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Research Note

Ai-based counterfactual reasoning for tourism research

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Introduction

This research introduces a novel method for uncovering potential causal relationships in tourism literature through artificial intelligence (AI)-based counterfactual reasoning and big data. Tourism generates massive volumes of device, transaction, and user-generated data, and these can be leveraged using AI algorithms to better understand tourism-related social phenomena (Park, Xu, Jiang, Chen, & Huang, 2020). Existing tourism studies have used deductive, fuzzy, inductive, and transductive AI models (Cevikalp & Franc, 2017) to extract insights from big data, but these often fail to capture potential causal effects (Guidotti, 2022), which is problematic for two reasons. *First*, decision-making by tourism stakeholders cannot be improved if AI models mainly rely on spurious correlations (Law & Li, 2007). *Second*, the failure of capturing potential causal effects in big data diminishes its perceived value for both tourism scholars and practitioners.

To better capture causality, extant literature has recommended experimental designs (Viglia & Dolnicar, 2020). Although highly effective, experimental designs rely heavily on previously established theories (Sun, Law, & Zhang, 2020). For example, research first introduces random utility theory, theorizing rational decision-making of tourists' hotel and destination choices, to then conduct experiments (Zhang, Grisolía, & Lane, 2023). This reliance may impede the discovery of potential causal relationships that sit beyond established theories. Experiments also have practical limitations (see Podsakoff & Podsakoff, 2019), and cannot combine multiple concepts and then control for all possible factors that may influence the concepts. The simpler the experimental design, the easier it is to establish causality. The availability of big data can overcome several limitations inherent in experimental

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designs. This research outlines an agenda that explains how tourism research can leverage big data and counterfactual reasoning AI algorithms to determine potential causal effects.

Reasoning approaches in AI tourism research

From the early rule-based decision support systems (Rita & Moutinho, 1994) to the most recent deep neural networks (Yang, Fan, Jiang, & Liu, 2022), several AI algorithms have been adopted in the tourism literature. From an overarching knowledge reasoning perspective, these algorithms can be classified as deductive, fuzzy, inductive, or transductive AI models (see Table 1).

Deductive AI models are rule-based and used for decision support by taking advantage of the rich embedded prior knowledge (e.g., Rita & Moutinho, 1994). *Fuzzy AI models* are used to develop knowledge from imprecise tourism data such as linguistic variables (e.g., Hasuike & Ichimura, 2013). *Inductive AI models* are used to discover underlying patterns in tourism big data and studies often use deep neural network-based models such as recurrent neural networks (e.g., Law, Li, Fong, & Han, 2019). *Transductive AI models* are used to discover knowledge in cases where collecting high-quality data to train classical neural networks is highly labor-intensive (e.g., Salur, Aydin, & Alghrsi, 2019).

Table 1 shows the aim of use, the respective AI models and illustrative examples for each reasoning approach. Despite their important contributions, the key limitation of the AI models underpinning these existing reasoning approaches is that they can rarely establish causal effects from the data (Verma, Dickerson, & Hines, 2020).

Introducing counterfactual reasoning

Counterfactual reasoning refers to the ability to imagine possible alternatives to life events that have already occurred. It is one of the most important human cognitive approaches to causal judgment (McGill, 2000). Recently, several counterfactual reasoning AI algorithms have been proposed and shown to demonstrate superior performance in supporting decision-making and disentangling causal effects (Verma et al., 2020), but these have not yet been adopted in tourism research.

Pearl and Mackenzie (2018) differentiate counterfactual reasoning AI algorithms from traditional AI models by proposing a causal ladder that classifies organisms' cognitive ability into three stages: observing, intervening, and imagining. Traditional AI models discover knowledge by observing associations. Experimental design discovers causal knowledge by intervening in conditions. Counterfactual reasoning AI algorithms capture causal effects by imagining counterfactual scenarios that do not exist in the real world and highlighting their complementary nature to experimental design.

Most modern AI models attempt to fit a function to the data. No matter how complex the model and how deep the neural network, the learning mechanism is still observing associations in the data, and thus belongs to the lowest stage of cognition (Pearl & Mackenzie, 2018). Experimental designs that can uncover causal relationships take one step further in cognition, but suffer from the limitations of complexity, ethical concerns, and other practical considerations. Counterfactual reasoning AI algorithms that can capture causal effects from imagined conditions are more powerful, and thus belong to the highest stage of cognition.

More specifically, counterfactual reasoning AI algorithms capture causal effects by constructing a counterfactual optimization problem (Guidotti, 2022). Let $f(X, Y|\Theta)$ be a function (with parameter Θ) learned in the collected tourism data (X, Y). Traditionally, this function is used by tourism scholars and practitioners for supporting decision-making. However, in counterfactual reasoning AI algorithms, an additional function, $m(\Delta) = f(X+\Delta, Y|\Theta) - f(X, Y|\Theta)$, is introduced to measure the effectiveness of potential strategy Δ, where $X+\Delta$ represents the counterfactual world in which strategy Δ has been applied.

The objective of this counterfactual optimization problem is to find the optimal strategy Δ that can change the reality to the desired outcome. The definition of optimal strategy Δ may vary slightly across the algorithms; however, normally we expect the optimal strategy Δ has minimal changes to the input X, as all changes require costs. In addition, we also expect the optimal strategy changes the least number of things; for example, either updating the facilities or training the staff of a hotel, but not

Table 1
Reasoning approaches of AI algorithms in tourism studies.

Reasoning approach	Aim of use	Adopted AI model	Illustrative examples
Deductive reasoning	Taking advantage of rich prior knowledge of AI models for decision support	Rule-based models; e.g., decision support systems	Rita and Moutinho (1994) proposed to utilize the expert system to enhance decision-making in national tourist offices
Fuzzy reasoning	Develop knowledge from imprecise data	Fuzzy logic-based models; e.g., fuzzy C-means clustering	Hasuike and Ichimura (2013) utilized simplified fuzzy reasoning to understand the tourist flow at attractions from Japan bullet train seat availability data
Inductive reasoning	Capture implicit general patterns in the collected big data	Traditional deep neural networks; e.g., recurrent neutral networks	Law et al. (2019) adopted deep neural networks to capture the patterns in search intensity indices for tourist forecasting
Transductive reasoning	Develop knowledge from a small number of high-quality data; e.g., focus on the case only a limited number of data is available for training AI models	Semi-supervised learning models; e.g., transductive support vector machine	Salur et al. (2019) adopted a semi-supervised artificial neural network to evaluate the sentiment of tourists' comments

necessarily doing both (Tan et al., 2021). Formally, this optimization problem can be represented as:

$$minmize\ C(\Delta) = \|\Delta\|_2^2 + \beta\|\Delta\|_0$$

$$s.t., m(\Delta) = f(X+\Delta, Y|\Theta) - f(X, Y|\Theta) > \varepsilon$$

where $\|\Delta\|_2^2$ is l_2-norm which indicates the total costs required for the potential strategy, $\|\Delta\|_0$ is the l_0-norm which indicates the number of things that need to be modified in the potential strategy, β is a balance parameter between these two criteria, ε is a value which ensures that the application of strategy Δ could change the reality to achieve the desired outcome. By solving this optimization problem via gradient descent, counterfactual reasoning AI algorithms can identify the causal effect-driven strategy Δ, which may change the reality to the desired outcome to support managerial decision-making. The potential causal links between antecedents and the problem investigated will be reported in the non-zero dimensions of Δ (Verma et al., 2020).

Future research opportunities

Uncovering causal effects is necessary to formulate effective strategies and decision-making (Law & Li, 2007). However, causal effects have been identified in tourism literature to date by primarily using experimental designs. While experimental designs are useful as part of intervening models of knowledge, they suffer from limitations, related to selection and comparison of multiple outcomes which are themselves connected to many factors.

Thus, complexity dampens the ability of experimental designs to establish causal relationships in multi-faceted problems affecting the value of the results for managerial decision-making. Counterfactual reasoning AI algorithms overcome this challenge by imagining outcomes in both business-as-usual and adverse conditions, allowing for the transferring of complex comparison and selection tasks from researchers to the algorithms themselves. Future tourism research could harness these AI algorithms in research problems[1] across several domains:

1) Tourist behavior: explaining choice behaviors and selection criteria as well as decision-making processes when there are perceived risks. In counterfactual optimization, X are factors related to tourists' choices under the conditions of perceived risks, Y is a label that shows whether tourists act on this behavior or not, and ε is a value that indicates the decision change;

2) Destination competitiveness: formulating efficient strategies to improve destination competitiveness. In counterfactual optimization, X are factors that determine destination competitiveness, Y is the set of indicators of destination competitiveness, and ε is the expected competitiveness improvement;

3) Sustainable tourism: identifying key factors that influence tourists' sustainability awareness and practices. In counterfactual optimization, X are factors that determine tourists' sustainability awareness or practices that demonstrate sustainability concerns, Y measures sustainable behaviors, and ε is the expected improvement in sustainable behaviors.

To conclude, causal effect-driven tourism decision-making is a critical area of future research as destinations and tourism managers navigate an increasingly complex business environment. Counterfactual reasoning AI algorithms offer a novel approach for future research to address the practical limitations of experimental design, allowing potential causal effects to be identified from tourism big data.

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Data availability

No data was used for the research described in the article.

Declaration of competing interest

Authors have no conflict of interests to declare.

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[1] These problems are challenging for experimental design due to many factors involved but rich data available.

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