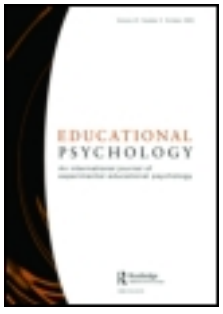

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Discipline social identification, study norms and learning approach in university students

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Discipline social identification, study norms and learning approach in university students

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Adopting a deep approach to learning is associated with positive academic outcomes. In the current paper, we extend this analysis in a university context by recognising that learners are not isolated individuals, but share important social identifications with others. Using online surveys at an Australian university, we examine the effects of discipline social identification and educational norms on the adoption of learning approaches. Students from a range of academic disciplines indicated their social identification with their discipline, their perceptions of peer norms within their discipline of study, and what their own learning approaches were. Results demonstrate a significant role of discipline-related social identification in predicting learning approaches, even after controlling for personal factors and quality of teaching. Moreover, perceived norms moderated this effect. Students' approaches to learning are affected not simply by their salient self-concepts, but by their salient *discipline-related* self-concepts and the norms embodied in the learning environment.

Keywords: discipline-related social identity; learning approach; norms; teaching quality; higher education

Traditional research on approaches to learning has focused on individual differences, factors relating to the teaching environment and the interaction between them. However, as recent research is beginning to investigate (Bliuc, Ellis, Goodyear, & Hendres, 2011a; Platow, Mavor, & Grace, 2013), the constructivist notion that learning is both individual *and social* (Palincsar, 1998) has not yet been fully explored, and social psychology has a significant contribution to make to understanding in this field. While student motivation, course structure, content quality, assessment type, workload and student personality undoubtedly impact upon the way in which students approach their learning in a particular course (Biggs, Kember, & Leung, 2001; Ramsden, 2003), the process is more complicated still. We argue that the way a student approaches learning in a particular course will be, in part, governed by his or her salient social identity, and the related perceived norms, much as behaviour in a range of other, non-educationally related areas is (e.g. healthy eating, Baker, Little, & Brownell, 2003; excercise, Hagger & Chatzisarantis, 2005; littering, Kallgren, Reno, & Cialdini, 2000; eating intentions,

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Louis, Davies, Smith, & Terry, 2007; choice of beer brand, Smith, Terry, & Hogg, 2006; recycling, Terry et al., 1999).

Learning approach is characterised in the literature as a relation between the learner and the material to be learned (Biggs, 1979). The 'approach' refers to the *way* a learner experiences and organises the subject matter to be learned and can differ across learners, tasks and contexts (Ramsden, 2003). These learning approaches can be broadly divided into two types: deep learning and surface learning (Biggs, 1999). Students are described as adopting a deep approach to learning when they focus on what the task is about, what the author of a text intended and how new information may fit into a larger framework and relate to other information. This kind of approach is characterised by an engagement with the material and an intention to understand, integrating new knowledge into existing frameworks, thinking critically, referring to a wide range of resources and questioning conclusions. In contrast, students described as adopting a surface approach focus on completing task-requirements and memorising what is necessary in the most efficient way possible. This kind of learning is generally characterised by a focus on isolated facts, rote memorisation strategies and selective information processing.

Research has also indicated that different learning approaches lead to different outcomes. A substantial body of educational research has focused on the impact of learning approach on academic outcomes such as grades (e.g. Artino, Rochelle, & Durning, 2010; Biggs, 1979; Lizzio, Wilson, & Simons, 2002; Richardson, Abraham, & Bond, 2012; Walsh, 2007) and while this is a complex relationship (Cassidy, 2004), there is a robust association between deep learning approaches and better academic outcomes (c.f. Bliuc et al., 2011a). Indeed, in a recent meta-analysis of factors affecting grade point average (GPA), Richardson et al. (2012) found that, although there is a long list of influencing factors, a deep learning approach was positively correlated with GPA (adding learning approaches to the model accounted for 9% of overall GPA variance).

Learning approaches, and particularly what leads students to adopt a deep learning approach, are, thus, of special interest to educators. However, determining the learning approach a particular student will take for a particular task is not straightforward. Learning approaches are not static individual differences. There are many personal and contextual factors that influence the way a particular student will relate to a particular task (Biggs, 1999; Biggs et al., 2001; Dolmans, Wolfhagen, & Ginns, 2010; Phan, 2009; Ramsden, 2003). Some of the person-level factors include the following: unique predisposition, motivation, life experience, prior knowledge, expectations and personality. At a context-level, school culture and values, assessment procedure, teaching quality, feedback model, clarity of teaching goals, duration of course, relevance to professional practice, time constraints, course structure and even the discipline area in which the student is studying are also all likely to influence learning approach (Baeten, Kyndt, Struyven, & Dochy, 2010; Biggs & Tang, 2007; Cousin, 2012; Entwistle, 2005; Nijhuis, Segers, & Gijselaers, 2008; Struyven, Dochy, Janssens, & Gielen, 2006; Trigwell & Prosser, 1991; Walsh, 2007).

Although a person-by-situation model, such as that suggested above, undoubtedly captures much of the variation in the way students relate to learning tasks, there is an important social dimension missing from this analysis. Researchers have begun to argue for a broader range of *social* and psychological factors underlying learning approaches (Bliuc et al., 2011a; Bliuc, Ellis, Goodyear, & Hendres, 2011b; Platow

et al., 2013; Yan & Kember, 2004). Using the social identity approach (Tajfel & Turner, 1986) as a unifying framework that describes how personal, situational and social factors are related, we can integrate the concept of social identification into pre-existing models in order to understand better how the type of learning approach employed is determined. The social identity approach, which includes both social identity theory (Tajfel & Turner, 1986) and self-categorisation theory (Turner, Hogg, Oakes, Reicher, & Wetherell, 1987), conceptualises the individual's sense of self as flexible, context dependent and comprised partly of social identities: 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). Applying this concept in an educational setting can give us valuable insight into the social factors at play in the teaching context. In the current paper, we use a concept of discipline-related social identity; the extent to which students perceived themselves as members of the group of students in their discipline area felt that being a student in their discipline is important to them, feel respect their fellow students, feel good about other students in their discipline, are comfortable telling others that they are a student in their discipline and feel that students in their discipline have a lot to be proud of. These aspects form part of an established scale, which is described fully below.

Some researchers have already begun to map this territory. Bliuc et al. (2011a) examined discipline-related social identity among other predictors of both learning approaches and academic achievement. The model proposed by Bliuc et al. holds that discipline-related social identity would predict academic achievement and that this would be mediated through the close association of discipline-related social identity with learning approach. That is, students who identified more strongly would be more likely to adopt a deep learning approach and, therefore, have better academic outcomes. The findings from this study supported this model, providing empirical support for the inclusion of discipline-related social identity in models of academic learning. Firstly, it was found that deep learning approaches were associated with better academic outcomes. Secondly, stronger identification as a psychology student was associated with a deep learning approach. And, thirdly, there was a significant indirect effect of discipline-related social identity on academic outcomes mediated *through* learning approach.

In a second paper, Bliuc et al. (2011b) again demonstrated the relationship between discipline-related social identity and deep learning in two additional samples and explored the relationship between social identification and perceptions of the learning community. In these studies, perceptions of the learning community were associated both with student identity and deep learning approaches, and completely mediated the relationship.

Independently developing a similar model of discipline-related social identity and learning approach, Platow et al. (2013) explored this relationship with a particular focus on the dynamic interplay between deep learning approaches and changes in the self-concept associated with a course of study. They argued that those who identify strongly as a psychology student would be more likely to develop an intrinsic interest in the course, as they are likely to share the normative interests they perceive psychology students to hold, and this would be expressed in a deep approach to learning. Reciprocally, those who pursue a deep learning approach may experience a consequent change in their self-concept and have a

stronger sense of shared identity with other students in the same course or discipline.

Platow et al. (2013) proposed a dynamic, cross-lagged model where the discipline-related social identity and learning approach are related to each other, and are reciprocally influential over time. Their longitudinal study in a first-year psychology course measuring discipline-related social identification, learning approach, learning outcomes (grade) and intention to continue provided partial support for the model. Discipline-related social identity and adoption of deep learning were significantly correlated at both measurement times; and a deep approach at Time 1 (i.e. Semester 1) positively predicted levels of psychology student identification at Time 2 (i.e. Semester 2). Discipline-related social identity was unrelated to surface learning. This is congruent with the findings of Bliuc et al. (2011a, 2011b), yet adds a crucial longitudinal element and emphasises the potentially positive feedback loop between identification and deep learning. Platow et al. also found that the relationship between deep learning at Time 1 and social identification as a psychology student at Time 2 was mediated by actual Time 1 learning (i.e. marks). Finally, although discipline-related social identity did not predict student performance beyond the effect of deep learning, it did independently predict intention to continue studying psychology.

The common thread running through these three recent studies is that those more strongly identified with a discipline-related social identity will employ a more engaged learning style. This represents an important step forward in the understanding of the social and psychological processes affecting the adoptions of a deep approach to learning. However, we argue that it is not only identification level that will impact study approach, but also each student's *construal of what that identity means*. What it means to be a 'psychology student', for example, may differ between any two given psychology students, while the understanding of what it means to study a particular field may vary across disciplines.

According to the social identity approach, an identity is an understanding of the self-in-context that contains information about norms, stereotypes about the in-group and relevant out-groups, and prototypes (i.e. a concept of the person who is most representative of *this* group, as compared to other groups) for in-group members (Turner et al., 1987). These understandings are derived from a comparative analysis of the self and the social context (McGarty, 1999). The net effect of this, as it applies to an educational context, is that every time a student thinks of him or herself as an 'engineering student' or a 'lawyer in training' or a 'member of the Monday-night tutorial' or even a 'night-before-the-exam crammer', these self-perceptions carry with them an understanding of a shared identity, a shared normative framework and regulations for what that means and ways 'people like me' behave (e.g. Haslam, Turner, Oakes, Reynolds, & Doosje, 2002). This normative framework is the student's perception of what those he or she considers similar to him or herself *do* and think they *should do* (Turner, 1991).

The social identity approach suggests that the strength of the effect the perceived normative framework will have on behaviour is determined by the extent to which the contextually salient self-perception (e.g. discipline-related social identity) is considered to be an important, central and definitive aspect of the self-concept (i.e. the extent to which the student identifies with it). When strongly identified with a particular group, the student will be more likely to be influenced by the norms of that reference group in choosing his or her own behaviour.

Through this process of normative influence, the more a person comes to define him or herself in terms of a particular group membership, the more he or she will think and act in terms of the group norm and prototypes (Turner, 1991). The behaviour of a student for whom the self-perception as a 'law student' is strongly self-defining would, thus, be expected to conform to what the student perceived to be the norms of the group 'law students'.

From this, it is clear that what students perceive to be the norms of their reference group (i.e. what they see as the meaning of the group membership they have applied to themselves) have an important role to play in influencing learning approaches and study behaviour. It is not only the strength of identification with a group that influences ultimate behaviour, but also what that group *means*. In this model, being strongly identified as a student in a given discipline is less likely to lead to a deep learning approach if the student sees the norm to be one of partying hard and cramming only to pass assessment.

It is here that the current paper provides a fundamental extension to the previous work on discipline-related social identity and learning approach. Accepting the points made by Bliuc et al. (2011a, 2011b) that social identification with fellow students influences learning approach and that of Platow et al. (2013) that learning approach also has an effect on the self-concept, this paper argues additionally that the meaning of the group with which the student identifies, and therefore, the perceived norms of that group will impact on the way in which strength of identification affects learning approach.

In order to test this model and address these issues, questions regarding learning approach and perceived learning norms were included within a larger study of student identity and attitudes sampled across a range of disciplines. As well as discipline-based social identification and learning approaches, the study also included perceived quality of teaching, personality and demographic information as important controls for alternative explanations of our data. In terms of personality, we expected that conscientiousness would be a particularly important factor likely to impact upon the approach to learning (e.g. Cheng & Ickes, 2009). We also expected perceptions of the quality of teaching to be an important influence on the learning behaviour. Further, in line with Platow et al. (2013), we would argue that adopting a particular learning approach would affect identification levels, depending on the level of congruence with the perceived norms of that identity. Although the data we present here represent a single time point, and, therefore, causal direction cannot be fully determined, the model put forward by Platow et al. is a dynamic one implying both causal directions. It is appropriate, therefore, to test both directions of the reciprocal effects model put forward by Platow et al., along with the moderating effects of norms that we have argued here, to see if either or both parts of the extended reciprocal model are plausible in this dataset. Therefore, as well as looking for the effects of identity and norms on learning approach, we will separately model the possibility that reported learning approach and perceived discipline norms will predict discipline identification.

Conceptually then, the factors under examination can be split into four thematic blocks. The first captures personal-level factors to explore an individual-differences model of learning approaches. We include age, gender, personality and language background in this block. Interactionist models that explore the interplay of personal factors and the learning context, in this case teaching quality, can be considered in block two. Our third block captures the main effects of a social identity contribution

to the explanatory model, by adding the discipline-related social identity and perceived norm variables. The final block explores the novel possibility that the perceived norms moderate the identity effects. Our novel contribution to this conceptual framework is the addition of the group reference norms, as a potential main effect and in interaction with identification.

We expected that:

(1) Participants' social identification as a student of their academic discipline will be associated with the adoption of a deep learning approach, but not with the adoption of a surface learning approach.
(2) Student-level factors (the personality factor conscientiousness) and context-level factors (perceptions of teaching quality) will significantly influence the learning approach adopted by participants, such that those who are more conscientious, and who have a more positive view of the learning environment will be more likely to adopt a deep learning approach.
(3) Discipline-related social identity and associated norms will significantly influence the adoption of a deep learning approach but not surface learning approach, *beyond* the effects of student and context factors.
(4) In accordance with a social identity model of normative influence, adoption of a deep learning approach will be predicted by an interaction between discipline-related social identity and discipline-related norms, where greater strength of identification with the discipline group and perceived deep learning norms of that group will lead to stronger deep learning approaches.
(5) Building on Platow et al.'s (2013) dynamic model, we also expect that taking a deep learning approach and perceiving the norms for one's discipline to promote deep learning will predict increased social identification with the discipline. That is, the interaction between the adoptions of a deep approach to learning and perceptions of peer deep learning norms will lead to stronger social identification.

Methods

Participants

Participants were 293 undergraduate students (164 female and 109 male, 20 unknown) from across approximately 20 different disciplines[1] at a moderately sized Australian university. Participants were part of a larger study of social and political attitudes and completed a version of the questionnaire that also included our measures. The mean age of our sample was 19 years, and 72% of students indicated that English was their first language. Participants were recruited by staff from the school of psychology visiting large classes that were selected based upon enrolment data. Participants completed an online survey within a few weeks of the beginning of the academic year. The sample for our investigation consisted of 145 students in the second year of their studies and 148 in their third year.[2]

Measures

Students' identification with their fellow students in their particular field of study was measured using an identification scale of five items that are widely used to measure social identification (see Haslam, 2004). Items were as follows: '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), 'I feel good about other students in my field of study', 'Students in my field of study have a lot to be proud of' and 'I have a lot of respect for students in my field of study'. In the current data, the scale was acceptably reliable ($\alpha = .88$).

Learning approach and norms

Students' learning approaches and perceived learning approach norms were measured using six items adapted from the revised version of the Study Process Questionnaire (SPQ; Biggs et al., 2001). Four items measured both learning approaches (e.g. 'I spend a lot of my free time finding out more about interesting topics dealt with in class'; 'I only study seriously those topics that I know will be assessed'.) and two items were used to assessed perceptions of norms among students in their field of study adapted from the SPQ ('Most students in my field of study prefer to focus on learning efficiently by memorising key information and minimising study time'., 'Most students in my field of study prefer to focus on understanding content fully and integrating new information with what they already know'). As this study was part of a larger study on student identity and social attitudes, we only had space for these six questions to address learning approach and norms. The items were chosen based on factor analysis of some pilot data so that the items would be representative of the larger constructs in the target population. Participants indicated their degree of agreement or disagreement with the statements on a seven-point Likert scale (ranging from strongly disagree to strongly agree).

Teaching quality

To examine course-level effects, perceived teaching quality (content, teaching, staff, and interest) was measured using four items on seven-point scales ranging from 'extremely low' to 'extremely high'. The items were: '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:', 'My respect for lecturers or professors teaching these courses is:' and 'My level of interest when it comes to studying in this field is:'. These questions were all highly correlated, loaded onto a single factor in preliminary factor analysis, and were, therefore, treated in our data as measuring one 'Teaching Quality' construct ($\alpha = .88$).

Person-level factors

To examine personal factors identified within the education literature as being important (e.g. Biggs, 1999), conscientiousness was measured using 24 items from the widely used Big-Five inventory (John, Naumann, & Soto, 2008; e.g. 'I am always prepared', 'I often forget to put things back in their proper place' (r); agree/disagree). Demographic variables, including age, gender, linguistic background and area of study, were also recorded.

Results

For our main analysis, multiple regression was chosen over SEM in this case because of the nature of the research questions. Our hypotheses address an incremental model, examining the effects of social identity factors over and above the already-established personal and contextual factors. As such, it was most useful to examine our data using sequential moderated multiple regression (Aiken & West, 1996; Tabachnick & Fidell, 2001).

Mean response values on all key scales (learning approaches, perceived norms and social identification with members of their discipline) were significantly above the mid-point of the scale ($p < .05$). Table 1 presents the means, standard deviations and correlations between the measures.

The first thing to be noted is the strong correlation between level of social identification with students in participants' field of study and perceptions of deep learning norms, such that those who identify more strongly with their discipline are more likely to perceive the norms among their fellow students to favour deep learning practices. Secondly, self-reported deep learning approaches are also associated with both discipline-related social identification and perceived deep learning norms, as expected. Deep learning approaches are also strongly related to teaching quality and significantly related to conscientiousness. It is worth noting the strengths of these relationships, in light of our contention that discipline-related social identity factors are a valuable addition to the model (see Table 1). Deep learning had the strongest association with teaching quality ($r = .412$, $p < .01$), followed by perceived deep learning norms ($r = .303$, $p < .01$), social identification ($r = .301$, $p < .01$) and conscientiousness ($r = .214$, $p < .01$). Finally, it should be noted that identification levels did *not* have a statistically significant relationship with self-reported surface learning habits, nor did we find a relationship with surface learning norms.

Predicting learning approach

To examine what role social identification might play in predicting learning approaches, two sets of multiple regression analyses were performed: one predicting

Table 1. Means and correlations of key variables.

	Mean (SD)	ID	DLA	SLA	DLN	SLN	QUAL	CONSC
Identification (ID)	4.19 (.68)	–						
Deep learning approach (DLA)	4.54 (1.17)	.301**	–					
Surface learning approach (SLA)	4.23 (1.42)	−.052	−.431**	–				
Deep Learning Norms (DLN)	4.50 (1.34)	.298**	.303**	−.038	–			
Surface Learning Norms (SLN)	4.46 (1.42)	−.073	−.045	.227**	−.327**	–		
Teaching quality (QUAL)	5.31 (.97)	.446**	.412**	.231**	.285**	−.105	–	
Conscientiousness (CONSC)	3.43 (.55)	.144*	.214**	−.251**	.001	−.026	.283**	–
Age	18.97 (2.44)	−.040	.046	−.120	−.063	−.040	.076	.064

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

deep learning and the other surface learning. We can see from Table 1 that discipline-related social identity variables have bivariate effects on deep learning approach that are of comparable size to both person and teaching context variables. We will now explore the incremental model to see what independent explanatory power these variables have, over and above that of these traditional predictors of learning approaches.

In block 1, personal variables (age, gender, conscientiousness and having a non-English-speaking background; NESB) were entered. For a deep learning approach, this model explained 7.3% of the variance, $F(4236) = 4.64$, $p < .001$, $R^2 = .073$. Of these, conscientiousness and gender were significant predictors, with deep learning being more associated with female and conscientious students (see Table 2). The same model predicted 9.9% of the variance in surface learning approach, $F(4237) = 6.49$, $p < .001$, $R^2 = .099$. In this case, all the block 1 variables were significant (see Table 3), with higher surface learning being associated with less conscientious students, being male, being younger and being from a non-English speaking background.

In block 2, perceived teaching quality was entered into each set of regressions, predicting deep learning, $F(5235) = 14.46$, $p < .001$, $R^2 = .24$, and surface learning, $F(5236) = 7.16$, $p < .001$, $R^2 = .13$. This model explained an additional 16.2% of the variance in deep learning, $F_{\text{Change}}(1235) = 49.90$, $p < .001$, and an additional 3.3% of the variance in surface learning approach, $F_{\text{Change}}(1236) = 8.97$, $p < .01$. Perceived teaching quality was a significant additional predictor for both learning styles, positively for deep learning and negatively for surface learning.

In the third block, discipline-related social identity main effect variables (level of social identification with students in participants' discipline and perceived norms of this group) were entered. For deep learning, $F(7233) = 13.07$, $p < .05$, $R^2 = .28$, the addition of discipline identification and perceived norms significantly accounted for a further 4.7% of variance, above and beyond that explained by the individual and environmental variables, $F_{\text{Change}}(2233) = 7.56$, $p < .01$, (see Table 2). Further, both discipline identification ($\beta = .13$, $p < .05$) and perceived deep learning norms ($\beta = .17$, $p < .01$) were significant independent predictors of a deep learning approach. In the case of surface learning, $F(7234) = 6.89$, $p < .05$ $R^2 = .17$, the discipline-related social identity and norm main effect variables in block 3 explained a further 3.9% of variance beyond that explained by the individual and environmental variables, $F_{\text{Change}}(2234) = 5.51$, $p < .01$. Of the social identity effects, only perceived surface learning norms ($\beta = .19$, $p < .01$) emerged as significant independent predictors (see Table 3).

Moderation effects of identity and norms on learning approach

The interaction terms for identification and perceived norms were included in block 4. In keeping with the practice in moderated multiple regression (Aiken & West, 1996), continuous interaction terms are computed as the product of the centred main effects terms, and interaction plots are based on predicted values at ±1 standard deviation on the continuous moderators. For a deep approach, $F(8, 232) = 12.03$, $p < .05$ $R^2 = .29$, a significant two-way interaction between discipline-related social identification and deep learning norms was found, ($\beta = .11$, $p < .05$). The significant moderation can be seen in Figure 1. Further analysis showed that for low-identifying students, the simple slope of deep learning norms vs. deep learning

Table 2. Regression coefficients, predicting deep learning.

Model		*B*	Std. err	*β*	*t*	Sig.
1	Constant	5.122	.256		19.980	.000
	Age	.015	.026	.035	.561	.575
	Gender	−.341	.152	−.141	−2.248	.025
	Conscientiousness	.496	.134	.233***	3.694	.000
	NESB	.036	.084	.027	.432	.666
2	Constant	5.264	.234		22.476	.000
	Age	.003	.024	.007	.127	.899
	Gender	−.411	.138	−.170**	−2.972	.003
	Conscientiousness	.230	.128	.108	1.798	.073
	NESB	.131	.078	.098	1.677	.095
	Teaching quality (Qual)	.522	.074	.432***	7.064	.000
3	Constant	5.305	.229		23.216	.000
	Age	.014	.023	.034	.602	.548
	Gender	−.447	.135	−.185**	−3.307	.001
	Conscientiousness	.241	.125	.114	1.933	.054
	NESB	.086	.077	.064	1.116	.265
	Qual	.391	.081	.323***	4.843	.000
	Discipline identification (ID)	.219	.111	.126*	1.979	.049
	Deep learning norms (DLN)	.150	.052	.172**	2.877	.004
4	Constant	5.230	.231		22.689	.000
	Age	.015	.023	.036	.650	.517
	Gender	−.421	.135	−.175**	−3.118	.002
	Conscientiousness	.246	.124	.116*	1.981	.049
	NESB	.093	.077	.070	1.220	.224
	Qual	.360	.082	.298***	4.408	.000
	Discipline identification (ID)	.284	.115	.163**	2.465	.014
	Deep learning norms (DLN)	.139	.052	.160**	2.667	.008
	ID × DLN interaction	.135	.070	.112*	1.925	.050

*$p < .05$, **$p < .01$, ***$p < .001$.

Table 3. Regression coefficients, predicting surface learning.

Model		*B*	Std. err	*β*	*t*	Sig.
1	Constant	3.586	.304		11.809	.000
	Age	−.063	.031	−.126*	−2.033	.043
	Gender	.440	.180	.152*	2.451	.015
	Conscientiousness	−.535	.159	−.208**	−3.359	.001
	NESB	.198	.100	.122*	1.970	.050
2	Constant	3.505	.300		11.685	.000
	Age	−.057	.031	−.113	−1.853	.065
	Gender	.481	.177	.166**	2.714	.007
	Conscientiousness	−.390	.164	−.152*	−2.374	.018
	NESB	.147	.100	.091	1.469	.143
	Qual	−.284	.095	−.195**	−2.994	.003
3	Constant	3.485	.294		11.838	.000
	Age	−.051	.030	−.102	−1.700	.090
	Gender	.490	.174	.169**	2.816	.005
	Conscientiousness	−.423	.161	−.165**	−2.622	.009
	NESB	.145	.099	.090	1.476	.141
	Qual	−.284	.103	−.195**	−2.756	.006
	Discipline identification (ID)	.143	.141	.068	1.018	.310
	Surface learning norms (SLN)	.192	.060	.194**	3.212	.002
4	Constant	3.516	.294		11.942	.000
	Age	−.054	.030	−.107	−1.786	.075
	Gender	.481	.174	.166**	2.770	.006
	Conscientiousness	−.413	.161	−.161*	−2.561	.011
	NESB	.157	.099	.097	1.588	.114
	Qual	−.248	.106	−.170*	−2.348	.020
	Discipline identification (ID)	.104	.143	.049	.725	.469
	Surface learning norms (SLN)	.185	.060	.187**	3.106	.002
	ID × SLN interaction	.115	.078	.091	1.471	.143

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

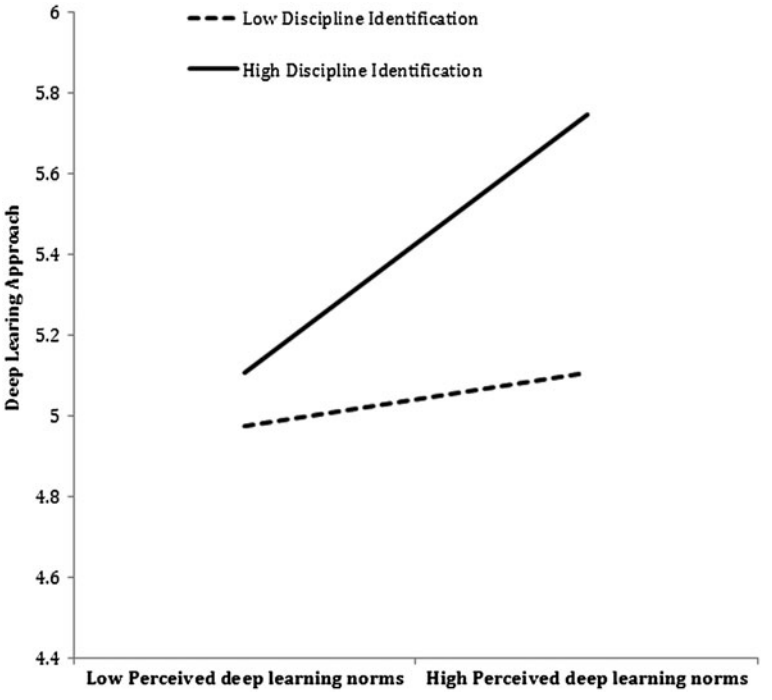

Figure 1. Interaction plot of discipline identification by deep learning norms predicting deep learning.

was not significant ($\beta = .058$, ns); however, for highly identified students, the simple slope was significant ($\beta = .156$, $p < .01$). As can be seen in Figure 1, the students adopting the highest level of deep learning are those who have high discipline-based social identification and perceive deep learning norms associated with that identity. There was no significant difference in deep learning approach between low and high identifiers when the perceived norms for the group were not supportive of deep learning. When predicting surface learning, the same interaction was entered in block 4, but was not found to be significant, $F_{\text{Change}}(1233) = 2.162$, $p = \text{ns}$, $R^2_{\text{Change}} = .01$, (see Table 3).

Reciprocal influence: predicting social identity from alignment of learning approach and norms

To test our final hypothesis, that an interaction between adoption of a deep approach to learning and perceived norms would lead to stronger social identification with one's discipline group, we considered the reciprocal regression predicting discipline social identity (see Table 4). In blocks 1 and 2, the same individual-level and course-level variables were entered as in the previous analyses. The individual-variable block was non-significant, but the model including the second block explained 20.5% of the variance, $F(5235) = 12.15$, $p < .001$, $R^2 = .21$. Conscientiousness predicted discipline social identity in block 1, but this effect disappeared in block 2. Perceived teaching quality was the only significant predictor in block 2 and remained

Table 4. Regression coefficients, predicting ID.

Model		*B*	Std. err	*β*	*t*	Sig.
1	Constant	4.130	.150		27.510	.000
	Age	−.012	.015	−.052	−.814	.416
	Gender	.045	.089	.032	.503	.616
	Conscientiousness	.217	.079	.178**	2.763	.006
	NESB	−.004	.049	−.005	−.078	.938
2	Constant	4.213	.137		30.755	.000
	Age	−.019	.014	−.081	−1.384	.168
	Gender	.003	.081	.002	.040	.968
	Conscientiousness	.061	.075	.050	.811	.418
	NESB	.052	.046	.067	1.132	.259
	Qual	.307	.043	.443***	7.107	.000
3	Constant	4.183	.137		30.502	.000
	Age	−.016	.014	−.066	−1.156	.249
	Gender	.015	.081	.011	.185	.854
	Conscientiousness	.057	.074	.047	.773	.440
	NESB	.023	.045	.030	.517	.606
	Qual	.233	.047	.336***	4.930	.000
	Deep learning approach (DLA)	.075	.038	.131*	1.979	.049
	Deep learning norms (DLN)	.082	.031	.165**	2.683	.008
4	Constant	4.170	.136		30.598	.000
	Age	−.012	.014	−.050	−.872	.384
	Gender	.011	.080	.008	.131	.896
	Conscientiousness	.057	.073	.047	.780	.436
	NESB	.019	.045	.025	.431	.667
	Qual	.223	.047	.321***	4.724	.000
	Deep learning approach (DLA)	.093	.039	.162*	2.399	.017
	Deep learning norms (DLN)	.079	.030	.158*	2.590	.010
	DLA × DLN	.040	.019	.123*	2.109	.036

*$p < .05$, **$p < .01$, ***$p < .001$.

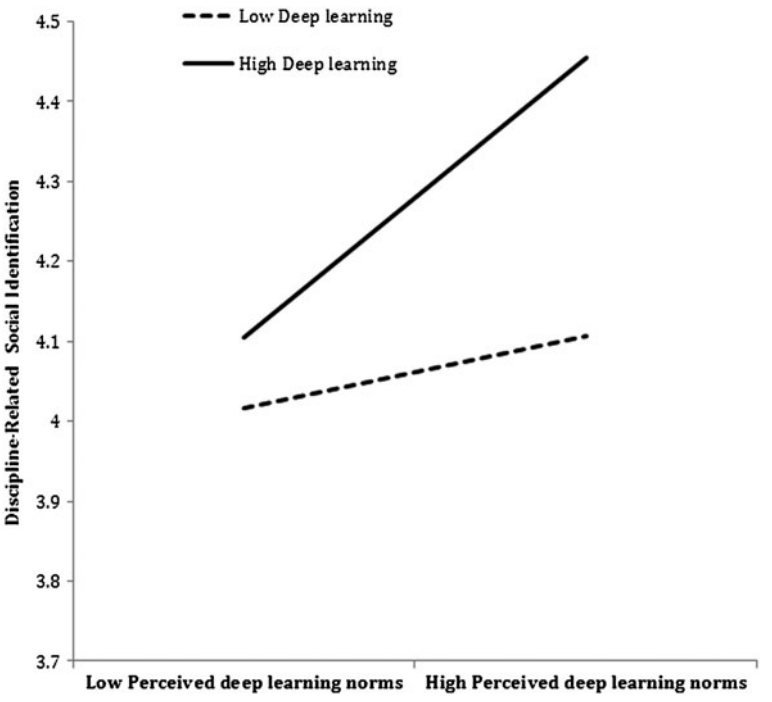

Figure 2. Interaction plot of deep learning approach by deep learning norms predicting discipline identification.

a significant predictor with the addition of further blocks, including the learning approach and norm variables.

In block 3, deep learning and perceived norms were entered as predictors $F(8232) = 11.13$, $p < .001$, $R^2 = .25$, explaining a further 4.5% of the variance, $F_{\text{Change}}(2233) = 7.01$, $p < .01$. The interaction term was then added in block 4 and was significant ($\beta = .12$, $p < .05$). The form of the moderation can be seen in Figure 2. For students with a low level of deep learning approach, the simple slope of deep learning norms on discipline-related social identification was not significant ($\beta = .038$, ns), whereas for students with a high deep learning approach, the simple slope was significant ($\beta = .15$, $p < .01$). The highest level of discipline-related social identification arises from the combination of one's own deep learning approach together with the perception that this is also normative in the discipline. Deep learning approach was only associated with a significantly higher discipline social identification when the perceived norms of the discipline aligned with that learning approach.

Discussion

The present study sought to evaluate the value of adding discipline-related social identity to models of learning approach. The important innovation reported here was the examination of a more complex relationship between discipline-related social identification and discipline-related learning norms, and the impact this may have on the learning approach taken. Learning approach has traditionally been

considered a product of context factors and individual differences. Bliuc et al. (2011a) and Platow et al. (2013) introduced social identification as a possible factor in predicting the learning approach students take in a tertiary education setting. The current paper supports the role of social identification but goes further, providing evidence for both the direct and moderating effect of perceived social norms for learning approach. We also extended the previous work in two other important ways: we sampled a wide sample of disciplines across a whole university and controlled for several important person and learning context factors, providing strong evidence for the robustness and additive impact of the discipline-related social identity effects beyond these other personal and contextual factors.

The pattern of zero-order correlations indicates that (1) students who identify more strongly with their discipline are likely to perceive the norms among their fellow students to favour deep learning practices, and (2) a self-reported deep approach to learning is associated with both discipline identification and perceived deep learning norms. These correlations are as predicted from both education and psychology literature (Biggs et al., 2001; Biggs & Tang, 2007; Bliuc et al., 2011a, 2011b; Platow et al., 2013; Ramsden, 2003) and suggest that, in line with our first hypothesis, participants' social identification as a student of their discipline is generally associated with deep learning.

To examine the second hypothesis, that student-, context- and social-level factors will all influence the learning approach adopted, we entered predictors of deep learning approach in four blocks. Results indicated that, as expected, in predicting a deep learning approach, personal (gender and conscientiousness), contextual (teaching quality measures) and social (identification and perceived norms) factors were all significant, independent predictors. In predicting surface learning, social identification had no significant effect, which is congruent with Hypothesis 4 and also consistent with the work of Bliuc et al. (2011a, 2011b) and Platow et al. (2013).

These results are consistent with the traditional learning approach literature, in that they demonstrate the role for personal and contextual factors in determining learning approach. They are also congruent with emerging social identity research in the area, in that level of identification with students in the participants' discipline was a significant predictor of deep learning, but not surface learning. The variance incrementally explained by the discipline-related social identity factors was relatively small, but, nonetheless, adds substantively to the explanatory model. The results also demonstrate a role for perceived norms, in that both surface and deep learning approaches were predicted by the related perceived norms among the reference group. In cases where participants perceived the norms of the reference group to be one of deep learning, they indicated a stronger tendency towards a deep learning approach and, similarly, when they perceived the norms for the reference group favoured surface learning, this perception predicted surface learning approaches.

These main effect relationships between identity, norms and learning approach were, however, modified by the interactive effect of identification and norms for deep learning. The positive relationship between discipline social identification and deep learning approach was moderated by the perceived content of the group norms, such that perceiving deep learning norms amplified the relationship (see Figure 1). For those not strongly identified with students in their discipline, these perceived norms had no significant effect. Put another way, the impact of perceiving

the norms of the group as favouring deep learning approaches was moderated by level of identification, such that only high identifiers were influenced by these norms and reported engaging in higher levels of deep learning.

We also tested the reciprocal relationship found by Platow et al. (2013) that shows the potential change of the self-concept, in terms of level of identification with the discipline, through taking a deep learning approach. We found support for this reciprocal effect for deep learning approach. By taking into account the effect of learning norms, we were able to extend the findings of Platow et al. by showing that this effect was moderated by the perceived normative content of the group. Students who adopted a deep learning approach, and perceived that this was the norm in their discipline, were more highly identified. Conversely, students for whom there was a mismatch between their own learning approach and the norms of their discipline (e.g. they were taking a deep approach, but their peers were not) did not show any difference in identification level between those taking a strong deep approach and those with a weaker deep approach. As expected, there were no main or moderation effects for surface learning.

Taken together, four clear findings emerge. First, in attempting to disentangle the complex web of factors that influence learning approaches, there is reason to examine factors at a personal, contextual *and more explicitly* social level. Secondly, as previously demonstrated (e.g. Bliuc et al., 2011a; Platow et al., 2013), there is a role for social identification in predicting the learning approach students will take, applying specifically in the case of a deep learning approach as opposed to a surface learning approach; this is likely to occur primarily because a deep approach to learning has implications for the way in which the academic discipline is related to the student's self-concept (Platow et al., 2013). Thirdly, this is the first study to demonstrate that the social identification effect on learning approach is moderated by the perceived norms for the group and, further, to demonstrate that these effects are present beyond those of personality and context variables. Finally, there is a bi-directional relationship between social identification and learning approach, moderated by the perceived norms of the reference group. That is, level of identification and deep learning approaches may influence one another reciprocally, and these effects are stronger in cases where the perceived group norms are congruent with a deep learning approach. This is reflective of a dynamic model of discipline-related social identity in education that captures both the influence of identification on learning behaviour and that of learning behaviour on social identification.

These findings contribute to the emerging picture of learning approach as partially determined by, and reciprocally involved with, social identifications as part of the learner's self-concept and emphasise the importance of the related normative content. In doing so, we also raise a number of possibilities for further research. Given the practical constraints of our sample, the reciprocal effects we demonstrated here are modelled in a single time only. Both directions of influence were supported in terms of the crucial identity by norms relationship, but with different patterns of significant covariates.[3] Further longitudinal studies like that of Platow et al. (2013) are needed to confirm causal influence for both aspects of the reciprocal relationship. Practical constraints also contributed to the limited number of items we were able to include measuring learning approach and norms. Moving forward, use of the full version of the R-SPQ-2F (Biggs et al., 2001) could be used to increase the reliability and power of these analyses.

Previous research has also primarily focused on samples from a single discipline (e.g. psychology students). Future studies should sample from a range of disciplines and incorporate measures of perceived norms (as we do here). Linking all these effects to actual academic performance is also important, with academic performance being both an outcome but also a potential mediator of discipline identification. Both Bliuc et al. (2011a) and Platow et al. (2013) find relationships between discipline-related social identity and academic performance mediated through deep learning. Platow et al. also find that the reciprocal effect of deep learning on identification is mediated through actual academic performance; that is, performing well in a course reinforces social identification with the discipline. Perhaps, academic performance (and the assessment structure) is another mechanism through which students perceive and reinforce their perceptions of the course learning norms. This is consistent with Biggs' work on approaches to learning (Biggs, 1979, 1999; Biggs et al., 2001; Biggs & Tang, 2007) and may provide interesting ground for further empirical exploration and theoretical integration (see also Osborne & Jones, 2011).

Considering these effects and the positive effects found elsewhere of social identity on study continuation (Christ, van Dick, Wagner, & Stellmacher, 2003), professionalism (Bennett, Roman, Arnold, Kay, & Goldenhar, 2005) security, belonging and commitment to an organisation (Lindgren & Wahlin, 2001) and a variety of other employment-related behaviours (Haslam, 2004), the development of discipline-related social identification is not only a positive educational force, but could also be considered a valuable graduate attribute of tertiary education (Platow, 2012).

Future work should explore ways educators can include these concepts in the pursuit of collaborative and peer learning (Topping, 2005). In light of our findings, it is worth exploring practical ways to foster both discipline-related social identity and productive study norms in student populations. Our findings and existing research in the social identity area (e.g. McGarty, Bliuc, Thomas, & Bongiorno, 2009; Thomas & McGarty, 2009; Thomas, McGarty, & Mavor, 2009a, 2009b) suggest that educators may be able to align discipline-related identities with productive study norms and foster strong identification among students through student interaction and guided discussion groups.

In summary, the current study provides support for the recent work proposing a role for discipline-related social identity processes in understanding students' learning approaches (e.g. Bliuc et al., 2011a), and also for the reciprocal effect of the particular learning approach chosen on self-concept change, as reflected in discipline social identity (Platow et al., 2013). We go beyond these approaches, demonstrating the important role of perceived norms, both as an independent effect and as a moderator of the relationship between identification and deep learning. We also show the reciprocal effect of deep learning on discipline identity and the moderating role of the perceived group norms on this relationship. All of these effects are demonstrated here after taking person and context factors in account. The social identity approach brings important complementary qualities to the existing learning approach literature and contributes significantly to an understanding of the reciprocal influence that discipline-based identities, norms and learning approaches have on each other, as students dynamically integrate a discipline-based identity within their self-concept.

Notes

1. Discipline was measured using a free-response item worded 'What is your main area of study (i.e. your chosen major, the discipline – e.g. Psychology, Biology etc)?'. A wide range of responses were given and coded into 20 categories (approximate percentages of the full sample below): accounting (9%), actuarial/statistics (3%), archaeology/anthropology (2%), Asia-pacific (1%), astronomy/physics (5%), biology/zoology (12%), history/philosophy/sociology (5%), economics (3%), literature/film/art/music (3.5%), languages (5%), business/commerce/marketing/management (4%), chemistry (3%), information technology (3%), finance (2.5%), development/environmental science (2%), electronic/engineering/mechanic/mechatronics (6%), international relations/politics (10%), law (10%), medical science (1%) and psychology (15%). Owing to the structure of this question, responses were highly variable and in many cases more than one response was given. This does not affect the participants' identification with their self-identified 'field of study' but it does prevent us from examining systematic effects across disciplines. However, we thank two anonymous reviewers for the suggestion that we may be able to analyse this data using a broader domain categorisation. To explore this, the disciplines were organised into 6 broad categories (approximate percentages of the full sample below: health & natural science (18%), business & economics (23%), arts & languages (14%), social science & history (21%), mathematics, physical sciences and engineering (18%) and law (7%)). We then performed analyses on the 48% of participants ($n = 141$) who fit neatly into one discipline area. We dummy coded the six domains into five variables and entered them in the first block of the sequential regressions in order to see if there were any effects for discipline grouping even prior to accounting for any other variables. Neither the total effect of the block (representing the main effect of discipline grouping) nor any of the individual grouping codes was significant. Therefore, there was no indication that the discipline-grouping variable was acting as a predictor of learning approach in this data, and we did not consider it further.
2. To explore the possibility that there were substantive differences between these two-year-level cohorts, independent samples *t*-tests were used to compare the means on the key variables of interest (identification, both learning approaches, learning approach norms, teaching quality and conscientiousness) between year levels. As none of the differences were significant, the year-level cohorts were collapsed and treated as one sample.
3. In simple models, the causal order of variables can be reversed without changing the implied covariation matrix, and therefore, the reciprocal relations are not informative. In the current case, however, the reciprocal model is not a simple reversal of all relations in the model, and the patterns of covariates are somewhat different, suggesting that the reciprocal models here represent substantively different, and separately testable, models of the underlying covariation matrix.

References

Aiken, L. S., & West, S. G. (1996). *Multiple regression testing and interpretation*. Newbury Park, CA: Sage.

Artino, A. R., Rochelle, J. S. L., & Durning, S. J. (2010). Second-year medical students' motivational beliefs, emotions, and achievement. *Medical Education, 44*, 1203–1212.

Baeten, M., Kyndt, E., Struyven, K., & Dochy, F. (2010). Using student-centred learning environments to stimulate deep approaches to learning: Factors encouraging or discouraging their effectiveness. *Educational Research Review, 5*, 243–260.

Baker, C., Little, T., & Brownell, K. (2003). Predicting adolescent eating and activity behaviors: The role of social norms and personal agency. *Health Psychology, 22*, 189–198.

Bennett, A., Roman, B., Arnold, L., Kay, J., & Goldenhar, L. (2005). Professionalism deficits among medical students: Models of identification and intervention. *Academic Psychiatry, 29*, 426–432.

Biggs, J. (1979). Individual differences in study processes and the quality of learning outcomes. *Higher Education, 8*, 381–394.

Biggs, J. (1999). What the student does: Teaching for enhanced learning. *Higher Education Research & Development, 18*, 57–75.

Biggs, J., Kember, D., & Leung, D. (2001). The revised two-factor study process questionnaire: R-SPQ-2F. *British Journal of Educational Psychology, 71*, 133–149.
Biggs, J., & Tang, C. (2007). *Teaching according to how students learn teaching for quality learning at university* (pp. 15–30). Maidenhead: Open University Press.
Bliuc, A.-M., Ellis, R. A., Goodyear, P., & Hendres, D. M. (2011a). The role of social identification as university student in learning: Relationships between students' social identity, approaches to learning, and academic achievement. *Educational Psychology: An International Journal of Experimental Educational Psychology, 31*, 559–574.
Bliuc, A.-M., Ellis, R. A., Goodyear, P., & Hendres, D. M. (2011b). Understanding student learning in context: Relationships between university students' social identity, approaches to learning and academic performance. *European Journal of Psychology of Education, 26*, 417–433.
Cassidy, S. (2004). Learning styles: An overview of theories, models, and measures. *Educational Psychology: An International Journal of Experimental Educational Psychology, 24*, 419–444.
Cheng, W., & Ickes, W. (2009). Conscientiousness and self-motivation as mutually compensatory predictors of university-level GPA. *Personality and Individual Differences, 47*, 817–822.
Christ, O., van Dick, R., Wagner, U., & Stellmacher, J. (2003). When teachers go the extra mile: Foci of organisational identification as determinants of different forms of organisational citizenship behaviour among schoolteachers. *British Journal of Educational Psychology, 73*, 329–341.
Cousin, G. (2012). Getting our students to engage: A review of two key contributions 10 years on. *Higher Education Research & Development, 31*, 15–20.
Dolmans, D., Wolfhagen, I., & Ginns, P. (2010). Measuring approaches to learning in a problem based learning context. *International Journal of Medical Education, 1*, 55–60.
Entwistle, N. (2005). Contrasting perspectives on learning. In F. Marton, D. Hounsell, & N. Entwistle (Eds.), *The experience of learning: Implications for teaching and studying in higher education* (3rd Internet ed., pp. 3–22). Edinburgh: University of Edinburgh, Centre for Teaching, Learning and Assessment.
Hagger, M., & Chatzisarantis, N. (2005). First and higher-order models of attitudes, normative influence and perceived behavioural control in the theory of planned behaviour. *British Journal of Social Psycholgoy, 44*, 513–535.
Haslam, S. A. (2004). *Psychology in organizations: The social identity approach* (2nd ed.). London: Sage.
Haslam, S. A., Turner, J. C., Oakes, P. J., Reynolds, K., & Doosje, B. (2002). From personal pictures in the head to collective tools in the world: How shared stereotypes allow groups to represent and change social reality. In C. McGarty, V. Y. Yzerbyt, & R. Spears (Eds.), *Stereotypes as explanations: The formation of meaningful beliefs about social groups* (pp. 157–185). Cambridge: Cambridge University Press.
John, O. P., Naumann, L. P., & Soto, C. J. (2008). Paradigm shift to the integrative big-five trait taxonomy: History, measurement, and conceptual issues. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), *Handbook of personality: Theory and research* (pp. 14–158). New York, NY: Guilford Press.
Kallgren, C. A., Reno, R. R., & Cialdini, R. B. (2000). A focus theory of normative conduct: When norms do and do not affect behavior. *Personality and Social Psychology Bulletin, 26*, 1002.
Lindgren, M., & Wahlin, N. (2001). Identity construction among boundary-crossing individuals. *Scandinavian Journal of Management, 17*, 357–377.
Lizzio, A., Wilson, K., & Simons, R. (2002). University students' perceptions of the learning environment and academic outcomes: Implications for theory and practice. *Studies in Higher Education, 27*, 27–49.
Louis, W., Davies, S., Smith, J., & Terry, D. (2007). Pizza and pop and the student identity: The role of referent group norms in healthy and unhealthy eating. *The Journal of Social Psychology, 147*, 57–74.
McGarty, C. (1999). *Categorization in social psychology.* London: Sage.
McGarty, C., Bliuc, A., Thomas, E., & Bongiorno, R. (2009). Collective action as the material expression of opinion-based group membership. *Journal of Social Issues, 65*, 839–857.

Nijhuis, J., Segers, M., & Gijselaers, W. (2008). The extent of variability in learning strategies and students' perceptions of the learning environment. *Learning and Instruction, 18*, 121–134.
Osborne, J. W., & Jones, B. D. (2011). Identification with academics and motivaiton to achieve in school: How the structure of the self influences academic outcomes. *Educational Psychology Review, 23*, 131–158.
Palincsar, A. S. (1998). Social constructivist perspectives on teaching and learning. *Annual Review of Psychology, 49*, 345–375.
Phan, H. P. (2009). Relations between goals, self-efficacy, critical thinking, and deep processing strategies: A path analysis. *Educational Psychology: An International Journal of Experimental Educational Psychology, 29*, 777–799.
Platow, M. J. (2012). PhD experience and subsequent outcomes: A look at self-perceptions of acquired graduate attributes and supervisor support. *Studies in Higher Education, 37*, 103–118.
Platow, M. J., Mavor, K. I., & Grace, D. M. (2013). On the role of discipline-related self-concept in deep and surface approaches to learning among university students. *Instructional Science, 41*, 271–285.
Ramsden, P. (2003). Approaches to learning. In P. Ramsden (Ed.), *Learning to teach in higher education* (pp. 39–61). London: Routledge.
Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin, 138*, 353–387.
Smith, J., Terry, D., & Hogg, M. (2006). Who will see me? The impact of type of audience on willingness to display group-mediated attitude-intention consistency *Journal of Applied Psychology, 36*, 1173–1197.
Struyven, K., Dochy, F., Janssens, S., & Gielen, S. (2006). On the dynamics of students' approaches to learning: The effects of the teaching/learning environment. *Learning and Instruction, 16*, 279–294.
Tabachnick, B., & Fidell, L. (2001). *Using multivariate statistics* (4th ed.). Boston, MA: Allyn & Bacon.
Tajfel, H., & Turner, J. (1986). The social identity theory of intergroup behaviour. In S. Worshel & W. Austin (Eds.), *Psychology of intergroup relations* (pp. 7–24). Chicago, IL: Nelson Hall.
Terry, D., Hogg, M., & White, K. (1999). The theory of planned behaviour: Self identity, social identity and group norms. *British Journal of Social Psychology, 38*, 225–244.
Thomas, E., & McGarty, C. (2009). The role of efficacy and moral outrage norms in creating the potential for international development activism through group-based interaction. *British Journal of Social Psychology, 48*, 115–134.
Thomas, E., McGarty, C., & Mavor, K. I. (2009a). Aligning identities, emotions and beliefs to create commitment to sustainable social and political action. *Personality and Social Psychology Review, 13*, 194–218.
Thomas, E., McGarty, C., & Mavor, K. I. (2009b). Transforming "apathy into movement": The role of prosocial emotions in motivating action for social change. *Personality and Social Psychology Review, 13*, 310–333.
Topping, K. J. (2005). Trends in peer learning. *Educational Psychology: An International Journal of Experimental Educational Psychology, 25*, 631–645.
Trigwell, K., & Prosser, M. (1991). Improving the quality of student learning: The influence of learning context and student approaches to learning on learning outcomes. *Higher Education, 22*, 251–266.
Turner, J. (1991). *Social influence*. Milton Keynes: Open University Press.
Turner, J., Hogg, M., Oakes, P., Reicher, S., & Wetherell, M. (1987). *Rediscovering the social group: A self-categorization theory.* Oxford: Blackwell.
Walsh, A. (2007). An exploration of Biggs' constructive alignment in the context of work-based learning. *Assessment & Evaluation in Higher Education, 32*, 79–87.
Yan, L., & Kember, D. (2004). Avoider and engager approaches by out-of-class groups: The group equivalent to individual learning approaches. *Learning and Instruction, 14*, 27–49.