. *Knowledge Based Systems*, *99*, 28-38. https://doi.org/10.1016/j.knosys.2016.01.030

Qiao, D., Lee, S.-Y., Whinston, A. B., & Wei, Q. (2021). Mitigating the Adverse Effect of Monetary Incentives on Voluntary Contributions Online. *Journal of Management Information Systems*, *38*(1), 82-107. https://doi.org/10.1080/07421222.2021.1870385

Qiu, L., & Kumar, S. (2017). Understanding voluntary knowledge provision and content contribution through a social-media-based prediction market: A field experiment. *Information Systems Research*, *28*(3), 529-546. https://doi.org/10.1287/isre.2016.0679

Raban, D., Gonen, R., Brady, C., & Mazor, M. (2014). Increased efficiency through pricing in online labor markets. *Journal of Electronic Commerce Research*, *15*(1), 58.

Raban, D. R. (2007). User-centered evaluation of information: A research challenge. *Internet Research*, *17*(3), 306-322. https://www.emeraldinsight.com/doi/abs/10.1108/10662240710758948

Raban, D. R., Barzilai, S., & Portnoy, L. (2019). The Unexpected Benefits of Paying for Information: The Effects of Payment on Information Source Choices and Epistemic Thinking. *Proceeding in the International Conference on Business Informatics Research*, Katowice, Poland.

Raban, D. R., & Harper, F. M. (2008). Motivations for answering questions online. *New media and innovative technologies*, *73*.

Raban, D. R., & Mazor, M. (2013). The Willingness to Pay for Information in Digital Marketplaces. *Proceeding in the International Conference on Business Informatics Research,* Warsaw, Poland.

Raban, D. R., & Rafaeli, S. (2006). The effect of source nature and status on the subjective value of information. *Journal of the Association for Information Science and Technology*, *57*(3), 321-329. https://onlinelibrary.wiley.com/doi/pdf/10.1002/asi.20280

Raban, D. R., & Rafaeli, S. (2007). Investigating ownership and the willingness to share information online. *Computers in Human Behavior*, *23*(5), 2367-2382. https://doi.org/10.1016/j.chb.2006.03.013

Rad, D., Dughi, T., Ignat, S., & Rad, G. (2021). The mediating role of social media context awareness on the relationship between autonomy need frustration and behavioral disengagement as coping mechanism. In M. Milcu (Ed.), *Rethinking applied psychology: research paradigms vs. practical approaches*. Editura Universitara, Bucureşti.

Rafaeli, S., & Ariel, Y. (2008). Online motivational factors: Incentives for participation and contribution in Wikipedia. *Psychological aspects of cyberspace: Theory, Research, Applications*, *2*(08), 243-267.

Rafaeli, S., & Raban, D. R. (2003). Experimental investigation of the subjective value of information in trading. *Journal of the Association for Information Systems*, *4*(5), 119-139. https://ssrn.com/abstract=999989

Rafaeli, S., Raban, D. R., & Ravid, G. (2005). Social and economic incentives in Google Answers. *Proceeding in the ACM Workshop Sustaining Community: The role and design of incentive mechanisms in online systems*, Sanibel Island, USA,

Rallis, S. F., & Rossman, G. B. (2009). Ethics and trustworthiness. In *Qualitative research in applied linguistics*, 263-287. Springer.

Randall, A., & Stoll, J. R. (1983). Existence value in a total valuation framework. *Managing air quality and scenic resources at national parks and wilderness areas*, 265-274.

Randhawa, K., Josserand, E., Schweitzer, J., & Logue, D. (2017). Knowledge collaboration between organizations and online communities: the role of open innovation intermediaries. *Journal of Knowledge Management*, *21* (6), 1293-1318.

Ranta, V., Aarikka-Stenroos, L., & Väisänen, J. M. (2021). Digital technologies catalyzing business model innovation for circular economy—Multiple case study. *Resources, Conservation and Recycling*, *164*, 105155.

Rao, A. R., Qu, L., & Ruekert, R. W. (1999). Signaling unobservable product quality through a brand ally. *Journal of Marketing Research*, *36*(2), 258-268.

Reeson, A., Duenser, A., & Lochner, M. (2017). Computer says no: robo-advice is growing but we still don't trust it. *Business + Economy*. https://theconversation.com/computer-says-no-robo-advice-is-growing-but-we-still-dont-trust-it-80751

Reeson, A., & Tisdell, J. (2007). *Markets, motivations and public goods: experimental investigations on the impact of institutions*.

Regner, T. (2004). Why Voluntary Contributions? Google Answers! *Proceeding in the 13th International Conference on Web Information System Engineering,* Paphos, Cyprus.

Repo, A. J. (1989). The value of information: Approaches in economics, accounting, and management science. *Journal of the American Society for Information Science*, *40*(2), 68. https://doi.org/10.1002/(SICI)1097-4571(198903)40:2<68::AID-ASI2>3.0.CO;2-J

Rich, R. F. (1991). Knowledge creation, diffusion, and utilization: Perspectives of the founding editor of Knowledge. *Science Communication*, *12*(3), 319-337. https://doi.org/10.1177/107554709101200308

Richter, G., Raban, D. R., & Rafaeli, S. (2015). Studying gamification: the effect of rewards and incentives on motivation. In *Gamification in education and business*. 21-46. Springer International Publishing.

Ridings, C. M., & Gefen, D. (2004). Virtual community attraction: Why people hang out online. *Journal of Computer-Mediated Communication*, *10*(1).

Rifkin, J. (2014). *The zero marginal cost society: The internet of things, the collaborative commons, and the eclipse of capitalism*. St. Martin's Press.

Ritter, A., Clark, S., & Etzioni, O. (2011). Named entity recognition in tweets: an experimental study. *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing,* Edinburgh, UK.

Roberts, J. A., Hann, I.-H., & Slaughter, S. A. (2006). Understanding the motivations, participation, and performance of open-source software developers: A longitudinal study of the Apache projects. *Management Science*, *52*(7), 984-999.

Rochet, J. C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, *1*(4), 990-1029. https://doi.org/10.1162/154247603322493212

Rochet, J. C., & Tirole, J. (2006). Two-sided markets: a progress report. *The RAND Journal of Economics*, *37*(3), 645-667. https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1756-2171.2006.tb00036.x

Rodan, S., & Galunic, C. (2004). More than network structure: How knowledge heterogeneity influences managerial performance and innovativeness. *Strategic Management Journal*, *25*(6), 541-562.

Roth, A. E. (2007). The art of designing markets. *Harvard Business Review*, *85*(10), 118.

Roth, A. E. (2008). What have we learned from market design? *The Economic Journal*, *118*(527), 285-310. https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-0297.2007.02121.x

Roy, P. K., Ahmad, Z., Singh, J. P., Alryalat, M. A. A., Rana, N. P., & Dwivedi, Y. K. (2018). Finding and Ranking High-Quality Answers in Community Question Answering Sites. *Global Journal of Flexible Systems Management*, *19*(1), 53-68. https://doi.org/10.1007/s40171-017-0172-6

Roy, P. K., Singh, J. P., Baabdullah, A. M., Kizgin, H., & Rana, N. P. (2018). Identifying reputation collectors in community question answering (CQA) sites: Exploring the dark side of social media. *International Journal of Information Management*, *42*, 25-35. https://doi.org/10.1016/j.ijinfomgt.2018.05.003

Rui, H., & Whinston, A. (2012). Information or attention? An empirical study of user contribution on Twitter. *Information Systems and e-Business management*, *10*(3), 309-324.

Rustam, D. D., & van der Weide, T. P. T. (2016). The knowledge market online learning (K-MALL) architecture for higher education. *Proceedings in the 2016 International Conference on Advanced Computer Science and Information Systems*, West Java, Indonesia. https://doi.org/10.1109/ICACSIS39041.2016

Ryan, P., & Williams, A. (2014). The Commercialisation of MOOCs. *Proceedings of the 12th APacCHRIE Conference*, Subang Jaya, Malaysia.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist*, *55*(1), 68.

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology*, *61*, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860

Sá, C., & Grieco, J. (2016). Open data for science, policy, and the public good. *Review of Policy Research*, *33*(5), 526-543.

Salameh, A., & Zamil, Z. (2020). The effects of reward systems and organizational structure on tacit knowledge sharing. *Management Science Letters*, *10*(10), 2229-2236. https://doi.org/10.5267/j.msl.2020.3.013

Salmon, F. (2009). It's expensive, so it must be good. *The Economist*. https://www.economist.com/blogs/freeexchange/2009/09/its_expensive_so_it_must_be_go

Sanderson, T., Reeson, A., & Box, P. (2017a). *Cultivating Trust: Towards an Australian Agricultural Data Market*. CSIRO. https://publications.csiro.au/rpr/pub?pid=csiro:EP177171

Sanderson, T., Reeson, A., & Box, P. (2017b). *Understanding and unlocking the value of public research data*. https://publications.csiro.au/rpr/download?pid=csiro:EP168075&dsid=DS2

Sanderson, T., Reeson, A., & Box, P. (2019). Optimizing Open Government: an economic perspective on data sharing. *Proceedings of the 12th International Conference on Theory and Practice of Electronic Governance,* Melbourne, Australia.

Saposnik, G., Redelmeier, D., Ruff, C. C., & Tobler, P. N. (2016). Cognitive biases associated with medical decisions: a systematic review. *BMC medical informatics and decision making*, *16*(1), 1-14. https://doi.org/10.1186/s12911-016-0377-1

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students*. Pearson Education.

Scheuer, S., Jache, J., Sumfleth, L., Wellmann, T., & Haase, D. (2021). Creating accessible evidence bases: Opportunities through the integration of interactive tools into literature review synthesis. *MethodsX*, *8*, 101558.

Schmidl, J. (2012). *Fostering Knowledge Exchange Based on Relevant Activities* Technische Universität München].

Schmitt, A., Borzillo, S., & Probst, G. (2012). Don't let knowledge walk away: Knowledge retention during employee downsizing. *Management Learning*, *43*(1), 53-74.

Schneckenberg, D. (2009). Web 2.0 and the empowerment of the knowledge worker. *Journal of Knowledge Management*. *13*(6), 509-520. https://doi.org/10.1108/13673270910997150

Schneider, C., Weinmann, M., & Vom Brocke, J. (2018). Digital nudging: guiding online user choices through interface design. *Communications of the Association for Computing Machinery*, *61*(7), 67-73.

Seaborn, K., & Fels, D. I. (2015). Gamification in theory and action: A survey. *International Journal of Human-Computer Studies*, *74*, 14-31. https://doi.org/10.1016/j.ijhcs.2014.09.006

Seely Brown, J., & Adler, R. (2008). Open education, the long tail, and learning 2.0. *Educause Review*, *43*(1), 16-20.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. John Wiley & Sons.

Seleim, A. A., & Khalil, O. E. (2011). Understanding the knowledge management-intellectual capital relationship: a two-way analysis. *Journal of Intellectual Capital*, *12*(4), 586-614. https://www.emeraldinsight.com/doi/abs/10.1108/14691931111181742

Serrat, O. (2017). On Internal Knowledge Markets. In O. Serrat (Ed.), *Knowledge Solutions: Tools, Methods, and Approaches to Drive Organizational Performance*, 969-977. Springer Singapore. https://doi.org/10.1007/978-981-10-0983-9_110

Servan-Schreiber, E., Wolfers, J., Pennock, D. M., & Galebach, B. (2004). Prediction markets: Does money matter? *Electronic markets*, *14*(3), 243-251.

Sha, A. S., Haller, A., & Shi, Y. (2022a). *Effects of label usage on question lifecycle in Q&A community* The 30th European Conference on Information Systems, Timisoara, Romania.

Sha, A. S., Haller, A., & Shi, Y. (2022b). *How Question Features Influence Page Traffic? A Comparative Study on General and Domain-specific Q&As. Proceeding in the 26th Pacific Asia Conference on Information Systems*, Taipei and Sydney.

Sha, S. A., Shi, Y., & Haller, A. (2020). How question quality drives Web performance in community question answering sites. *arXiv e-prints*, arXiv: 2012.06263.

Shah, C., Kitzie, V., & Choi, E. (2014). Modalities, motivations, and materials – investigating traditional and social online Q&A services. *Journal of Information Science*, *40*(5), 669-687. https://doi.org/10.1177/0165551514534140

Shah, C., Oh, S., & Oh, J. S. (2009). Research agenda for social Q&A. *Library & Information Science Research*, *31*(4), 205-209.

Shah, C., & Pomerantz, J. (2010). Evaluating and predicting answer quality in community QA. Proceedings of the 33rd International ACM SIGIR Conference on Research and Development in Information Retrieval, Geneva, Switzerland.

Shah, D. (2015). *MOOC Trends in 2015: The Death of Free Certificates* (2015 MOOC Roundup Series, Issue. https://www.class-central.com/report/death-of-free-certificates/

Shah, D. (2016). *edX's 2016: Year in Review* (MOOC-Roundup-2016, Issue. https://www.class-central.com/report/edx-2016-review/

Shah, D. (2017). *200 universities just launched 600 free online courses.* (Class Central, Issue. https://qz.com/1120344/200-universities-just-launched-600-free-online-courses-heres-the-full-list/

Shah, D. (2020). By the numbers: MOOCs during the pandemic. *The Report by Class Central*.

Shah, S. K. (2006). Motivation, governance, and the viability of hybrid forms in open-source software development. *Management Science*, *52*(7), 1000-1014.

Shampanier, K., Mazar, N., & Ariely, D. (2007). Zero as a special price: The true value of free products. *Marketing Science*, *26*(6), 742-757.

Shapiro, C., & Varian, H. R. (1998). Versioning: the smart way to sell information. *Harvard Business Review*, *107*(6), 107.

Shapiro, C., Varian, H. R., & Becker, W. (1999). Information rules: a strategic guide to the network economy. *Journal of Economic Education*, *30*, 189-190.

Shen, D., Van Alstyne, M., Lippman, A., & Benbya, H. (2012). Barter: Mechanism design for a market incented wisdom exchange. *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work,* Seattle, USA.

Shi, Y., & Li, X. (2017). The Time Preference of Chinese Tend to be Less Affected by Positive Emotions: As Proved by an Experimental Study. *Journal of Economics and Behavioral Studies*, *9*(4), 201-216.

Shi, Y., Li, X., Haller, A., & Campbell, J. (2018). Knowledge pricing structures on MOOC platform-A use case analysis on edX. *Proceedings of the 22nd Pacific Asia Conference on Information Systems, Yokohama, Japan.*

Shiller, B. R. (2014). First degree price discrimination using big data.

Shivendu, S., & Zhang, R. (2016). The Impact of Digitization on Information Goods Pricing Strategy. *Proceedings of the 22nd Americas Conference on Information Systems*, San Diego, USA.

Shtok, A., Dror, G., Maarek, Y., & Szpektor, I. (2012). Learning from the past: answering new questions with past answers. *Proceedings of the 21st International Conference on World Wide Web*, Lyon France.

Silic, M., & Lowry, P. B. (2020). Using design-science based gamification to improve organizational security training and compliance. *Journal of Management Information Systems*, *37*(1), 129-161. https://doi.org/10.1080/07421222.2019.1705512

Sim, T. S. (2021). *Exploratory research into intellectual property commercialisation: The role of polytechnics in facilitating small and medium enterprise development in Singapore,* The University of Adelaide.

Simmhan, Y. L., Plale, B., & Gannon, D. (2005). A survey of data provenance in e-science. *ACM Special Interest Group on Management of Data (SIGMOD) Record*, *34*(3), 31-36. https://doi.org/10.1145/1084805.1084812

Singh, J. B., Chandwani, R., & Kumar, M. (2018). Factors affecting Web 2.0 adoption: exploring the knowledge sharing and knowledge seeking aspects in health care professionals. *Journal of knowledge management*, *22*(1), 21-43. https://doi.org/10.1108/JKM-08-2016-0320

Skyrme, D. (2012). *Capitalizing on knowledge*. Routledge.

Sloan, S., Bodey, K., & Gyrd-Jones, R. (2015). Knowledge sharing in online brand communities. *Qualitative Market Research: An International Journal*, *18*(3), 320-345. https://doi.org/10.1108/QMR-11-2013-0078

Smith, J. K. (1983). Quantitative versus qualitative research: An attempt to clarify the issue. *Educational researcher*, *12*(3), 6-13.

Song, A. K. (2019). The Digital Entrepreneurial Ecosystem—a critique and reconfiguration. *Small Business Economics*, *53*(3), 569-590.

Soutar, G. N., & Turner, J. P. (2002). Students' preferences for university: A conjoint analysis. *International Journal of Educational Management*, *16*(1), 40-45. https://www.emeraldinsight.com/doi/abs/10.1108/09513540210415523

Spasojevic, M., Rossetto, M., Sparrow, B., Ray, C., Salguero-Gomez, R., Poelen, J., Adams, V., Madin, J., Penone, C., & Alroy, J. (2020). Open Science principles for accelerating trait-based science across the Tree of Life. *Nature Ecology & Evolution*. https://doi.org/10.1038/s41559-020-1109-6

Spence, M. (1976). Informational aspects of market structure: An introduction. *The Quarterly Journal of Economics*, 591-597.

Spence, M. (2002). Signaling in retrospect and the informational structure of markets. *American Economic Review*, *92*(3), 434-459.

Srisamran, P., & Ractham, V. V. (2020). Impact of knowledge adoption and cognitive learning in the knowledge transfer process. *International Journal of Knowledge Management*, *16*(3), 1-16.

Srivastava, R., & Rangarajan, D. (2008). Understanding the salespeople's "feedback-satisfaction" linkage: what role does job perceptions play? *Journal of Business & Industrial Marketing*.

Steckler, A., & McLeroy, K. R. (2008). The importance of external validity. *Am J Public Health*, *98*(1), 9-10. https://doi.org/10.2105/ajph.2007.126847

Stewart, I., Yang, D., & Eisenstein, J. (2020). Characterizing collective attention via descriptor context: A case study of public discussions of crisis events. Proceedings of the International AAAI Conference on Web and Social Media, Atlanta, USA.

Stieglitz, S., & Dang-Xuan, L. (2013). Emotions and information diffusion in social media—sentiment of microblogs and sharing behavior. *Journal of Management Information Systems*, *29*(4), 217-248.

Stigler, G. J. (1961). The economics of information. *Journal of Political Economy*, *69*(3), 213-225.

Strik, N. P., Hamstra, M. R. W., & Segers, M. S. R. (2021). Antecedents of Knowledge Withholding: A Systematic Review & Integrative Framework. *Group & Organization Management*, *46*(2), 223-251. https://doi.org/10.1177/1059601121994379

Stringer, E. T. (2013). *Action research*. Sage Publications.

StudyAssist. (2016). *Australian Government Study AssistStudent: Student Contribution Amounts* (Information for students about government assistance for financing tertiary study, Issue. http://studyassist.gov.au/sites/studyassist/helppayingmyfees/csps/pages/student-contribution-amounts

Sturges, P. (2002). Remember the human: the first rule of netiquette, librarians and the Internet. *Online Information Review*, *26*(3), 209-216.

Su, L., Li, Y., & Li, W. (2019). Understanding Consumers' Purchase Intention for Online Paid Knowledge: A Customer Value Perspective. *Sustainability*, *11*(19), 5420.

Su, L., Zhang, R., Li, Y., & Li, W. (2018). *What drives trust in online paid knowledge? The role of customer value*, *Proceeding in the 22nd Pacific Asia Conference on Information Systems,* Yokohama, Japan.

Sudarsanam, S., Sorwar, G., & Marr, B. (2003). Valuation of intellectual capital and real option models. PMA Intellectual Capital Symposium,

Sudarsanam, S., Sorwar, G., & Marr, B. (2006). Real options and the impact of intellectual capital on corporate value. *Journal of Intellectual Capital*, *7*(3), 291-308. https://www.emeraldinsight.com/doi/abs/10.1108/14691930610681410

Suh, A., & Wagner, C. (2017). How gamification of an enterprise collaboration system increases knowledge contribution: an affordance approach. *Journal of knowledge Management*, *21*(2), 416-431. https://doi.org/10.1108/JKM-10-2016-0429

Sultanov, K., Khamdamov, U., Sultanov, D., & Abdullaev, M. (2021). Mathematical Model of Information Exchange through the Educational Platforms. *Proceedings in the International Conference on Information Science and Communications Technologies*, Tashkent, Uzbekistan. https://doi.org/10.1109/ICISCT52966.2021

Sun, Y., Dong, X., & McIntyre, S. (2017). Motivation of user-generated content: Social connectedness moderates the effects of monetary rewards. *Marketing Science*, *36*(3), 329-337.

Sun, Y., Ni, L., Zhao, Y., Shen, X. L., & Wang, N. (2019). Understanding students' engagement in MOOCs: An integration of self-determination theory and theory of relationship quality. *British journal of Educational Technology*, *50*(6), 3156-3174.

Sundararajan, A. (2004). Nonlinear pricing of information goods. *Management Science*, *50*(12), 1660-1673.

Sundaresan, S., & Zhang, Z. (2020). Knowledge-sharing rewards in enterprise social networks: effects of learner types and impact of digitisation. *Enterprise Information Systems*, *14*(5), 661-679. https://doi.org/10.1080/17517575.2020.1737884

Susman, G. I., & Evered, R. D. (1978). An Assessment of the Scientific Merits of Action Research. *Administrative Science Quarterly*, *23*(4), 582-603. https://doi.org/10.2307/2392581

Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research*, *14*(1), 47-65.

Sutanto, J., & Jiang, Q. (2013). Knowledge seekers' and contributors' reactions to recommendation mechanisms in knowledge management systems. *Information & Management*, *50*(5), 258-263. https://doi.org/10.1016/j.im.2012.11.004

Sutton, J. (1991). *Sunk costs and market structure: Price competition, advertising, and the evolution of concentration*. MIT press.

Szulanski, G. (1996). Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic management journal*, *17*(2), 27-43. https://doi.org/ 10.1002/smj.4250171105

Taj, S. A. (2016). Application of signaling theory in management research: Addressing major gaps in theory. *European management journal*, *34*(4), 338-348.

Tang, Q., Gu, B., & Whinston, A. B. (2012). Content contribution for revenue sharing and reputation in social media: A dynamic structural model. *Journal of Management Information Systems*, *29*(2), 41-76.

Tanriverdi, H., & Du, K. (2020). Corporate Strategy Changes and Information Technology Control Effectiveness in Multibusiness Firms. *MIS Quarterly*, *44*(4).

Tanriverdi, H., Rai, A., & Venkatraman, N. (2010). Research commentary—reframing the dominant quests of information systems strategy research for complex adaptive business systems. *Information Systems Research*, *21*(4), 822-834.

Tausczik, Y. R., Wang, P., & Choi, J. (2017). Which Size Matters? Effects of Crowd Size on Solution Quality in Big Data Q&A Communities. *Proceedings in the 11th Conference on WEB and Social Media,* Montreal, Canada.

Teddlie, C., & Tashakkori, A. (2010). Overview of contemporary issues in mixed methods research. *Sage handbook of mixed methods in social and behavioral research*, *2*, 1-44.

Teece, D. J. (1998). Capturing value from knowledge assets: The new economy, markets for know-how, and intangible assets. *California management review*, *40*(3), 55-79. http://journals.sagepub.com/doi/10.2307/41165943

Teece, D. J. (2008). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. In *The Transfer And Licensing Of Know-How And Intellectual Property: Understanding the Multinational Enterprise in the Modern World*, 67-87. World Scientific.

Terwiesch, C., & Xu, Y. (2008). Innovation contests, open innovation, and multiagent problem solving. *Management Science*, *54*(9), 1529-1543.

Tharenou, P., Donohue, R., & Cooper, B. (2007). *Management research methods*. Cambridge University Press.

Thierauf, R. J. (1999). *Knowledge management systems for business*. Greenwood Publishing Group.

Thomala, L. L. (2022). *Number of users paying for knowledge and its annual growth rate in China from 2015 to 2021 with forecasts until 2023*. Statista.com. Retrieved 1st Jan from https://www.statista.com/statistics/1289035/china-paid-knowledge-user-size/#:~:text=In%202021%2C%20the%20number%20of,market%20would%20surpass%20500%20million

Thomas-Hunt, M. C., Ogden, T. Y., & Neale, M. A. (2003). Who's really sharing? Effects of social and expert status on knowledge exchange within groups. *Management Science*, *49*(4), 464-477.

Thomas, A., & Gupta, V. (2022). The role of motivation theories in knowledge sharing: an integrative theoretical reviews and future research agenda. *Kybernetes*, *51*(1), 116-140. https://doi.org/10.1108/K-07-2020-0465

Tian, Y., Mao, L., Zhou, M., & Cao, Q. (2021). Knowledge-based psychological ownership and knowledge hiding: The roles of loss of knowledge power and emotional intelligence. *Social Behavior and Personality: an International Journal*, *49*(8), 1-13.

Tippmann, E., Sharkey Scott, P., & Parker, A. (2017). Boundary Capabilities in MNCs: Knowledge Transformation for Creative Solution Development. *Journal of Management Studies*, *54*(4), 455-482. https://doi.org/10.1111/joms.12253

Toba, H., Ming, Z.-Y., Adriani, M., & Chua, T.-S. (2014). Discovering high quality answers in community question answering archives using a hierarchy of classifiers. *Information Sciences*, *261*, 101-115. https://doi.org/10.1016/j.ins.2013.10.030

Tong, J., & Mitra, A. (2008). Knowledge maps and organisations: an overview and interpretation. *International Journal of Business Information Systems*, *3*(6), 587-608. http://dx.doi.org/10.1504/IJBIS.2008.018992

Treem, J. W., & Leonardi, P. M. (2013). Social media use in organizations: Exploring the affordances of visibility, editability, persistence, and association. *Annals of the International Communication Association*, *36*(1), 143-189.

Tsai, M. T., & Lee, K. W. (2006). A study of knowledge internalization: from the perspective of learning cycle theory. *Journal of knowledge management*, *10*(3), 57-71. https://doi.org/10.1108/13673270610670858

Tschimmel, K. (2012). Design Thinking as an effective Toolkit for Innovation. Proceedings in the Conference of Action for Innovation: Innovating from Experience. https://doi.org/10.13140/2.1.2570.3361

Ukueberuwa, M. (2018). *Return of the MOOCs: An innovative non-profit shows how Internet-based education can help contain the spiraling costs of college.* (City Journal, Issue. https://www.city-journal.org/html/return-moocs-15650.html

Utz, S., & Levordashka, A. (2017). Knowledge networks in social media. In *The Psychology of Digital Learning*, 171-186. Springer.

Vallas, S., & Schor, J. B. (2020). What do platforms do? Understanding the gig economy. *Annual Review of Sociology*, *46*, 273-294.

Van Alstyne, H. B. M. (2013). Internal Knowledge Markets: Design From The Outside In. *Sloan Management Review*, *52*(2), 66-77.

Van Alstyne, M. V. (1999). A proposal for valuing information and instrumental goods. Proceedings of the 20th International Conference on Information Systems, Atlanta, USA.

van Velsen, L., & Melenhorst, M. (2009). Incorporating user motivations to design for video tagging. *Interacting with Computers*, *21*(3), 221-232.

Van Wijk, R., Jansen, J. J. P., & Lyles, M. A. (2008). Inter- and Intra-Organizational Knowledge Transfer: A Meta-Analytic Review and Assessment of its Antecedents and Consequences. *Journal of Management Studies*, *45*(4), 830-853. https://doi.org/10.1111/j.1467-6486.2008.00771.x

Vasilescu, B., Serebrenik, A., Devanbu, P., & Filkov, V. (2014). How social Q&A sites are changing knowledge sharing in open-source software communities. Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing,

Vassileva, J. (2002). Motivating participation in peer-to-peer communities. Proceedings of the International Workshop on Engineering Societies in the Agents World, Madrid, Spain.

Vassileva, J. (2012). Motivating participation in social computing applications: a user modeling perspective. *User Modeling and User-adapted Interaction*, *22*(1), 177-201. https://doi.org/10.1007/s11257-011-9109-5

Vaughan, L., & Romero-Frías, E. (2014). Web search volume as a predictor of academic fame: An exploration of Google trends. *Journal of the Association for Information Science and Technology*, *65*(4), 707-720.

Venkatachalam, L. (2004). The contingent valuation method: a review. *Environmental Impact Assessment Review*, *24*(1), 89-124. https://doi.org/10.1016/S0195-9255(03)00138-0

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204.

Villasalero, M. (2013). Signaling, spillover and learning effects of knowledge flows on division performance within related diversified firms. *Journal of Knowledge Management*, *17*(6), 928-942. https://doi.org/10.1108/JKM-03-2013-0101

Voelpel, S. C., Dous, M., & Davenport, T. H. (2005). Five steps to creating a global knowledge-sharing system: Siemens' ShareNet. *The Academy of Management Executive*, *19*(2), 9-23.

W Chen, X. W. K. Z. (2017). Engaging Voluntary Contributions in Online Communities: A Hidden Markov Model. *MIS Quarterly*, *42*, 83-100.

Wallis, J. C., Rolando, E., & Borgman, C. L. (2013). If we share data, will anyone use them? Data sharing and reuse in the long tail of science and technology. *PloS one*, *8*(7), e67332. https://cloudfront.escholarship.org/dist/prd/content/qt32c171hw/qt32c171hw.pdf?t=nruob5

Walsh, R. G., Loomis, J. B., & Gillman, R. A. (1984). Valuing option, existence, and bequest demands for wilderness. *Land Economics*, *60*(1), 14-29.

Wang, C., Jin, X.-L., Zhou, Z., Fang, Y., Lee, M. K., & Hua, Z. (2015). Effect of perceived media capability on status updates in microblogs. *Electronic Commerce Research and Applications*, *14*(3), 181-191.

Wang, D.-p., & Li, J.-l. (2014). Knowledge Pricing of Knowledge Service Network in Agile Supply Chain. *Proceedings of the 9th International Symposium on Linear Drives for Industry Applications*, Hangzhou, China.

Wang, G., Gill, K., Mohanlal, M., Zheng, H., & Zhao, B. Y. (2013). Wisdom in the social crowd: an analysis of Quora. *Proceedings of the 22nd international conference on World Wide Web,* Janeiro, Brazil.

Wang, G., Liu, X., & Fan, W. (2011). *A knowledge adoption model-based framework for finding helpful user-generated contents in online communities*. *Proceeding in the 32nd International Conference on Information Systems,* Shanghai, China.

Wang, J., & Liu, L. (2019). Study on the mechanism of customers' participation in knowledge sharing. *Expert Systems*, *36*(5), e12367. https://doi.org/10.1111/exsy.12367

Wang, M., Rieger, M., & Hens, T. (2015). How Time Preferences Differ: Evidence from 53 Countries. *Journal of economic psychology*, *52*. https://doi.org/10.1016/j.joep.2015.12.001

Wang, Q., Wang, B., & Guo, L. (2015). Knowledge Base Completion Using Embeddings and Rules. *Proceedings of the 24th International Joint Conference on Artificial Intelligence,* Buenos Aires, Argentina.

Wang, S., & Noe, R. A. (2010). Knowledge sharing: A review and directions for future research. *Human Resource Management Review*, *20*(2), 115-131.

Wang, X. H., Zhang, D. Q., Gu, T., & Pung, H. K. (2004). Ontology based context modeling and reasoning using OWL. *Proceedings of the Second IEEE Annual Conference on Pervasive Computing and Communications Workshops*, Orlando, USA.

Wang, Z., & Scheepers, H. (2012). Understanding the intrinsic motivations of user acceptance of hedonic information systems: towards a unified research model. *Communications of the Association for Information Systems*, *30*(1), 17. https://doi.org/10.17705/1CAIS.03017

Wasko, M. M., & Faraj, S. (2000). "It is what one does": why people participate and help others in electronic communities of practice. *The Journal of Strategic Information Systems*, *9*(2), 155-173. https://doi.org/10.1016/S0963-8687(00)00045-7

Wasko, M. M., & Faraj, S. (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*, 35-57.

Waters, J. (2014). *Pricing information goods with piracy and heterogeneous consumers.* University of Warwick.

Weaver, W. (1949). *The mathematics of communication* (Vol. 181).

Weber, M. (1987). Decision making with incomplete information. *European Journal of Operational Research*, *28*(1), 44-57.

Wei, X., Chen, W., & Zhu, K. (2015). Motivating user contributions in online knowledge communities: virtual rewards and reputation. *Proceeding in the 48th Hawaii International Conference on System Sciences, Hawaii, USA.*

Wei, X. D., & Nault, B. R. (2014). Monopoly versioning of information goods when consumers have group tastes. *Production and Operations Management*, *23*(6), 1067-1081. https://onlinelibrary.wiley.com/doi/pdf/10.1111/poms.12180

Weiss, L. M. (1999). Collection and connection: The anatomy of knowledge sharing in professional service firms. *Academy of Management Proceedings*, *1999*(1), A1-A6.

Welle Donker, F., Van Loenen, B., & Bregt, A. K. (2016). Open Data and Beyond. *ISPRS International Journal of Geo-Information*, *5*(4), 48.

West, J. (2002). Information for Sale: My Experience with Google Answers. *Searcher*, *10*(9), 14-17.

Whelan, E. (2007). Exploring knowledge exchange in electronic networks of practice. *Journal of Information Technology*, *22*(1), 5-12.

Williams, C. (2007). Research methods. *Journal of Business & Economics Research*, *5*(3).

Wise, A. F., Cui, Y., Jin, W., & Vytasek, J. (2017). Mining for gold: Identifying content-related MOOC discussion threads across domains through linguistic modeling. *The Internet and Higher Education*, *32*, 11-28.

Wolf, P., Jakob, M. C., & Meissner, J. (2009). Why sharing boundary crossing? Understanding the motivation for knowledge sharing in virtual Communities of Practice. *Proceedings in the IEEE International Technology Management Conference,* Nottingham, UK. https://doi.org/10.1109/ITMC.2009

Wolfram, D. (2015). The symbiotic relationship between information retrieval and informetrics. *Scientometrics*, *102*(3), 2201-2214.

Wozniak, D. (2012). Gender differences in a market with relative performance feedback: Professional tennis players. *Journal of Economic Behavior & Organization*, *83*(1), 158-171.

Wu, B. (2021). Influence of MOOC learners discussion forum social interactions on online reviews of MOOC. *Education and Information Technologies*, *26*(3), 3483-3496. https://doi.org/10.1007/s10639-020-10412-z

Wu, H., & Lu, N. (2018). Service provision, pricing, and patient satisfaction in online health communities. *International Journal of Medical Informatics*, *110*, 77-89. https://doi.org/10.1016/j.ijmedinf.2017.11.009

Wei, X., Chen, W., & Zhu, K. (2015). Motivating User Contributions in Online Knowledge Communities: Virtual Rewards and Reputation. *Proceedings in the 48th Hawaii International Conference on System Sciences*, 3760-3769, Hawaii, USA.

Yadav, V., & Bethard, S. (2019). A survey on recent advances in named entity recognition from deep learning models. *arXiv preprint arXiv:1910.11470*.

Yan, Z., Kuang, L., Huang, N., & Hong, Y. (2018). Spillover Effects of Financial Incentives on Non-Incentivized User Engagement: Evidence from an Online Knowledge Exchange Platform. *Journal of Management Information Systems*, *36*(1), 289-320. https://doi.org/10.1080/07421222.2018.1550564

Yang, B., Tang, H., Hao, L., & Rose, J. R. (2022). Untangling chaos in discussion forums: A temporal analysis of topic-relevant forum posts in MOOCs. *Computers & Education*, *178*, 104402.

Yang, D., Kraut, R. E., & Rose, C. P. (2016). Exploring the Effect of Student Confusion in Massive Open Online Courses. *Journal of Educational Data Mining*, *8*(1), 52-83.

Yang, D., Piergallini, M., Howley, I., & Rose, C. (2014). Forum thread recommendation for massive open online courses. *Proceedings of the 7th International Conference on Educational Data Mining*, London, UK.

Yang, J., Adamic, L. A., & Ackerman, M. S. (2008). Competing to Share Expertise: The Taskcn Knowledge Sharing Community. *Proceedings in the International Conference on Weblogs and Social Media*, Washington, USA.

Yang, J., Adamic, L. A., & Ackerman, M. S. (2014). Crowdsourcing and knowledge sharing: strategic user behavior on taskcn. *Proceedings of the 9th ACM Conference on Electronic Commerce, Chicago, USA.*

Yang, S. C., & Farn, C.-K. (2009). Social capital, behavioural control, and tacit knowledge sharing—A multi-informant design. *International Journal of Information Management*, *29*(3), 210-218. https://doi.org/10.1016/j.ijinfomgt.2008.09.002

Yang, X., & Ye, H. J. (2019). Commercialized Content on Social Media Platforms: Exploring the Drivers of the Viewership of Paid Q&A. Proceedings of the 52nd Hawaii International Conference on System Sciences, Hawaii, USA.

Yang, Y., Chen, P.-y., & Pavlou, P. (2009). *Managing open innovation contests in online market. Proceedings of the 30th International Conference on Information Systems*, Phoenix, USA.

Ye, H., Kankanhalli, A., & Feng, Y. (2010). Why do they return help? Examining the motives of reciprocity in online communities. *Proceedings of the 14th Pacific Asia Conference on Information Systems*, Taipei, Taiwan.

Ye, H. J., Feng, Y., & Choi, B. C. (2015). Understanding knowledge contribution in online knowledge communities: A model of community support and forum leader support. *Electronic Commerce Research and Applications*, *14*(1), 34-45.

Yeh, C. C., & Ku, E. C. (2019). Process innovation capability and subsequent collaborative team performance in travel planning: a knowledge exchange platform perspective. *Current Issues in Tourism*, *22*(1), 107-126.

Ylöstalo, H. (2020). The role of scientific knowledge in dealing with complex policy problems under conditions of uncertainty. *Policy & Politics*, *48*(2), 259-276.

Yoo, C. C., Khern-am-nuai, W., Tanlamai, J., & Adulyasak, Y. (2021). Haters Gonna Hate? How Removing Downvote Option Impacts Discussions on Online Forum. How Removing Downvote Option Impacts Discussions on Online Forum.

Yoon, C., & Rolland, E. (2012). Knowledge-sharing in virtual communities: familiarity, anonymity and self-determination theory. *Behaviour & Information Technology*, *31*(11), 1133-1143. https://doi.org/10.1080/0144929X.2012.702355

Yousef, A. M. F., Chatti, M. A., Schroeder, U., & Wosnitza, M. (2014). What drives a successful MOOC? An empirical examination of criteria to assure design quality of MOOCs. *Proceedings of the IEEE 14th International Conference on Advanced Learning Technologies*, Athens, Greece.

Yu, Y., Khern-am-nuai, W., & Pinsonneault, A. (2018). The Impact of Performance-Contingent Monetary Incentives on User-Generated Content Contribution. *E-business and Ecommerce Digital Commerce*, 1-5.

Wang, Y., Jia, Y., Liu, D., Jin. X., & Cheng, X. (2015). Open web knowledge aided information search and data mining. *Journal of Computer Research and Development*, *52*(2), 456-474. http://dx.doi.org/10.7544/issn1000-1239.2015.20131342

Kuang, L., Huang, N., Hong, Y., & Yan, Z. (2018). Spillover Effects of Financial Incentives on Non-Incentivized User Engagement: Evidence from an Online Knowledge Exchange Platform. *Journal of Management Information Systems*, *36*(1), 289-320. https://doi.org/10.1080/07421222.2018.1550564

Zander, U., & Kogut, B. (1995). Knowledge and the Speed of the Transfer and Imitation of Organizational Capabilities: An Empirical Test. *Organization Science*, *6*(1), 76-92. https://doi.org/10.1287/orsc.6.1.76

Zhang, C. B., Li, N., Han, S. H., Zhang, Y. D., & Hou, R. J. (2021). How to alleviate social loafing in online brand communities: The roles of community support and commitment. *Electronic Commerce Research and Applications*, *47*, 101051. https://doi.org/10.1016/j.elerap.2021.101051

Zhang, J., Dang, Q., Lu, Y., & Sun, S. (2013). Suffix Tree Clustering with Named Entity Recognition. Proceedings in the International Conference on Cloud Computing and Big Data, Washington, USA.

Zhang, M., Zhang, Y., Zhao, L., & Li, X. (2020). What drives online course sales? Signaling effects of user-generated information in the paid knowledge market. *Journal of Business Research*, *118*, 389-397. https://doi.org/10.1016/j.jbusres.2020.07.008

Zhang, P. (2013). The affective response model: A theoretical framework of affective concepts and their relationships in the ICT context. *MIS Quarterly*, 247-274.

Zhang, W., Jiang, Y., Zhou, W., & Pan, W. (2022). Antecedents of knowledge-seeking intentions and efforts within new product development teams: empirical evidence from knowledge-based Chinese companies. *Journal of Knowledge Management*. https://doi.org/10.1108/JKM-08-2021-0617

Zhang, X., Jiang, S., Xiao, Y. & Cheng, Y. (2018) Global challenges and developmental lessons in the knowledge sharing economy. *Journal of Global Information Technology Management. 21,* 167-171. https://doi.org/10.1080/1097198X.2018.1505071

Zhang, X., Liu, S., & Chen, X. (2017). Social capital, motivations, and knowledge sharing intention in health Q&A communities. *Management Decision, 55*(7). 1536-1557. https://doi.org/10.1108/MD-10-2016-0739

Zhang, X., Liu, S., Deng, Z., & Chen, X. (2017). Knowledge sharing motivations in online health communities: A comparative study of health professionals and normal users. *Computers in Human Behavior*, *75*, 797-810. https://doi.org/10.1016/j.chb.2017.06.028

Zhang, X., & Liu, Y. (2021). The Effect of Monetary Incentive Mechanisms on UGC Contributors. *Proceeding in the14th China Summer Workshop on Information Management*, Chongqing, China.

Zhang, Y., Lu, T., Phang, C. W., & Zhang, C. (2019). Scientific Knowledge Communication in Online Q&A Communities: Linguistic Devices as a Tool to Increase the Popularity and Perceived Professionalism of Knowledge Contribution. *Journal of the Association for Information Systems*, *20*(8), https://doi.org/10.17705/1jais.00 563

Zhang, Y., Zhang, M., Luo, N., Wang, Y., & Niu, T. (2019). Understanding the formation mechanism of high-quality knowledge in social question and answer communities: A knowledge co-creation perspective. *International Journal of Information Management*, *48*, 72-84. https://doi.org/10.1016/j.ijinfomgt.2019.01.022

Zhang, Z., & Jasimuddin, S. M. (2012). Knowledge market in organizations: incentive alignment and IT support. *Industrial Management & Data Systems*, *112*(7), 1101-1122. https://www.emeraldinsight.com/doi/abs/10.1108/02635571211255041

Zhang, Z., Nan, G., Li, M., & Tan, Y. (2016). Duopoly Pricing Strategy for Information Products with Premium Service: Free Product or Bundling? *Journal of Management Information Systems*, *33*(1), 260-295.

Zhang, Z., & Sundaresan, S. (2010). Knowledge markets in firms: knowledge sharing with trust and signalling. *Knowledge Management Research & Practice*, *8*(4), 322-339. https://doi.org/10.1057/kmrp.2010.22

Zhang, Z. J., & Jasimuddin, S. M. (2008). Pricing strategy of online knowledge market: The analysis of Google Answers. *International Journal of E-Business Research*, *4*(1), 55.

Zhang, Z. J., Zeng, Z., & Zhang, L. (2016). Knowledge expertise and mass amateurization on internet-based knowledge markets. *Journal of Industrial Integration and Management*, *1*(01), 1650002. https://doi.org/10.1142/S2424862216500020

Zhao, D., Li, X. Y., & Ma, H. (2014). How to crowdsource tasks truthfully without sacrificing utility: Online incentive mechanisms with budget constraint. *Proceedings in the IEEE Annual Joint Conference: INFOCOM, IEEE Computer and Communications Societies*, Toronto, Canada.

Zhao, L., Detlor, B., & Connelly, C. E. (2016). Sharing Knowledge in Social Q&A Sites: The Unintended Consequences of Extrinsic Motivation. *Journal of Management Information Systems*, *33*(1), 70-100. https://doi.org/10.1080/07421222.2016.1172459

Zhao, L., Lu, Y., Wang, B., Chau, P. Y., & Zhang, L. (2012). Cultivating the sense of belonging and motivating user participation in virtual communities: A social capital perspective. *International Journal of Information Management*, *32*(6), 574-588.

Zhao, S., Jiang, Y., Peng, X., & Hong, J. (2020). Knowledge sharing direction and innovation performance in organizations: do absorptive capacity and individual creativity matter? *European Journal of Innovation Management*, *24*(2), 371-394.

Zhao, Y., Peng, X., Liu, Z., Song, S., & Hansen, P. (2020). Factors that affect asker's pay intention in trilateral payment-based social Q&A platforms: From a benefit and cost perspective. *Journal of the Association for Information Science and Technology*, *71*(5), 516-528. https://doi.org/10.1002/asi.24262

Zhao, Y., Zhao, Y., Yuan, X., & Zhou, R. (2018). How knowledge contributor characteristics and reputation affect user payment decision in paid Q&A? An empirical analysis from the perspective of trust theory. *Electronic Commerce Research and Applications*, *31*, 1-11. https://doi.org/10.1016/j.elerap.2018.07.001

Zheng, H., Li, D., & Hou, W. (2011). Task design, motivation, and participation in crowdsourcing contests. *International Journal of Electronic Commerce*, *15*(4), 57-88. https://www.tandfonline.com/doi/pdf/10.2753/JEC1086-4415150402

Zheng, Y., Zhang, X., & Xiao, Y. (2018). Making the Most Cost-effective Decision in Online Paid Q&A Community: An Expert Recommender System with Motivation Modeling and Knowledge Pricing. *Proceedings of the Web Conference*, Lyon, France.

Zheng, Y., Zhao, K., & Stylianou, A. (2013). The impacts of information quality and system quality on users' continuance intention in information-exchange virtual communities: An empirical investigation. *Decision Support Systems*, *56*, 513-524.

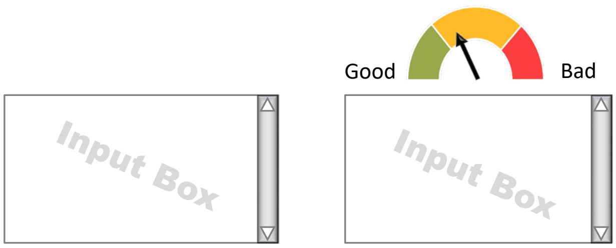
Zhu, M., Sari, A., & Lee, M. M. (2018). A systematic review of research methods and topics of the empirical MOOC literature (2014–2016). *The Internet and Higher Education*.

Ziemba, E., & Eisenbardt, M. (2016). Incentives encouraging prosumers to knowledge sharing–framework based on Polish study. *Online Journal of Applied Knowledge Management (OJAKM)*, *4*(2), 146-166.

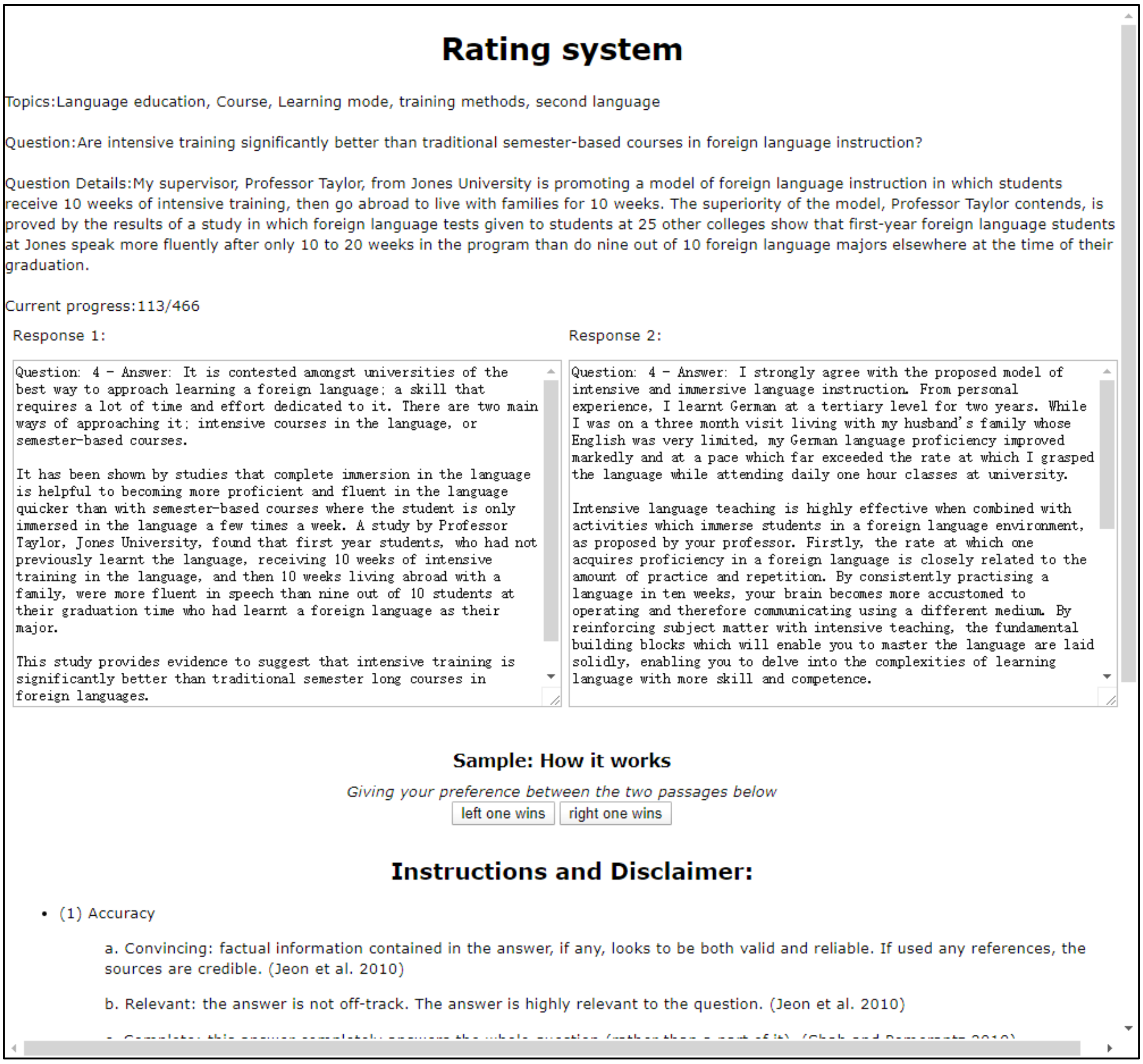
Zingal, F., & Becker, F. (2013). Drivers of optimal prices in two-sided markets: the state of the art. *Journal Für Betriebswirtschaft*, *63*(2), 87-116.

Zingeser, L. B., & Berndt, R. S. (1990). Retrieval of nouns and verbs in agrammatism and anomia. *Brain and Language*, *39*(1), 14-32.

Appendix 1. A conceptual illustration of the design of the first study's digital nudge



Appendix 2. Graders' environment



Rating system

Topics:Language education, Course, Learning mode, training methods, second language

Question:Are intensive training significantly better than traditional semester-based courses in foreign language instruction?

Question Details:My supervisor, Professor Taylor, from Jones University is promoting a model of foreign language instruction in which students receive 10 weeks of intensive training, then go abroad to live with families for 10 weeks. The superiority of the model, Professor Taylor contends, is proved by the results of a study in which foreign language tests given to students at 25 other colleges show that first-year foreign language students at Jones speak more fluently after only 10 to 20 weeks in the program than do nine out of 10 foreign language majors elsewhere at the time of their graduation.

Current progress:113/466

Response 1:

Question: 4 - Answer: It is contested amongst universities of the best way to approach learning a foreign language; a skill that requires a lot of time and effort dedicated to it. There are two main ways of approaching it; intensive courses in the language, or semester-based courses.

It has been shown by studies that complete immersion in the language is helpful to becoming more proficient and fluent in the language quicker than with semester-based courses where the student is only immersed in the language a few times a week. A study by Professor Taylor, Jones University, found that first year students, who had not previously learnt the language, receiving 10 weeks of intensive training in the language, and then 10 weeks living abroad with a family, were more fluent in speech than nine out of 10 students at their graduation time who had learnt a foreign language as their major.

This study provides evidence to suggest that intensive training is significantly better than traditional semester long courses in foreign languages.

Response 2:

Question: 4 - Answer: I strongly agree with the proposed model of intensive and immersive language instruction. From personal experience, I learnt German at a tertiary level for two years. While I was on a three month visit living with my husband's family whose English was very limited, my German language proficiency improved markedly and at a pace which far exceeded the rate at which I grasped the language while attending daily one hour classes at university.

Intensive language teaching is highly effective when combined with activities which immerse students in a foreign language environment, as proposed by your professor. Firstly, the rate at which one acquires proficiency in a foreign language is closely related to the amount of practice and repetition. By consistently practising a language in ten weeks, your brain becomes more accustomed to operating and therefore communicating using a different medium. By reinforcing subject matter with intensive teaching, the fundamental building blocks which will enable you to master the language are laid solidly, enabling you to delve into the complexities of learning language with more skill and competence.

Sample: How it works

Giving your preference between the two passages below

left one wins | right one wins

Instructions and Disclaimer:

- (1) Accuracy

  a. Convincing: factual information contained in the answer, if any, looks to be both valid and reliable. If used any references, the sources are credible. (Jeon et al. 2010)

  b. Relevant: the answer is not off-track. The answer is highly relevant to the question. (Jeon et al. 2010)

Appendix 3. Post-hoc analysis details

Five post hoc checks were performed to confirm the validity of conclusions in Study 1, including:

1. a consistency check for the RTQA's performance against human experts rated scores
2. a check for potential detrimental impact if the writer received initial negative feedback
3. a check for possible fatigue effect
4. a check for contributors' main motivational factors' influence
5. a check for five control variables (i.e., gender, age, income, prior experience of contributing knowledge content online, and money attitude)

RTQA performance consistency check

The mechanism's performance was validated via two methods, and both methods show the RTQA (the nudge) worked well.

First, during the pilot test, participants were asked whether they thought the proposed nudge was motivating both their extrinsic and intrinsic motivation to contribute or not. All participants answered 'Yes'.

Second, the nudge' scores were validated against human experts' knowledge-quality scores to show that the mechanism designed in this study was effective in nudging knowledge sharers to write more quality knowledge contributions. I chose 108 answers that were written by the participants in the treatment group (because they saw the nudge) and retrieved their final scores reported by the proposed mechanism and the knowledge-quality scores that the human experts gave them. A Pearson correlation test was used to validate the linear association between the two scores. The result was $r(108) = 0.769$, $p < 0.001$, which indicates a strong positive linear relationship. Further, I performed an intra-class correlation coefficient (two-way mixed, mean-rating, $k = 2$, consistent type) to test the reliability of the nudge. As Table 49 shows, the result of ICC (3, 2) is 0.869, which suggests the nudge provided strongly reliable scores. Further, Figure 18 visualises the reliability test which compares the human experts' scores with the nudge's feedback scores.

	ICC	95% CI		F test with true value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Average measures	0.869	0.808	0.910	7.614	107	107	<0.001

Table 49. Intra-class correlation coefficient for the treatment mechanism

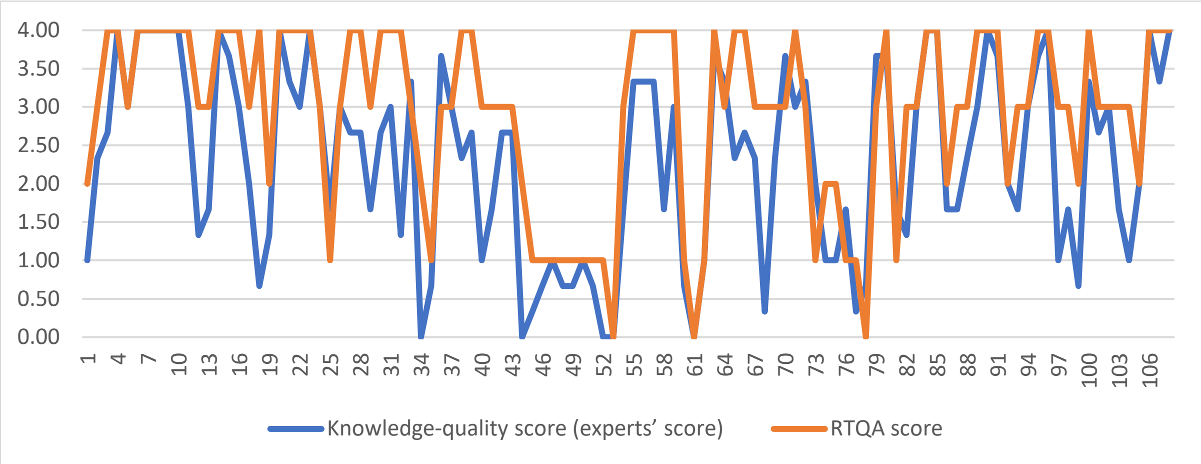


Figure 18. Comparison between the scores that were given by the nudge and the knowledge-quality scores given by the human experts (x-axis: question number)

Potential detrimental impact if the writer received initial negative feedback

The nudge was also found to not cause a significant detrimental impact on people's knowledge sharing if the nudge reported a low grade initially.

One may wonder whether the nudge only causes positive feedback on knowledge sharing. That is, if a writer found his or her answer was graded very low, the nudge would reduce his or her efforts when contributing other answers or the writer would even give up the writing process entirely.

To test this argument, there is a need to retrieve the scores that the nudge reported to answerers for the first question they answered. The scores were divided into two groups:

1. Group A: people received a bad score (RTQA Score <=2, max = 4) when answering the 1st question.

2. Group B: people received a good score (RTQA Score >2, max = 4) when answering the 1st question.

If the argument is true, then, compared to Group B, Group A' answerers should answer fewer questions and devote less time to contribute.

However, based on the result of ANOVA (see Table 50), the assumption was rejected: the negative feedback would cause a significant negative impact on a person's engagement to share knowledge.

		Group A (Bad score)	**Group B (Good score)**	**ANOVA**	
				F	Sig
Number of questions answered	Mean	3.200	3.2963	0.040	0.843
	Stand error	1.227	1.299		
Time devoted to the experiment	Mean	2983s (49.7 mins)	3364s (56.1 mins)	0.567	0.457
	Stand error	1164.8	1389.1		

Table 50. ANOVA table for possible detrimental impact caused by initial negative feedback

Contributors' primary motivational factors' influence

Another test was performed to observe and validate if there is an interactive effect between the intrinsic motivation (if any) and the effect that the nudge mechanism causes. The result shows that no clear interaction effect was found.

In this study, only 14 (out of 71) participants reported that they were primarily driven by intrinsic motivational factors. Also, after performing another ANOVA to observe whether the interactive effect between the intrinsic motivation level and the nudge mechanism's effect, the researcher of this study found (summarised in Table 51) that the interaction effects did not reach statistical significance.

Interaction	**SS**	**df**	**F**	**Sig**
Number of questions answered * Intrinsically motivated	0.870	70	0.424	0.517
Knowledge-quality score (experts' score) * Intrinsically motivated	0.253	70	0.196	0.659

Table 51. ANOVA table for primary motivational factors' influence

Possible effect caused by accumulation of fatigue

The result also confirms that although the software changed knowledge-sharing behaviour constantly, the participants did not accumulate significant fatigue during the experiment. Accumulation of fatigue can cause a stalling effect (i.e., users become less likely to contribute quality answers because the effect an incentive brings diminishes over time), and this is a common issue identified in previous research for online communities (Chen et al., 2017). To examine this, there is a need to test whether the proposed software motivates user's contributions and would diminish the quality entries. If that is the case, the answers may receive higher scores than the ones in the later rounds. To control this potential bias, the contributors' kth answer data were retrieved and the average scores and the standard deviation of the scores of each contributor's kth answer were calculated.

As indicated in Table 52 and Figure 19, the result shows that the temporal changes in average scores obtained did not diminish over time. This also indicates that the software provided a strongly reliable result.

k^{th} answer	**Count control**	**Count treatment**	**Average scores (control)**	**Std. dev. of scores (control)**	**Average scores (treatment)**	**Std. dev. of scores (treatment)**

1	34	35	1.58	1.25	2.28	1.28
2	31	34	1.75	1.13	2.39	1.21
3	24	22	1.51	1.19	2.30	1.19
4	17	11	1.61	1.35	2.30	1.12
5	10	5	2.17	1.14	2.73	1.61
6	5	4	1.87	1.33	2.42	1.71
Total	**122**	**111**	**1.69**	**1.20**	**2.35**	**1.23**

Table 52. Descriptive statistics for the scores

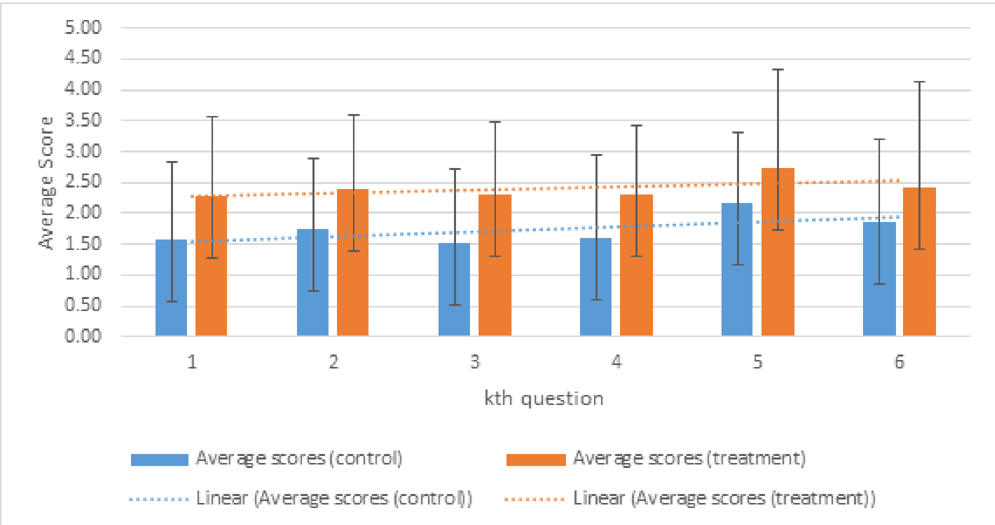


Figure 19. Temporal score difference

Also, a two-way ANOVA test was performed to validate this finding, and the result (see Table 53) indicates that there are no significant differences among the average scores for the contributions of the participants in the treatment group ($p > 0.999$). This finding suggests that no temporal change in the nudge's effect existed or that the effect did not significantly affect the scores that the human-raters gave; this suggests that the proposed nudge had a robust effect on contribution quality. Note that only a few diligent high achievers wrote more than five questions during the experiment, so the high average scores the answerers achieved for their 5th and 6th answers may cause outlier bias.

Source	SS	df	MS	F	Sig
Corrected Model	30.958[a]	11	2.814	1.852	0.047
Intercept	560.988	1	560.988	369.199	<0.001
kth_answer	4.007	5	0.801	0.527	0.755
Treatment	14.048	1	14.048	9.245	0.003
kth_answer * Treatment	.251	5	0.050	0.033	0.999
Error	334.284	220	1.519		
Total	1289.366	232			
Corrected Total	365.242	231			

a. R Squared = 0.085 (Adjusted R Squared = 0.039)
b. Dependent Variable: The average score given by the human raters

Table 53. ANOVA Table for possible temporal changes in motivational power

A check for five control variables (i.e., gender, age, income, prior experience of contributing knowledge content online, and money attitude)

Lastly, this study listed five control variables, and as Table 54 shows, none of the control variables are significant.

Controls	Dependent	SS	MS	F	Sig
Gender	Time	0.219	0.219	0.208	0.650
	Length	0.485	0.485	0.458	0.502
	Score	1.392	1.392	1.300	0.259
Income	Time	0.190	0.190	0.180	0.673
	Length	1.395	1.395	1.318	0.256
	Score	2.026	2.026	1.892	0.175
Age	Time	0.239	0.239	0.227	0.636
	Length	0.383	0.383	0.362	0.550
	Score	0.571	0.571	0.533	0.468
Prior Experience	Time	0.090	0.090	0.085	0.771
	Length	0.147	0.147	0.138	0.711
	Score	0.085	0.085	0.080	0.779
Money Attitude	Time	8.755	1.094	1.039	0.419
	Length	5.254	0.657	0.620	0.757
	Score	4.468	0.559	0.522	0.835

Table 54. This study’s control variables resolved potential confounding effects

Appendix 4. Demographics statistics of the Study 2

Table 55 summarises the demographics information about the participants summoned in Study 2 (Chapter 4). Note that some of the participants who participated in Stage 2 did not attend Stage 4, and vice versa.

Factor	Group	Stage 2: (Define) Online Interview				Stage 4: (Deliver) Prototype Testing			
		Male (n=26)		Female (n = 20)		Male (n=27)		Female (n = 14)	
		N	Percent	N	Percent	N	Percent	N	Percent
Age	<21	2	7.69%	4	20.00%	2	7%	2	14.29%
	21-25	7	26.92%	6	30.00%	10	37%	4	28.57%
	26-30	14	53.85%	8	40.00%	14	52%	7	50.00%
	>30	3	11.54%	2	10.00%	1	4%	1	7.14%
Working status	Employed	14	53.85%	6	30.00%	7	26%	2	14.29%
	Not working/ Studying	8	30.77%	9	45.00%	19	70%	7	50.00%
	Prefer not to answer or did not respond	4	15.38%	5	25.00%	1	4%	6	42.86%
How many MOOCs taken	1-3	15	57.69%	11	55.00%	8	30%	11	78.57%
	4-6	5	19.23%	5	25.00%	12	44%	1	7.14%
	6 or higher	6	23.08%	4	20.00%	7	26%	2	14.29%
Highest level of education completed	College/Bachelor's degree or lower	11	42.31%	9	45.00%	9	33%	3	21.43%
	Master's degree	12	46.15%	6	30.00%	15	56%	7	50.00%
	Doctoral Degree	1	3.85%	1	5.00%	2	7%	0	0.00%
	Prefer not to answer or did not respond	2	7.69%	4	20.00%	1	4%	4	28.57%
Groups	Group A	N/A				2	4.88%	8	19.51%
	Group B					6	14.63%	7	17.07%
	Group C					1	2.44%	7	17.07%
	Group Control					4	9.76%	6	14.63%

Table 55. Demographics of Participants, Age, Working Status, MOOC Experiences, Education Level, and Groups

Appendix 5. Google Trends Scores Frequency Distributions

As Figure 20 shows, the frequency distributions of the trending scores that I collected for performing analysis on DAP datasets were normal.

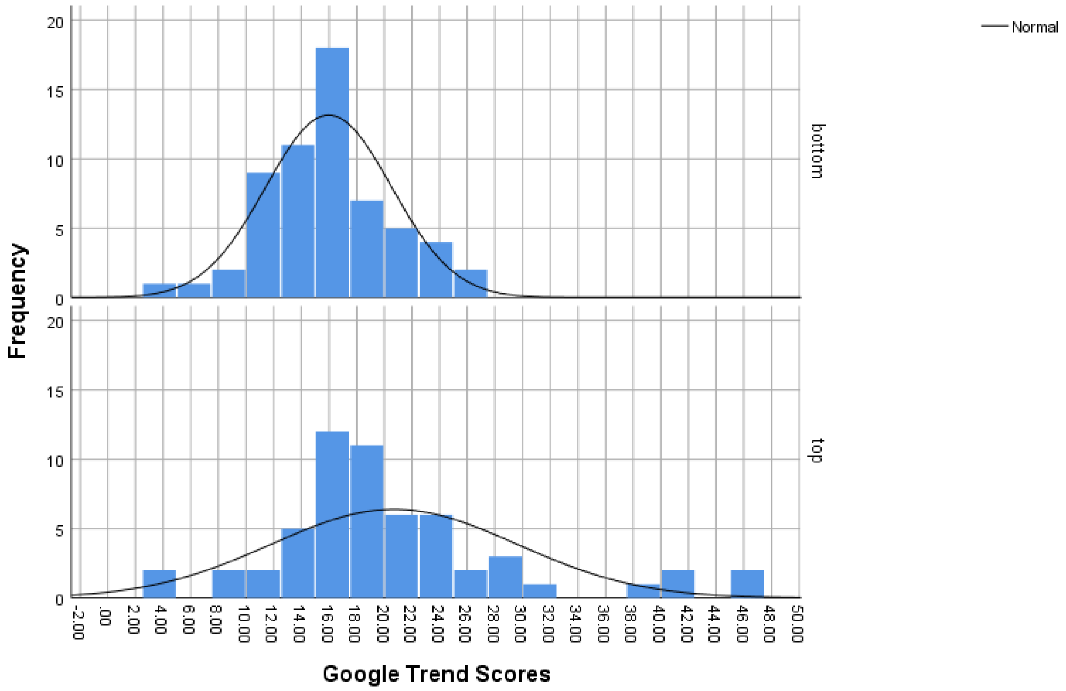


Figure 20. Google Trends Scores Frequency Distributions: Top 60 vs. Bottom 60

Appendix 6. A count summary of the disciplinary dummies of DAP dataset

Table 56 gives a summary of the disciplinary dummies of DAP dataset. Note that most of the data collections stored on CSIRO DAP were categorized as "Big Science", which concurs with Gregory et al.'s (2019) observation that big science research has a longer history and stronger preference of sharing data.

Variables	Cases
Big science	560
Maths and Physics	32
Chemistry	15
Earth science	134
Environmental science	168
Biomedicine	75
Agriculture	97
Computer science and engineering	60
Humanities	20
Aggr. Math, physics and chemistry (including astronomy) * contributors' average reputation	47
Aggr. Math, physics, and chemistry (including astronomy) * lead researcher's reputation	47
Aggr. Math, physics, and chemistry (including astronomy) * description richness	47
Aggr. Biomedicine * description richness	75
Aggr. Earth and environmental studies * lineage richness	302
Aggr. Earth and environmental studies * Optional fields completeness	302
Aggr. Social science and economics * lineage richness	20
Aggr. Social science and economics * description richness	20

Table 56. A summary of the disciplinary dummies

Appendix 7. Publications and peer review information about the chapters in this thesis

The following table describes the status of the chapters as of the publication date of this thesis.

Study #	Chapter #	Status
Study 1	Chapter 4	Under review
Study 2	Chapter 5	In Proceedings of the 24^{th} Pacific Asia Conference on Information Systems (PACIS 2020), Dubai, UAE, 2020.
Study 3	Chapter 6	In Proceedings of the 22^{nd} Pacific Asia Conference on Information Systems (PACIS 2018), Yokohama, Japan, 2018.
Study 4	Chapter 7	In Proceedings of the 35^{th} Australian and New Zealand Academy of Management Conference (ANZAM Conference 2022), Gold Coast, Australia, 2022.
Study 5	Chapter 8	Under review
Study 6	Chapter 9	N/A

Table 57. Statement of status of the chapters in this thesis