Learning behaviour & learning outcomes: the roles for social influence and field of study.

Lillian Smyth[a], Kenneth I. Mavor [a,b], Michael J. Platow [c]

[a] *Medical Education Unit, Australian National University, Canberra, Australia*

[b] *School of Psychology and Neuroscience, University of St Andrews, Scotland.*

[c] *Research School of Psychology, Australian National University, Canberra, Australia*

Corresponding Author:

Lillian Smyth

Medical Education Unit
ANU Medical School
Florey Building
54 Mills Road
The Australian National University
Acton, ACT, 2601

Email: Lillian.Smyth@anu.edu.au

Abstract:

Research has demonstrated a significant role of discipline social identification in predicting learning approaches, even controlling for individual differences. Smyth, Mavor, Platow, Grace and Reynolds. (2015) suggest that learners share discipline-based social identifications, and that this identification, in combination with relevant norms, influences the adoption of learning approaches. The current paper extends this analysis in two directions. First, the effect of broad field of study is examined for systematic differences across content domains. Secondly, the model examines effects on student perceptions of teaching quality and intentions to continue within a discipline. Results provide support for Smyth et al.'s (2015) model, demonstrating links between discipline identification, perceived norms, learning approaches and outcomes. Strongly identified students, students who perceived deep learning norms and students taking a deep learning approach all reported more positive outcomes. Disciplinary variations in responses to learning approaches and outcomes were also found, broadly in line with that found in the Biglan-Becher literature.

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1. Introduction

The intent of the current paper is to outline the emerging body of literature tracing the social processes involved in tertiary education and build on this literature through empirical testing of a developed model of student learning. Drawing on both educational and social psychological theory and research, this paper demonstrates the value of including models of social influence in our understanding of the nature of the educational context. Two key concepts are used throughout. First, it is assumed that students engage with and approach learning in the manner outlined in the work of Biggs and colleagues (Biggs 1989, 1999; Biggs et al. 2001; Biggs and Tang 2007a, 2007b) on learning approaches. That is, learning behaviour is flexible, context dependent and subject to a host of influences. Further, learning approaches can be roughly dichotomised into those that prioritise understanding (deep learning) and those that prioritise efficiency, often at the cost of mastery (surface learning). Second, it is assumed that an individual's sense of self is partially socially constructed and is similarly flexible and context dependent. Using the social identity approach (Tajfel and Turner 1986; Turner et al. 1987) as an organising framework, the social- and self-processes involved in tertiary education are considered, particularly with regard to the processes of social influence that stem from social identification and perceived norms. These two theoretical foundations are then used as a base from which models of the process of tertiary learning may be understood and developed.

Recent literature (Bliuc et al. 2011a, 2011b; Platow et al. 2013) has established relationships between these two key concepts of social identification and deep learning approaches, and has begun to map their dynamic, longitudinal mutual influence. The current study situates this advance in the context of Biggs' broader 3P model of the learning process (Presage, Process, Product), while simultaneously developing the social identity aspect through the inclusion of norms.

This integrated model has both practical and theoretical value, as well as implications for the way courses are designed and delivered. The nature of a student's learning approaches and the social influences on their cognition and behaviour both have flow-on impacts on high value outcomes, including: academic achievement, student course perception and evaluations, student engagement with the discipline and intentions to continue. The inclusion of learning approaches, social influence variables and their interactions in the same model allows for a more rounded understanding of the student experience and provides some clear suggestions for course design. Further, these course design insights are applicable across a wide range of educational contexts. The learning approaches model is applicable across a wide range of content, delivery mode and education types (e.g. in study groups,Yan and Kember 2004; across disciplines, Laird et al. 2008; using different assessment types, Heijne-Penninga et al. 2008; using a variety of course designs, Wang et al. 2013; in private tertoary institutions, Kek et al. 2007). The consideration of social and normative dimensions further broadens this usefulness (by controlling for variations in culture, values, and teaching structure, by considering the subjective perceptions of student norms) and the implications for teaching and learning to be applicable internationally and across disciplines, in the context of tertiary education.

1.1 Learning Approaches

Learning approaches are a popular and enduring model of student learning. The model proposed by Marton and Säljö (1976), and developed by Biggs (1979, 1999), suggests that students relate to the task or subject material they are given in one of two ways: (1) Deep

Learning: engaging and seeking to understand intent and broader implications, or (2) Surface Learning: focusing on completion of task requirements and often resorting to memorisation. This model has inspired considerable research on ways in which educators can shape these approaches and the relationships these approaches may have to crucial academic outcomes (e.g., Ramsden 2003; Trigwell and Prosser 1991; Zeegus 2001).

Learning approaches themselves have been explored in depth (e.g. Biggs et al. 2001; Biggs 1999; Walsh 2007; Biggs 1979; Biggs and Tang 2007b, 2007a; Entwistle 2000; Ramsden 2003; Struyven et al. 2006; Yan and Kember 2004; Cassidy 2004; Entwistle 2005; Trigwell and Prosser 1991; Baeten et al. 2010; Ramsden 1991; Zeegus 2001) and will therefore only be outlined briefly here. Importantly, a learning "approach" is understood as not something a student *has*, but rather something a student *takes* in a particular situation, to a particular task: it is a way of organising, understanding and relating to a task that is assumed to be context-dependent (Biggs 1999). In tertiary education students, a deep learning approach is characterised by active integration of new knowledge, thinking critically, referring to a wide range of resources and questioning conclusions. Tertiary education students adopting a surface approach, on the other hand, focus chiefly on meeting task-requirements and learning only what is necessary in the most efficient way possible. This kind of learning is generally characterised by a focus on isolated facts, rote memorization strategies, and selective information processing.

1.2 Discipline-Related Social Identification and Learning Approaches

Researchers have recently argued in favour of considering social self-definition in terms of academic discipline as an important factor underlying learning approaches (Platow et al. 2013; Bliuc et al. 2011a, 2011b). This recent work integrates the concept of discipline-based social identification into pre-existing learning approach models. The social identity approach, which includes both social identity theory (Tajfel and Turner 1986) and self-categorization theory (Turner et al. 1987), conceptualizes the individual's sense of self as flexible, context dependent, and comprised partly of what are referred to as social identities. Social identities are the cognitive representations that result from seeing oneself as a member of particular social groups, the associated sense of belonging, and the cognitive and emotional significance attached to those memberships. Each social identity also carries with it norms for behaviour (an idea of what members of the group do, and are supposed to do). The combination of the extent to which an individual identifies with a social identity (i.e. perceives it as self-defining) and the nature of the perceived norms has a demonstrable effect on behaviour (e.g. healthy eating, Baker et al. 2003; eating intentions, Louis et al. 2007; excercise, Hagger and Chatzisarantis 2005).

In this vein, Bliuc et al. (2011a, 2011b) examined discipline-related social identity as a predictor of both learning approaches and academic achievement. The model these authors proposed holds that discipline-related social identification predicts academic achievement, and that this is mediated through deep learning approaches. That is, students who identified more strongly with their disciplines would be more likely to adopt a deep learning approach and, thereby, have better academic outcomes. The findings from their studies supported the model; deep learning approaches were associated with better academic outcomes, and stronger identification with the discipline was associated with a deep learning approach. As expected, there was also a significant indirect effect of discipline-related social identity on academic outcomes mediated *through* learning approach.

In a parallel development, Platow et al. (2013) explored the relationship of social identification, deep learning approach and grades, with a particular focus on the changes in self-concept associated with a course of study when adopting deep learning approaches.

Platow et al,'s (2013) proposed model is a dynamic, cross-lagged model in which the discipline-related social identity and learning approach are related to each other, and are reciprocally influential over time. Their study provided partial support for the model, in that deeper learning approaches at Time 1 predicted increased identification levels, but the opposite path (Time 1 identification predicting changes in deeper learning approaches) was not confirmed.

Smyth and colleagues (Smyth, Mavor, Platow, Grace and Reynolds, 2015) build on these findings through the addition of an explicit normative dimension to the understanding of the relationship between discipline-related social identification and learning approaches. This latter model especially takes into account discipline-related learning norms, and the impact they may have on the learning approach taken. The authors conducted a campus-wide online study, in which students were asked to report on discipline-related social identification, discipline-related learning approaches and the learning norms they perceived in their discipline. These variables were then entered into a sequential regression model, including person variables (personality, demographics), context variables (teaching quality) and the social psychological variables in separate, successive blocks. The social identity and normative influence variables predicted learning approach over and above person and context factors.

Smyth et al.'s (2015) findings indicate a need to examine normative influence as well as social identification when exploring factors that predict learning approaches. In line with previous work of Bliuc et al.(2011a) and Platow et al.(2013), they find a significant, positive effect of social identification in predicting the extent to which students adopt a deep learning approach. The model also demonstrates that the social identification effect on learning approach is *moderated* by the perceived norms for the group and these effects are present beyond those of person and context variables. That is, it is not only the strength of identification with a group that influences ultimate learning approach behaviour, but also what that group membership *means*, in terms of norms for desirable group behaviour.

1.3 Learning Approach and Student Outcomes

As might be suggested by the kinds of activities that define learning approaches, they have divergent impacts on both learning and academic outcomes. Deeper learning approaches are commonly associated with more positive education outcomes (Biggs 1979; Walsh 2007; Richardson et al. 2012; Lizzio et al. 2002; e.g. Artino et al. 2010; Platow et al. 2013). For instance, self-reported learning approaches have been demonstrated to predict student perceptions of the course, overall course satisfaction, and perceptions of teaching quality (Lizzio et al. 2002). This influence of learning approach on course perceptions is a useful relationship to consider for two reasons. First, universities seek to maximise positive student experiences of courses and, second, there is evidence for a relationship between course satisfaction and better grades and better long-term information retention (Ramsden 1991).

Further to which, student engagement with the discipline and intentions to continue also can be linked to learning approaches (Platow et al., 2013). These variables are of interest in a conceptualisation of the education process that suggests that tertiary education should help initiate the student into a community of practice, not just transmit the necessary knowledge to them (e.g. O'Donnell and Tobbell 2007; Barrie 2006). In this understanding, intentions to continue to engage with the community: (e.g., by continuing study, seeking relevant employment or finding out more about relevant topics) can be considered an equally important academic outcome.

1.4 Presage, procedure, and product

In integrating the above concepts into a broader model, it is necessary to consider the process of learning in a tertiary context. Biggs (1989) conceptualised this process in terms of the “3 Ps”: presage, procedure and product. This model is the foundation of the learning approaches model, in that the presage factors are expected to interact and produce a particular learning approach, or procedure. This learning approach then predicts the outcome. This 3-stage conceptualisation maps easily onto the learning approaches model in use in the current paper.

The first stage of the 3P model, the “presage”, is characterised as the factors that precede learning. These factors include both student factors and the structure of the learning context. Student factors can include things such as individual differences (e.g. personality), prior knowledge, life experience and expectations. In our model, the presage stage of this model is captured in two parts. The person-level variation is addressed in our measurement of personality and demographics. In order to gain a complete picture of the presage, however, we also examine the structure of the learning context and the nature of the content. As this is a multi-disciplinary sample (across 13 courses in 6 different disciplines and multiple year levels) and there is evidence that, between academic disciplines, we would expect some variation style of teaching (Lindbolm-Ylänne et al. 2006), method of teaching, preparation time, hours of contact and research involvement (Neumann 2001), as well as the typical kinds of tasks involved in studying in the discipline (Ramsden 2003), field of study is included as a clustering variable in the model, broken up in line with a Biglan-Becher style typology (further detail in method section. For detail on typology, see, for example: Becher and Trowler 2001; Biglan 1973).

The second stage of the Biggs conceptualisation is the “procedure” stage, which captures the process and experience of learning. This was originally conceptualised as simply learning approaches. In our model, however, we consider the learning process as the dynamic social experience of being a student, as well as the individual approaches students take to their learning.

Finally, the “product” stage of Biggs’ model is described as the end-product of education: the outcomes. In the current study, perceived teaching quality and intention to continue variables are the outcomes of interest.

1.5 The current study

The current paper, then, builds on recent developments in the learning approaches model that are informed by contemporary social psychological theory related to self-concepts, identities and group processes, particularly social norms (Bliuc et al. 2011a; Platow et al. 2013; Smyth et al. 2015; Smyth et al. 2017). In doing so, we extend the learning approaches model beyond the original person-by-situation framework, in which learning approaches are determined by the interaction between student factors and the learning environment. This extended model includes dynamic social and normative effects in shaping learning approaches. In applying the normative influence model described above, we consider not only the processes that lead to the more conventionally desirable learning strategies (i.e. deep learning approaches), but also the way in which these social and normative processes might combine to produce a surface learning approach.

As this is a complex model, we had a range of expectations for trends in the data. The overall model to be tested, allowing for disciplinary variation, can be seen in Figure 1. Broad initial expectations were that, in the first instance, learning approach should impact on student outcomes, such that deep and surface learning should be inversely related and deep learning approaches should positively impact (and surface learning should negatively impact) both outcomes (perceived quality of teaching and intention to continue). Identification levels and perceived norms were also considered a possible influence on outcomes, independently of learning approaches.

<<Figure 1 about here>>

1.5.1 Field of study

With regard to variations by field of study, we had some clear expectations drawn from the literature. First, we expected students in “soft” disciplines to report deeper learning approaches (Laird et al. 2008) . Similarly, students in applied disciplines were expected to have a greater focus on procedure and task completion, rather than knowledge frameworks (Neumann et al. 2002) and, therefore, report less deep learning than students in pure disciplines. Perceived norms should vary by discipline, as the nature of norms are greatly determined by both learning context and fellow students (Turner 1991; Smyth et al. 2015).

We also expected that outcomes (perceived teaching quality and intention to continue) should be related to the learning approach taken (Lizzio et al. 2002; Biggs 1999; Platow et al. 2013) and therefore expect higher ratings of teaching quality and stronger intentions to continue in soft and pure disciplines, as compared to hard or applied disciplines. We did not, however, necessarily expect any differences in discipline identification, as the self-selection of degree-choice should mean that the majority of students consider their area of study at least somewhat self-defining. We expect that variation in the level of identification within each discipline group would be broadly comparable.

1.5.2 Replication and extension of Smyth et al (2015)

Other expectations for the current research were drawn from the replication and extension of Smyth et al.'s (2015) work. It was expected that personality variables should partially predict discipline-related social identification and perceived study norms. Previous research suggests conscientiousness should be related to stronger perceived deep-learning norms and higher levels of identification, as well as deeper learning approaches and better academic outcomes (Chamorro-Premuzic and Furnham 2008; O'Connor and Paunonen 2007). The other personality variable to be examined, extraversion, may also predict deeper learning approaches. The expected prediction here is only partial, but not negligible and so has been included in the model.

Higher levels of discipline-related social identification, stronger deep learning norms and their interaction were also expected to positively predict deep learning approaches. It was expected that the form of the interaction would be such that the influence of norms was accentuated at higher levels of identification. The converse would also be apparent for strongly identified students who perceive strong surface learning norms. That is, the influence of surface learning norms should undercut the identification- deep learning approach relationship at higher levels of identification.

2. Method

2.1 Participants

Participants were 315 undergraduate students (136 female and 117 male, 2 unknown) from across 13 courses from 6 different disciplines, at a moderately-sized Australian university. Participants were part of a larger longitudinal study of discipline social identification and learning approaches. The analyses explored here are based on participants who only participated at single time point[1]. Participants were recruited during lecture time and completed a pen-and- paper survey within a few weeks of the beginning of the semester. Ages of participants ranged from 16 to 62 years (mean = 19.95). 74% of students indicated that English was their first language. The sample for investigation consisted of students ranging from one to six years into their studies (median = 1st year; 113 students (37%) were post 1st year).

2.2 Measures

Participants indicated their degree of agreement or disagreement with the following scale items on a seven-point Likert scale (ranging from strongly disagree to strongly agree), unless specified otherwise. In example items below an (r) indicates a reversed item.

2.2.1 Person-level Factors

The most relevant aspects of the Big-Five personality model (John et al. 2008) are conscientiousness and extraversion. Conscientiousness has a robust relation to both learning approaches and academic outcomes (O'Connor and Paunonen 2007; Chamorro-Premuzic and Furnham 2004, 2008) and there is some evidence that extraversion predicts deeper learning approaches (McManus et al. 2004). Conscientiousness and extraversion were measured using 12 items each, from the widely used Big-Five inventory (John et al. 2008; e.g., "I often forget to put things back in their proper place."(r), " I don't mind being the centre of attention."). The two inventories were reliable (α_{consc}=.80, α_{extr}=.87). Demographic variables, including age, gender, linguistic background and field of study were also recorded.

2.2.2 Field of study

The thirteen courses sampled fall into six main discipline areas: humanities and social sciences, computing, commerce/marketing, psychology and mathematics. These were categorised using a Biglan-Becher style typology of disciplines (Becher and Trowler 2001; Biglan 1973), divided along two dimensions: paradigm development and pragmatism (Umbach 2007). This is a commonly used typology that was developed from Kolb (1981) and is a common basis for exploring disciplinary variation in learning approaches (e.g. Lindbolm-Ylänne et al. 2006; Neumann et al. 2002; Laird et al. 2008; Kember and Leung 2011). The paradigm development dimension is broken into hard (areas in which there are clear paradigms, rules and laws, e.g. chemistry and physics) and soft (areas in which there is little consensus on theory methods and problems, e.g. history and literature). The pragmatism dimension is divided into pure (disciplines in which few practical applications are considered, e.g. pure mathematics and philosophy) and applied disciplines (which concentrate on applications, e.g. engineering and accounting). These two dimensions combine to form a 2 by 2 matrix of possible categorisation: hard-pure, hard-applied, soft-pure and soft-applied. In the current study, there was an even split of hard (mathematics, engineering and computing) and soft (humanities & social sciences, psychology and commerce/ marketing) disciplines and one applied discipline per grouping (commerce and engineering)[2]. Dividing our data like this allows for comparisons across the 6 individual disciplines, as well as by the hard/soft and pure/applied dimensions.

2.2.3 Identification

Identification as a student in their particular field of study was measured using a scale of seven items that are widely used to measure social identification (see Haslam 2004). Items included: "Being a student in my field of study is important to me ", "I would RATHER NOT tell other people that I am a student in my field of study" (r), and "I have a lot of respect for students in my field of study". In the current data, the scale was acceptably reliable (α = .74).

2.2.4 Learning Approaches and Norms

Students' learning approaches were measured using 12 items adapted from the revised version of the Study Process Questionnaire (SPQ; Biggs et al. 2001). Six items measured each learning approach (e.g., "I spend a lot of my free time finding out more about interesting topics dealt with in class" (deep); "I only study seriously those topics that I know will be assessed." (surface)). In the current data, both scales were acceptably reliable (α_{deep} = .77, $\alpha_{surface}$ = .76).

Six items were used to assess perceptions of norms among students in their field of study adapted from the SPQ (three for each kind of norm; e.g., "Most students in my field of study prefer to focus on learning efficiently by memorizing key information and minimizing study time." (surface norms), "Most students in my field of study prefer to focus on understanding content fully and integrating new information with what they already know" (deep norms)). In the current data, both scales were considered an acceptable balance of reliability and construct coverage given their short length ($\alpha_{deep\ norms}$ = .60, $\alpha_{surface\ norms}$ = .69).

2.2.5 Teaching Quality

To examine course-level outcomes, perceived teaching quality was measured using four items on seven-point scales ranging from "extremely low" to "extremely high". Items included: "The quality of course content in my field of study (e.g. the lectures and tutorials) is:", "The quality of teaching in my field of study is:". These questions were all highly correlated, and loaded onto a single factor in preliminary factor analysis, and were, therefore, treated in our analysis as measuring one "Teaching Quality" construct (α=.68).

2.2.6 Intention to continue

As an outcome measure, we examined student intentions to continue in a variety of ways. Drawing on scales used in previous research (Platow et al. 2013; Smyth et al. 2015), the items focused on a range of possible continuation behaviours. Participants were asked to indicate the extent to which they intended to: continue studies in the field, pursue a relevant career, find out more about topics covered, retain only the information they need (r), make sure none of their friends take this course (r), and choose a course as different as possible next semester (r). The items were all highly correlated and were, therefore, treated as a single "intention to continue" scale, which, in the current data, was acceptably reliable (α = 0.73).

3. Results

Data were analysed in three steps. Firstly, means and correlations of key variables were examined to see if the patterns were broadly consistent with previous research. Secondly, the data were divided by discipline group (math, engineering, computing, psychology, commerce and business (henceforth "commerce") and humanities and social sciences (henceforth "humanities"); and by over-arching discipline category (hard vs. soft paradigm), to examine differences between these groups on key variables. ANOVA and post-hoc comparisons were used to examine the nature of any differences. Finally, a full path model was tested, exploring the complex interrelationships between these variables and their implications for outcomes. As our data were collected in a stratified sample (students within discipline groups), we analysed the data clustered by thirteen course groups. We used Mplus (Muthén and Muthén 1998-2012) to handle both the clustering by discipline and the complexity of the model. While our sample size and uneven cell sizes did not allow for a full multi-level model, we used a random intercepts model to capture the non-independence inherent in collecting data in nested course and discipline groups. While we recognise the possible theoretical value of a full random slopes model, our data do not allow this analysis.

3.1 Preliminary Analysis

Table 1 presents the means, standard deviations, and correlations between all variables. There are few relationships between any of the pure demographics (age, gender, year and language background) and our key variables of interest and, moreover, those relationships that are significant are small in size. To simplify and focus the model on our key variables of interest the demographic variables were not included in the path analysis[3]. The personality variables, on the other hand, were correlated with the learning approach, social identity and norm scales and were, therefore, retained in the path model.

<<*Table 1 about here*>>

There are several important things to be noted about the correlational associations in the whole sample. First, stronger discipline identification is related to deeper learning approaches ($r = .347$, $p<.01$) and deeper learning norms ($r = .340$, $p<.01$), as we would expect from the previous literature. Second, self-reported deeper learning approaches also demonstrate the pattern of relationships we would expect, being positively associated with deep learning norms ($r = .302$, $p<.01$) and greater levels of conscientiousness ($r = .341$, $p<.01$) and negatively associated with surface learning approaches ($r = -.351$ $p<.01$) and surface learning norms ($r = -.149$, $p<.01$). Third, we note that our outcome measures are associated positively with discipline-related identification ($r = .442$, $p<.01$ and $r = .387$, *p*<.01, for perceived quality and intention to continue, respectively), deep learning approaches (r = .324, *p*<.01, r = .398, *p*<.01) and deep learning norms (r = .286, *p*<.01 and r = 238, *p*<.01). These outcomes are also negatively associated with surface learning approaches (r = .-.268, p<.01 and r = -.418, *p*<.01).

3.2 Discipline-group comparisons

To address our expectations on discipline differences, the six discipline groups were divided broadly into hard (engineering, computer science, mathematics; N=158) and soft (humanities, commerce and psychology; N = 157) categories. These sub-categories were large enough for meaningful analysis (n>150; Lizzio et al. 2002). They were, therefore, compared on all key variables to examine systematic discipline-category-based differences. The variables compared were identification, learning approaches and perceived norms, as well as personality, perceived teaching quality and intentions to continue. Category means on all key variables are presented in Table 2. Independent sample t-tests were conducted on all key variables. To account for family-wise error effects in multiple t-tests, a conservative confidence level of .01 was used in significance testing. Only deep learning approaches (*t* (312) = 3.14, *p*<.01), perceived teaching quality (*t* (295) =4.03, *p*<.01) and intentions to continue (*t* (299) = 3.93, *p*<.01) differed between these two broad categories, with the soft group scoring more highly on all three variables.

Differences in all key variables were then compared across all six discipline groups using ANOVA. Means and standard deviations across the six discipline groups can be seen in Table 2, and F-statistics can be seen in Table 3. Significant differences among discipline groups were found on all variables, except conscientiousness and discipline identification. Post hoc comparisons using the Tukey HSD test indicated a range of pair-wise differences, as indicated in Table 2 (group means that share subscript symbols do not significantly differ).

<<Tables 2 & 3 about here>>

Disciplines did not significantly differ on identification or deep learning norms scores. Deep learning approach scores differed such that the engineering (*M* =3.99) and commerce (*M* = 4.03) groups scored significantly lower than the humanities (*M* = 4.66) and psychology (*M* = 4.69) groups. Surface learning approach scores showed the expected converse pattern, with the psychology group (*M* =3.45) scoring significantly lower than the engineering (*M* =4.18) and commerce (*M* =4.39) groups. Mean scores on outcomes were also divergent. Commerce (*M*= 4.39) and engineering (*M*= 4.48) students scored, on average, significantly lower than humanities (*M*= 5.17) and psychology students (*M*= 5.60) on intentions to continue. Teaching quality scores significantly differed between such that humanities and psychology students reported greater teaching quality, on average.

The overall trends indicate that the engineering and commerce groups (the applied disciplines) differ significantly from the humanities and psychology (soft-pure disciplines) on many key variables. The hard-pure disciplines (computing and mathematics) showed less consistent trends, in that these disciplines were not significantly different from either the soft-pure or applied groupings. The scores for theses disciplines fell in a consistent descriptive pattern (below those for soft-pure and above those for applied) across deep learning, surface learning, surface learning norms, perceived teaching quality and intention to continue, but not significantly so.

3.3 Full model testing

We next tested the full conceptual model (see Figure 1), clustering the data at a course level to account for the systematic differences in the student experience identified above. In order to control for expected main effects identified in (Smyth et al. 2015), we added personality factors at the first stage of the path model, predicting our main social and norm variables. The full theoretical model was a good fit (χ^2 *(2) = 2.931, p=.2309;* χ^2/df = 1.4655, RMSEA=.040, CFI = .998, TFI = .955, SRMR = 0.012). The model can be seen in Figure 2[4].

<Figure 2 about here>>

In our model, for the personality aspects conscientiousness and extraversion, a few significant relationships emerged (for path weights, see Table 4). In predicting discipline social identification, effects were such that more conscientious and more extraverted students were more strongly identified with their discipline. In predicting deep learning norms, we found that more conscientious students were more likely to perceive norms supportive of a deep approach. Finally, in predicting surface learning norms, there were no significant effects for either personality factor.

<<Table 4 about here>>

The next stage of the model predicted learning approaches, with the social variables (identification, learning norms, their interaction), and personality as predictors. This stage of the model is shown in our model diagram (see Figure 2) and also Table 4. Surface learning approaches were negatively predicted by discipline identification levels (β = -.24 p<.001) and positively predicted by surface learning norms (β = .29, p<.001), but the interaction was not significant as a predictor of surface learning approach.

In predicting deep learning approaches, four of the relationships with the social identification and norm variables were significant and in the direction we would expect: stronger identification (β =.29 p<.001), stronger deep learning norms (β = .18 p<.001), weaker surface learning norms (β = -.12 p<.01), and the identification by deep learning norms interaction (β = .11 p<.001), all predicted deeper learning approaches. The identification by surface norm interaction, however, also predicted weaker deep learning approaches (β = -.102 p<.001).

<Figures 3 & 4 about here>>

The form of the interactions can be seen in Figures 3 and 4. Considering first the expected identification by deep norm interaction, the form of the interaction indicates that, overlaid on the positive main effect of norms, identification accentuates the normative effect at higher levels of identification. The second interaction, identification by surface norms, indicates that stronger surface learning norms decrease the adoption of deep learning approaches, but only in strongly identified students.

Simple slopes analysis[5] indicated that, for deep learning norms at low levels of identification (-1 SD), the relationship between perceived deep learning norms and deep learning approaches was non-significant ($\beta = .059$, $p = .389$). At high levels of identification (+1 SD), however, this relationship was positive and significant ($\beta = .278$, $p<.001$; see Figure 3. The relationship between surface learning norms and deep learning approaches is similarly non-significant at low levels of identification (-1 SD; $\beta = -.021$, $p = .653$). At high levels of identification (+1 SD), however, this relationship was negative and significant ($\beta = -.163$, $p<.001$), in that stronger surface learning norms were inversely related to deeper learning approaches (see Figure 4).

We then consider the outcome variables. First, the learning approaches and social variables were allowed to predict perceived course-based teaching quality. In predicting perceived teaching quality, we find that there were significant positive paths from deep learning approaches ($\beta = .11$, $p <.01$), deep learning norms ($\beta = .12$ $p<.05$) and discipline identification ($\beta = .32$ $p<.001$), as well as a significant negative path from surface learning approaches ($\beta = -.142$, $p<.001$). The main effect of identification on teaching quality was moderated by an identification by surface learning norm interaction. The form of the interaction can be seen in Figure 5. Stronger surface learning norms predicted stronger perceptions of good teaching quality, but only in students who were weakly identified. Simple slopes analysis indicated that, for students who were strongly identified, there was no significant effect of surface learning norms on perceived teaching quality (β = -.003, p = .974). For students who were weakly identified with their discipline, however, the effect of surface learning norms was significant and positive (β = .248, p = .007).

<Figure 5 about here>>

In predicting intentions to continue, we found five significant effects. Firstly, conscientiousness was a positive predictor (β = .14 p<.01), whereas extraversion was a negative predictor (β = -12 p<.01) of intention to continue. Both learning approaches were also significant predictors, in the directions we would expect (deep learning approach: β = .14 p<.001; surface learning approach: β = -.23 p<.01), as was perceived teaching quality (β = .41, p<.001).

4. Discussion

The current paper sought to build on recent literature that demonstrates the positive relationships of discipline-based social identification, perceived study norms and their interaction with learning approaches. The study adds to this literature by exploring differences across discipline groups and exploring two important outcome measures, perceived teaching quality and intentions to continue. We then cluster data by discipline group to control for within-discipline dependencies, allowing us to draw some inferences across disciplines that encompass the full range of the Biglan-Becher typology.

The pattern of zero-order correlations indicates two key things. Firstly, in line with the findings of Smyth et al. (2015), students who identify more strongly with their discipline were likely to perceive the norms among their fellow students to favour deep learning practices and take a deeper learning approach. Further, more strongly identified students also perceive the quality of teaching to be higher and are more likely to intend to continue in the field. Secondly, student outcomes (in this case perceptions of course-based teaching quality and intentions to continue with study or relevant employment) are related not only to individual factors (conscientiousness) but also to the learning approaches taken, as suggested by Lizzio, et al. (2002) and Platow et al. (2013). The pattern of correlations found in these data are as predicted from both education and psychology literature (Ramsden 2003; Bliuc et al. 2011b; Platow et al. 2013; Bliuc et al. 2011a; Biggs and Tang 2007a; Biggs et al. 2001).

4.1 Disciplinary variation

The six discipline groups were divided broadly into hard and soft categories. Deep learning approaches, perceived teaching quality and intentions to continue scores differed between these two categories, with the soft disciplines scoring more highly on all three dimensions. This suggests that, in accordance with the literature and our expectations, students in “soft” disciplines were taking deeper learning approaches and responded more positively on the outcome measures.

Differences between all six constituent disciplines were then explored, to trace differences that may lie along the pure/applied dimension, as well as discipline-specific effects. Significant differences among discipline groups were found on all variables, except conscientiousness and discipline identification. The lack of difference in identification was as expected and indicated that the extent to which students consider their field of study self-defining does not vary with content domain.

With regard to learning approaches and learning norms, we find that mean scores for applied disciplines were significantly more surface-oriented than those in soft-pure disciplines, but not significantly different to mean scores in the hard-pure disciplines. This pattern is repeated in the outcome scores, in that the soft-pure disciplines, had significantly higher averages on both outcomes, as compared to the engineering group (the commerce group scored with the engineering group on intention to continue but was not significantly lower on teaching quality). These trends support previous literature (e.g. Laird et al. 2008) that suggests that students in soft-pure disciplines take deeper learning approaches and report the associated more positive outcomes. The applied courses also demonstrated the expected effects, indicating a trend toward surface learning and surface learning norms. The vocational, procedural, job-specific nature of these courses’ content may drive this tendency toward surface learning. Lizzio et al. (2002) find similar effects in their datasets, in that commerce students in their sample who had stronger surface learning approaches achieved higher grades. Their explanation similarly focused on the applied nature of the field.

That we find these differences in learning approaches and outcomes, despite no between-discipline differences in identification levels or perceived deep learning norms, has important implications. What this suggests, in the first instance, is that there are meaningful discipline-based differences in the learning approach and outcome variables, and that these are not simply artefacts of baseline differences in identification between courses. That is, the reason we find deeper learning approaches in humanities and social science courses, is not that students in this discipline are simply more strongly identified. That there were no significant differences between disciplines on social identity and deep learning norms indicates that these discipline variations are not attributable to identification-related sampling error. There are real, meaningful variations in the student experience across disciplines. These differences likely take the form of teaching methods, typical tasks and research involvement (Lindbolm-Ylänne et al. 2006; Neumann 2001; Ramsden 2003).

4.2 Full model

Having established clear differences between student experience in various fields of study, we then tested our full model, clustering data by discipline group to control for within-discipline dependencies. The model was a good fit for the data and yielded several important findings.

We find that discipline-related identification and perceived deep learning norms significantly predicted deep learning approaches (see Figure 2 and Table 4). Similarly, surface learning approach was predicted by surface learning norms and negatively predicted by discipline-related social identification. The main effect relationships between identity, norms and deep learning approach were, however, moderated by the interactive effect of identification and norms for deep learning. All of these findings are in keeping with the emerging literature on social identity in education (Platow et al. 2013; Bliuc et al. 2011a, 2011b; Smyth et al. 2015).

The positive relationship between deeper learning norms and deep learning approach was moderated by the strength of student identification with the associated group, such that the effect was contingent on stronger identification (see Figure 3). Only those who identified strongly were influenced by the deep learning norms and therefore reported engaging in higher levels of deep learning. For those who reported a lower level of identification, there was no significant effect of perceived norm. What this suggests is that norms alone are not sufficient to drive students to adopt a deeper learning approach.

We can interpret this interaction in a complementary, alternative manner, if we consider the norm strength to be moderating the identification- learning approaches relationships. In this understanding, there is a significant positive relationship between identification and deep learning approaches. The form of the interaction suggests, however, that the effect of the perceived norms of that group modify this relationship. There is little difference in learning approaches between students who are strongly or weakly identified, when norms are not perceived to support deep learning. When the norms are strong, however, this difference is significant and positive (i.e. when norms are supportive of deeper learning approaches, more strongly identified students are significantly more likely to adopt a deep learning approach than weakly identified students).

The second interaction provides further evidence of this relationship. The identification by surface learning norm interaction is such that stronger surface learning norms mitigate the positive relationship of identification with deep learning approaches in highly identified students. This relationship is non-significant for low identifiers. Once again, for students strongly identified with their discipline, the nature of the perceived norms of the discipline group influence the adoption of learning approaches. This suggests that stronger discipline-related social identification will only lead to deeper learning approaches when the norms for that identity are perceived to support deep learning. Both these interpretations of the interaction are congruent with those that can be drawn from the findings of Smyth et al.(Smyth et al. 2015), but are also in line with findings we would expect, working from work from Jetten and colleagues on the role for norms in the identification-behaviour relationship (Jetten, Spears and Manstead, 1996; 1997).

In the final stage of the model, the learning approaches are, as we would expect, negatively correlated and predict the outcome variables. That is, deeper learning approaches predict more positive perceptions of teaching quality and stronger intentions to continue, whereas surface learning approaches negatively predict both outcomes (see Figure 2). This supports indications in the literature that deeper learning approaches are related to greater course satisfaction (Lizzio et al. 2002) and stronger intention to continue (Platow et al. 2013).

The one unexpected effect, when it comes to these outcome measures, was the identification by surface norm interaction. What we find here is that, for students weakly identified with their discipline, weaker perceived surface learning norms were associated with perceptions of significantly lower teaching quality. That is, the lowest rating of teaching quality were from students who were both weakly identified and perceived weak surface learning norms among their fellow students. One explanation here can be drawn from a consideration of the larger pattern of main effects. Overall, stronger discipline identification was associated with deeper learning approach. As such, it is reasonable to infer that more weakly identified students are taking more surface-oriented learning approaches. This, coupled with being in course in which their peers are *not* engaged in surface learning, likely leads to poorer comparative performance and a poorer understanding of the material. Poorer academic performance, in turn, can lead to a perception that the teaching is to blame, and therefore of poorer quality (e.g. Greenwald and Gillmore 1997).

Some limitations of the current methodology need to be borne in mind when interpreting our findings. The core limitation of the data is that it represents a single time-point "snapshot" of student responses. As has been discussed, learning approaches, social identification and norm processes are all inherently dynamic, context dependent and in a state of constant feedback. As such, these findings are limited in their ability to covey the complexity and changeability of these process. Instead, these findings should be treated as an indicative illustration of the shape and directions of the patterns of influence, which can be expanded upon through longitudinal and experimental research that captures causality and change over time. A second limitation is in the inclusion of students for whom the "field of study" question may be complex or ambiguous. While we attempted to capture the prevailing norms in the area of study most central to the student's identity, the reality of modern tertiary education is that fewer and fewer students are studying in a single discipline and many who are early in their study careers do not have a clear idea of which aspects or content domains in their studies may be self-defining. Given that our pattern of findings with regard to discipline differences falls in line with the existing literature, we do not foresee any problems in applying our findings. However, future research may clarify the pattern of findings, by categorising disciplines in a more granular way and allowing students to align themselves with multiple fields, or none at all.

4.3 Conclusion

Taken together, the findings indicate several key things. First, the data indicate disciplinary variations that mesh well with the literature on the Biglan-Becher typology (Becher and Trowler 2001). Secondly, we replicate the findings of Smyth et al (2015), indicating a key role of discipline-related social identification, perceived norms and their interaction in predicting learning approaches. In the current data we control for personal differences by measuring personality and control for some contextual variations by clustering data by discipline. Over and above both the personal and contextual influences, we still find a significant role for the social-identity and norm factors. Thirdly, we replicate the findings in the existing literature indicating that deeper learning approaches are associated with better outcomes. In the current data, these outcomes were: (1) perceived teaching quality, indicating that those who took a deeper approach had a better experience of the course, and (2) intention to continue, indicating that those who took a deep approach were more engaged with the community of practice in their discipline.

There are valuable practical and theoretical implications from these findings. They suggest that we need to consider a more complex view of the determination of learning approaches in tertiary education. Students are driven, not only by their own personalities and by the features of their learning context, but also by their perceived social environment.

Policy-makers and educators would gain from including these aspects in their considerations, when designing curricula or planning course activities. While student factors and learning environment do combine to predict learning approaches, including discipline social identification and perceived norms in the model allows us to predict learning approaches with greater accuracy. It also allows educators to begin to engage with the existing literature on the mechanisms of social influence in designing their courses, such that interventions and models designed to influence group behaviour in other domains can be more easily translated to the educational domain. There already exists a large body of social psychological research on the ways in which social influence through social identification and perceived norm is enacted and how we can harness this for positive change (Postmes et al. 2005; Postmes et al. 2001; Turner 1991; White et al. 2009; McGarty et al. 2009; Thomas and McGarty 2009; Thomas et al. 2009b, 2009a; Bliuc et al. 2006; Musgrove and McGarty

2008). With the inclusion of social identification and norms in our understanding of the learning process, we can then draw on this social influence literature to improve the effectiveness of the ways in which we attempt to shape student approaches to learning and educational outcomes.

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Footnotes

(1) The current sample was compared to the sample from the longitudinal dataset, using ANOVA. No significant differences were found in any of the variables used in the final model. As such, the dataset analysed here was considered equally representative of the broader population.

(2) Ordinarily, computing courses would be treated as “applied”, as they are technological courses. In the current sample, however, the computing courses surveyed were both coding-language based, theoretical courses focusing on the theoretical science of computing and were much closer to the Becher conceptualisation of a “pure” discipline as “cumulative, atomistic structure, concerned with universals, simplification and a quantitative emphasis.”(Neumann et al. 2002) .

(3) A model containing these variables was tested, but was a much poorer fit for the data and would not change the interpretation of the main models presented.

(4) For the sake of clarity, the personality variables are excluded from the figure. These variables were associated with measures at all stages of the model (as suggested by the literature), but are not the focus of the current paper. To facilitate a clearer focus on the novel aspect- social processes-, these paths are reported in full in Table 4, but not included in the figure.

(5) We thank Chris Sibley for his excellent tutorial example on calculating simple slopes in MPlus, available online (Sibley 2013).

Table & Figure Captions

Table 1: Means, standard deviations and correlations of key variables

Table 2: Means and standard deviations, by group

Table 3: one-way ANOVA, by discipline (6 groups)

Table 4: path weights, restricted model

Figure 1: Conceptual map of relationships

Figure 2: Full model. (χ^2 *(2) = 2.931, p=.2309;* χ^2/df = 1.4655, RMSEA=.040, CFI = .998, TFI = .955, SRMR = 0.012).

Figure 3: Form of the identification by deep-learning-norm interaction

Figure 4: Form of the identification by surface-learning-norm interaction, predicting deep learning approaches.

Figure 5: Form of the identification by surface-learning-norm interaction, predicting perceived quality of teaching.

Table 1: Means, standard deviations and correlations of key variables

	Mean (SD)	Age	GEND	NESB	Year	CONSC	EXTR	ID	DLA	SLA	DLN	SLN	QUAL
Gender (GEND)	-	.039	-										
NESB	-	.025	-.052	-									
Year	-	.285**	.119*	-.014	-								
Conscientiousness (CONSC)	4.58 (.859)	.025	-.197**	-.058	.016	-							
Extraversion (EXTR)	4.15 (1.032)	.068	-.129*	-.078	.076	.042	-						
Discipline Identification (ID)	5.28 (.771)	-.013	-.078	-.035	-.046	.169**	.122*	-					
Deep Learning Approach (DLA)	4.44 (.927)	.102	-.129*	.064	-.119*	.341**	.032	.347**	-				
Surface Learning Approach (SLA	3.75 (1.028)	-.029	.009	.053	.177**	-.170**	.033	-.224**	-.351**	-			

Deep Learning Norms (DLN)	4.60 (.807)	.025	-.179**	.097	-.097	.175**	-.015	.340**	.302**	-.070	-		
Surface Learning Norms (SLN)	4.66 (.997)	.019	.016	-.046	.030	-.003	.072	.005	-.149**	.272**	-.108	-	
Perceived Teaching Quality (Qual)	5.43 (1.034))	.023	-.203**	-.087	-.158**	.234**	.073	.442**	.324**	-.268**	.286**	.032	-
Intention to Continue (Cont)	5.11 (.996)	-.006	-.179**	-.107	-.241**	.328**	-.097	.387**	.398**	-.418**	.238**	-.103	.537**

**p<.01, *, p<.05

Table 2: Means & SDs by group

	Category		Hard			Soft		
	Hard	Soft	Maths	Engineering	IT	H&SS	Commerce	Psychology
Conscientiousness	4.51 (.851)	4.66 (.865)	4.51 (.846)$_{a}$	4.37 (.868)$_{a}$	4.88 (.808)$_{a}$	4.43 (.790)$_{a}$	4.54 (.888)$_{a}$	4.74 (.871)$_{a}$
Extraversion	4.07 (.913)	4.25 (1.106)	3.98 (.953)$_{b}$	4.30 (.758)$_{b,c}$	4.30 (.847)$_{b,c}$	4.05 (.894)$_{b}$	4.77 (1.012)$_{c}$	4.16 (1.142)$_{b,c}$
Discipline Identification	5.32 (.832)	5.24 (.661)	5.41 (.701)$_{d}$	5.03 (1.050)$_{d}$	5.32 (1.138)$_{d}$	5.08 (.659)$_{d}$	5.05 (.607)$_{d}$	5.32 (.664)$_{d}$
Deep Learning Approach	4.27^{α} (.905)	4.57^{α} (.923)	4.31 (.807)$_{e,f}$	3.99 (1.158)$_{e}$	4.77 (.734)$_{e,f}$	4.66 (.887)$_{f}$	4.03 (.744)$_{e}$	4.69 (.932)$_{f}$
Surface Learning Approach	3.83 (1.057)	3.62 (.959)	3.73 (1.033)$_{g,h}$	4.18 (1.165)$_{h,i}$	3.80 (.753)$_{g,h}$	3.52 (.989)$_{g,h}$	4.39 (.895)$_{i}$	3.45 (.881)$_{g}$
Deep Learning Norms	4.48 (.764)	4.67 (.816)	4.55 (.698)$_{j}$	4.21 (.943)$_{j}$	4.60 (.644)$_{j}$	4.70 (.921)$_{j}$	4.40 (.850)$_{j}$	4.74 (.776)$_{j}$
Surface Learning Norms	4.72 (1.069)	4.59 (.941)	4.77 (.999)$_{k,l}$	4.78 (1.194)$_{k,l}$	4.03 (1.201)$_{k}$	4.17 (1.180)$_{k}$	5.19 (.866)$_{l}$	4.53 (.831)$_{k}$

Perceived Teaching Quality	5.17$^{\alpha}$ (1.119)	5.67$^{\alpha}$ (.905)	5.31 (1.047)$_{m,n}$	4.77 (1.286)$_{m}$	4.97 (1.048)$_{m,n}$	5.81 (.777)$_{n}$	5.15 (.884)$_{m,n}$	5.76 (.901)$_{n}$
Intention to Continue	4.84$^{\alpha}$ (1.064)	5.33$^{\alpha}$ (.876)	4.98 (.980)$_{o,p}$	4.48 (1.218)$_{o}$	4.50 (1.112)$_{o,p}$	5.17 (1.005)$_{p,q}$	4.39 (.797)$_{o}$	5.60 (.678)$_{o,p,q}$

$^{\alpha}$denotes a significant difference (hard vs. soft).

Note: discipline means sharing a subscript letter do not significantly differ.

Table 2: Means & SDs by group

	Category		Hard			Soft		
	Hard	Soft	Maths	Engineering	IT	H&SS	Commerce	Psychology
Conscientiousness	4.51 (.851)	4.66 (.865)	4.51 (.846)$_{a}$	4.37 (.868)$_{a}$	4.88 (.808)$_{a}$	4.43 (.790)$_{a}$	4.54 (.888)$_{a}$	4.74 (.871)$_{a}$
Extraversion	4.07 (.913)	4.25 (1.106)	3.98 (.953)$_{b}$	4.30 (.758)$_{b,c}$	4.30 (.847)$_{b,c}$	4.05 (.894)$_{b}$	4.77 (1.012)$_{c}$	4.16 (1.142)$_{b,c}$
Discipline Identification	5.32 (.832)	5.24 (.661)	5.41 (.701)$_{d}$	5.03 (1.050)$_{d}$	5.32 (1.138)$_{d}$	5.08 (.659)$_{d}$	5.05 (.607)$_{d}$	5.32 (.664)$_{d}$
Deep Learning Approach	4.27$^{\alpha}$ (.905)	4.57$^{\alpha}$ (.923)	4.31 (.807)$_{e,f}$	3.99 (1.158)$_{e}$	4.77 (.734)$_{e,f}$	4.66 (.887)$_{f}$	4.03 (.744)$_{e}$	4.69 (.932)$_{f}$
Surface Learning Approach	3.83 (1.057)	3.62 (.959)	3.73 (1.033)$_{g,h}$	4.18 (1.165)$_{h,i}$	3.80 (.753)$_{g,h}$	3.52 (.989)$_{g,h}$	4.39 (.895)$_{i}$	3.45 (.881)$_{g}$
Deep Learning Norms	4.48 (.764)	4.67 (.816)	4.55 (.698)$_{j}$	4.21 (.943)$_{j}$	4.60 (.644)$_{j}$	4.70 (.921)$_{j}$	4.40 (.850)$_{j}$	4.74 (.776)$_{j}$

Surface Learning Norms	4.72 (1.069)	4.59 (.941)	4.77 (.999)$_{k,l}$	4.78 (1.194)$_{k,l}$	4.03 (1.201)$_{k}$	4.17 (1.180)$_{k}$	5.19 (.866)$_{l}$	4.53 (.831)$_{k}$
Perceived Teaching Quality	5.17^{α} (1.119)	5.67^{α} (.905)	5.31 (1.047)$_{m,n}$	4.77 (1.286)$_{m}$	4.97 (1.048)$_{m,n}$	5.81 (.777)$_{n}$	5.15 (.884)$_{m,n}$	5.76 (.901)$_{n}$
Intention to Continue	4.84^{α} (1.064)	5.33^{α} (.876)	4.98 (.980)$_{o,p}$	4.48 (1.218)$_{o}$	4.50 (1.112)$_{o,p}$	5.17 (1.005)$_{p,q}$	4.39 (.797)$_{o}$	5.60 (.678)$_{o,p,q}$

$^{\alpha}$denotes a significant difference (hard vs. soft).

Note: discipline means sharing a subscript letter do not significantly differ.

Table 4: Path weights, restricted model

Path from	to	Beta	*p*
Conscientiousness to:			
	Discipline Identification	.161	.002
	Deep Learning Norms	.175	.001
	Surface Learning Norms	-.009	.853
	Deep Learning Approaches	.247	.000
	Surface Learning Approaches	-.130	.000
	Intention to Continue	.150	.004
Extraversion to:			
	Discipline Identification	.123	.010
	Deep Learning Norms	-.033	.547
	Surface Learning Norms	.075	.231
	Intention to Continue	-.127	.000
Discipline Identification to:			
	Deep Learning Approaches	.304	.000
	Surface Learning Approaches	-.264	.000
	Perceived Teaching Quality	.287	.000
Deep Learning Norms to:			
	Deep Learning Approaches	.146	.001
	Perceived Teaching Quality	.100	.000
Surface Learning Norms:			
	Deep Learning Approaches	-.100	.005
	Surface Learning Approaches	.292	.000
	Perceived Teaching Quality	-.118	.164
Identification by DL Norm Interaction to:			
	Deep Learning Approaches	.141	.000
Identification by SL Norm Interaction to:			
	Deep Learning Approaches	-.102	.000
	Perceived Teaching Quality	-.161	.000
Deep Learning Approaches to:			
	Perceived Teaching Quality	.111	.001

Intention to Continue	.117	.000
Surface Learning Approaches to:		
Perceived Teaching Quality	-.178	.000
Intention to Continue	-.214	.002
Perceived Teaching Quality to:		
Intention to Continue	.382	.000

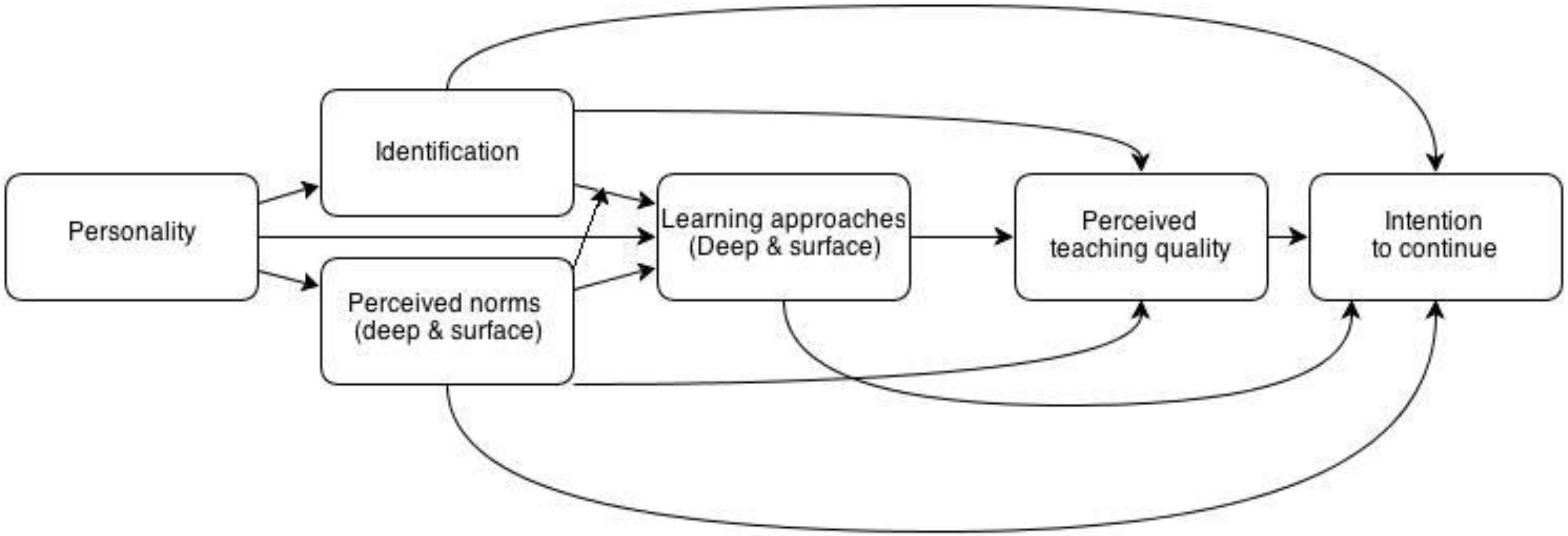
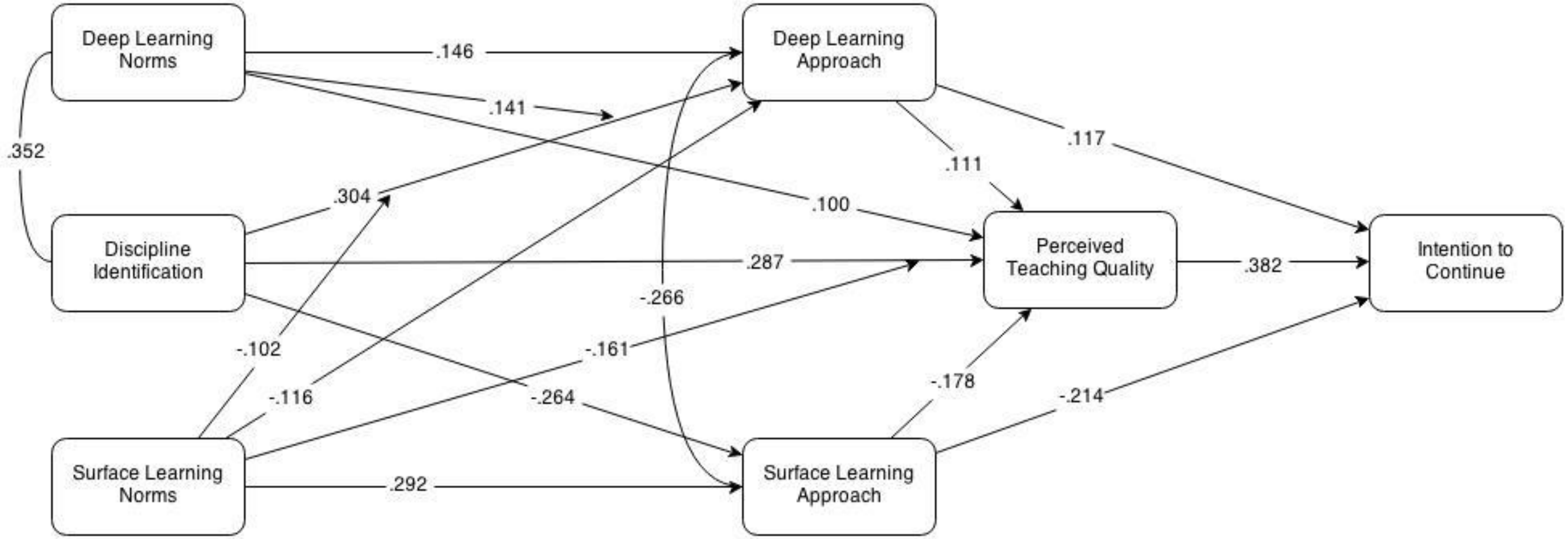

Identification
Personality
Perceived norms (deep & surface)
Learning approaches (Deep & surface)
Perceived teaching quality
Intention to continue

Figure 1



Deep Learning Norms
Discipline Identification
Surface Learning Norms
Deep Learning Approach
Surface Learning Approach
Perceived Teaching Quality
Intention to Continue
.352
.146
.141
.304
.100
.287
-.102
-.116
-.161
-.264
-.266
.292
.111
.117
.382
-.178
-.214

Figure 2

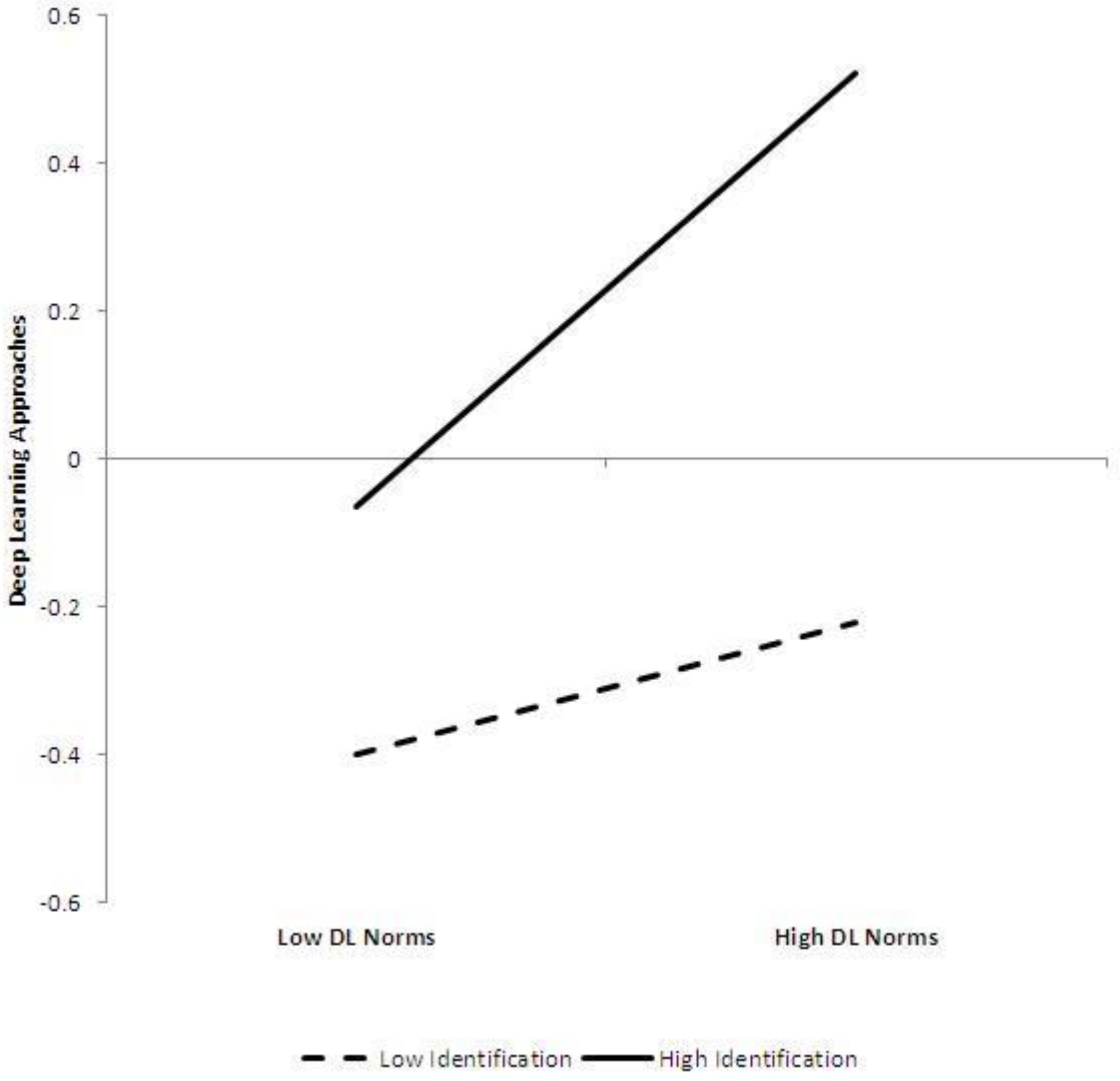

0.6
0.4
0.2
0
-0.2
-0.4
-0.6
Deep Learning Approaches
Low DL Norms
High DL Norms
Low Identification
High Identification

Figure 3

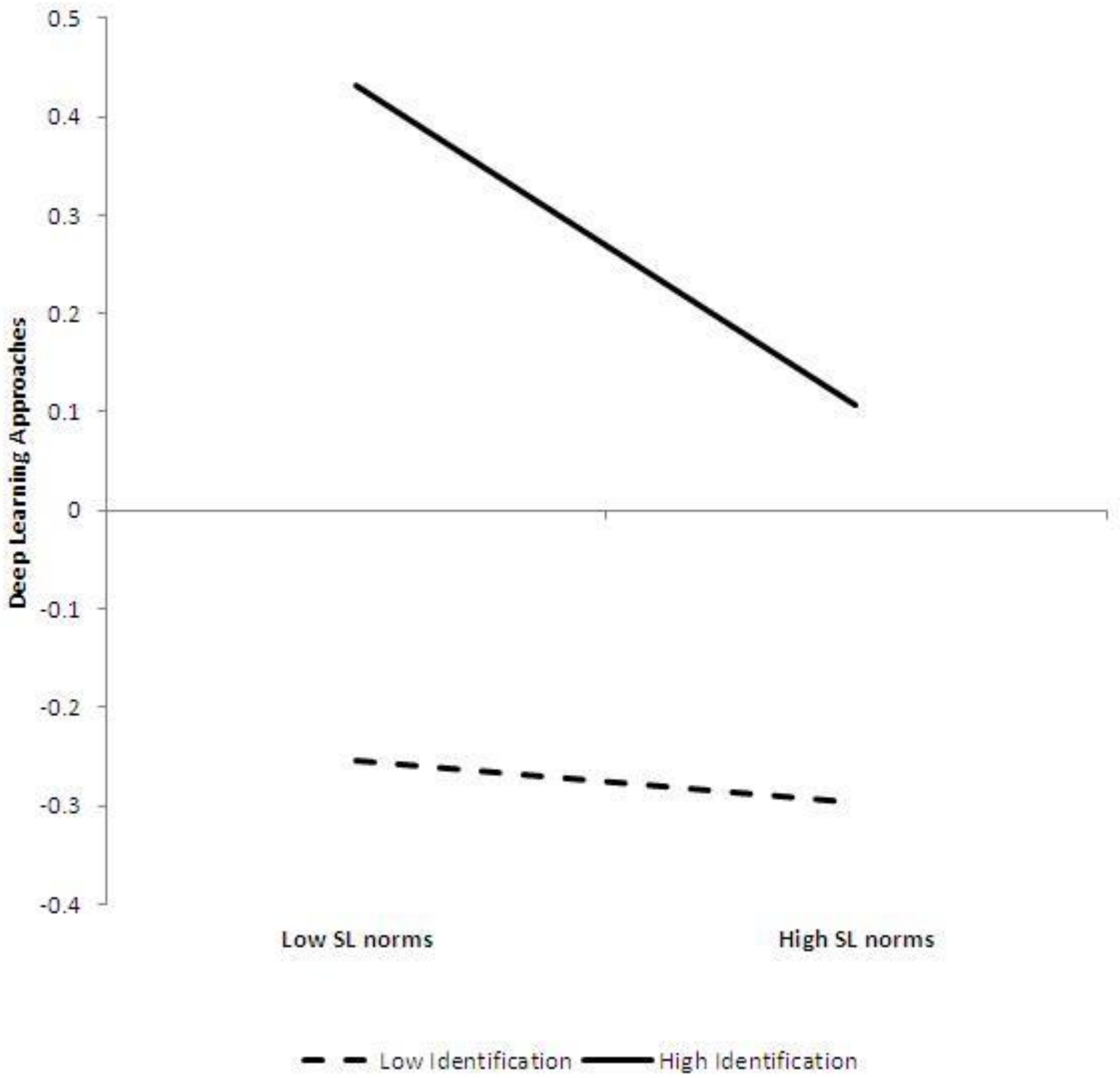

0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
Deep Learning Approaches
Low SL norms
High SL norms
Low Identification
High Identification

Figure 4

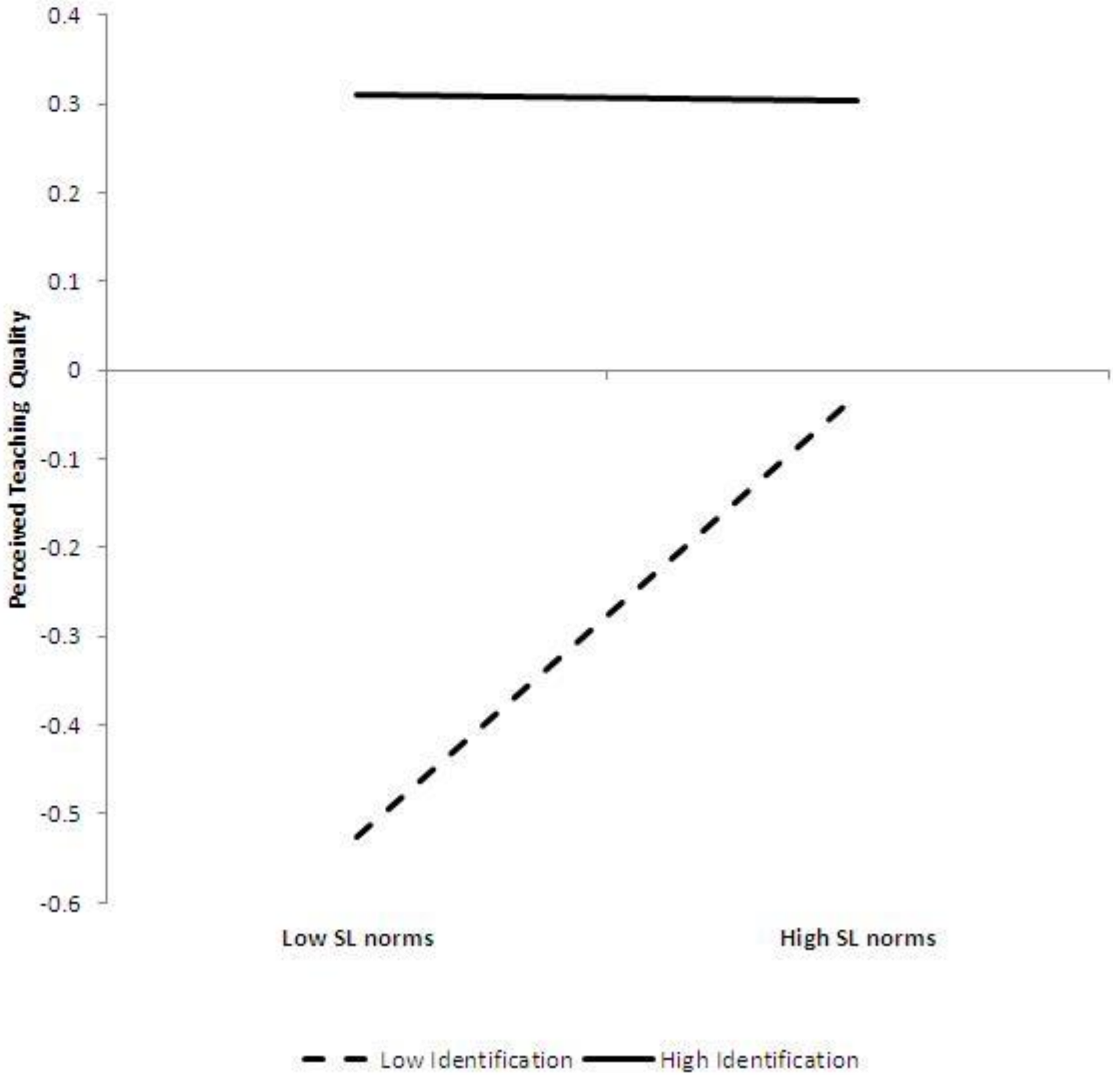

0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
Perceived Teaching Quality
Low SL norms
High SL norms
Low Identification
High Identification

Figure 5