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Reciprocal modeling of university students' perceptions of the learning environment, engagement, and learning outcome: A longitudinal study

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ABSTRACT

While researchers have proposed a reciprocal and bidirectional relationship among students' perceptions of their learning environment, engagement, and learning outcomes in college learning, scant research has effectively tested this assertion using longitudinal data. The present study examined this relationship with the use of an auto-/cross-lagged longitudinal structural equation modelling across a lag of 2.5 years. University students' (N = 966) perceptions of the learning environment, engagement, generic skills, and GPA were surveyed and collected at sophomore and senior years. In addition to significant auto-lagged effects, the cross-lagged results showed unidirectional predicting paths from prior perceptions to subsequent engagement, and reciprocal and bidirectional relationship between engagement and generic skills. The results provided partial support for the reciprocity of these variables, and confirmed the important role of engagement in the process of college student learning, which extends previous cross-sectional findings in theoretical meaningful ways.

1. Introduction

Student learning in higher education has been the focus of extensive research over many decades. A substantial body of research has documented the significance of students' perceptions of the learning environment (Prosser & Trigwell, 1999; Ramsden, 1997), approaches to learning (SAL; Marton & Saljo, 1976; Biggs, 1993), self-regulated learning (SRL; Pintrich & Zusho, 2007; Zimmerman, 2008), and engagement (Coates, 2007; Kahu, 2013). Researchers have generally shown that these factors are critical to college success. Students who perceive positive learning experiences, exhibit deep learning approaches, employ metacognitive strategies, and put forth effort in learning, are more likely to achieve academic success, greater generic skills development, and higher levels of satisfaction than those who do not (Dent & Koenka, 2016; Diseth, Pallesen, Brunborg, & Larsen, 2010; Guo, 2018; Pascarella & Terenzini, 2005; Zusho, 2017). Furthermore, by categorizing these variables into groups of presage (input/antecedent), process (environment/stage), and product (outcome/consequence), researchers have modeled the relationships among these variables as bidirectional and reciprocal (Biggs, 1999; Kahu, 2013; Llorens, Schaufeli, Bakker, & Salanova, 2007; Zusho, 2017; Skinner, Furrer, Marchand, & Kinderman, 2008): Presage variables lead to process variables, which lead to product variables, which then spiral up to presage variables. For instance, students' positive perceptions of the learning environment lead to increased engagement and deeper learning approaches, which in turn improve perceptions. Likewise, increased engagement promotes better learning outcomes, which in turn motivate students to be more engaged.

However, little is known about the longitudinal interplay among these above-mentioned variables that allows the control of prior variance and investigation of reciprocal relations over time (Guo, Yang, Zhang, & Gan, 2022; Richardson, 2006). Indeed, past studies have largely examined unidirectional regression paths of these variables based on cross-sectional data, which constrains the capacity of interpreting reciprocal relationships between the variables in the models of student learning. In other words, the longstanding theoretical assertion that these variables are reciprocally connected over time has not been empirically tested by previous longitudinal studies. Guo and colleagues (Guo, 2018; Guo et al., 2022) investigated the relationship among university students' perceptions of the learning environment, engagement,

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and their learning outcomes. Engagement was found as an important factor mediating the effects of perceptions of the learning environment on learning outcomes. However, the reciprocal relationships between these variables cannot be drawn due to the cross-sectional nature of these studies. The main objective of the present study is thus to deal with this limitation by investigating reciprocal relationships among students' perceptions of the learning environment, engagement, and learning outcomes from a longitudinal modeling perspective. The findings from this study can contribute to developing a better understanding of how students learn in higher education.

2. Student engagement and learning models in higher education

Three influential models have been constructed to account for student learning in higher education. The first model centers on student engagement and its impact on learning. Researchers generally acknowledge the critical role of student engagement in learning (Bowen, 1977; Kahu, 2013; Loes, Pascarella, & Umbach, 2012; Zepke, 2014). It is widely believed that the more a student engages and invests time and effort in academic-related activities, the more he/she will gain from college (Pace, 1998; Zusho, 2017). Indeed, student engagement is so prominent that it is often uncritically accepted and connected with student success (Thomas, 2012; Zepke, 2014).

Being an overarching meta-construct that tries to include all things in teaching and learning (Zepke, 2014), however, student engagement has been criticized for its unclear conceptualization and measurement. Researchers agree that engagement is a multidimensional construct but debate on the number and nature of its dimensions. Fredricks and colleagues has proposed a most widely accepted conceptualization of engagement consisting of three distinct but interrelated dimensions of behavior, cognition, and affect (Kahu, 2013; Zepke, 2014). As Fredricks, Blumenfeld, and Paris (2004) suggested, behavioral engagement refers to positive conduct, involvement, and participation in academic and social activities. Cognitive engagement focuses on students' use of self-regulated learning, deep learning strategies, and investment in comprehending complex ideas. Affective engagement reflects the pleasure, enthusiasm, attachment, belonging, and positive reactions to and relationships with others or school. Besides, scholars have also proposed other conceptualizations of engagement, including dimensions of academic (Reschly & Christenson, 2006), agentic (Reeve & Tseng, 2011), social-behavioral (Linnenbrink-Garcia, Rogat, & Koskey, 2011), and volitional (Filsecker & Kerres, 2014). Student self-report survey measures are most commonly used to assess student engagement in general. However, as Fredricks and colleagues concluded (Fredricks, Filsecker, & Lawson, 2016; Fredricks & McColskey, 2012), there are some overlaps between these dimensions and the survey items measuring these dimensions are often inconsistent across studies. For instance, items measuring behavioral engagement in one study may be used to measure cognitive engagement in another study (Christenson, Reschly, & Wylie, 2012).

Another major limitation in engagement research, as Skinner et al. (2008) proposed, is the unclear distinction between indicators and facilitators of engagement. The broad definition of engagement makes it difficult to distinguish the state of engagement from its antecedents and consequences. Researchers have proposed frameworks to address the relationship of these variables. For instance, after summarizing and discussing four main perspectives of student engagement research (i.e., behavioral, psychological, sociocultural, holistic), Kahu (2013) proposed a conceptual framework to integrate these perspectives. At the center of her model is student engagement with three dimensions of affect, cognition, and behavior. Two types of antecedents are proposed to predict engagement: distal structural factors (e.g., curriculum, discipline, student background) and proximal psychosocial factors (e.g., teaching, workload, motivation). The model also includes two types of consequences as outcome variables: distal consequences refer to outcomes such as learning achievement and satisfaction, and proximal consequences refer to outcomes such as retention and personal growth. Skinner et al. (2008) also proposed a model based on the self-system model of motivational development. In this model, they differentiated internal dynamics from external dynamics of engagement. The internal dynamics consist of positive engagement and negative engagement (i.e., disaffection), which are further divided into two dimensions of behavior and emotion. As they suggested, emotional engagement is usually hypothesized to predict behavioral engagement. In the external dynamics, context and self were proposed as two main facilitators that predict engagement. A supportive context enhances positive self-evaluation, which in turn facilitates student engagement and finally learning outcomes.

Apart from student engagement, there are two other prominent perspectives of student learning in higher education: Student approaches to learning (SAL) and self-regulated learning (SRL). The SAL research is often traced back to the seminal phenomenographic studies conducted in the 1970s (Marton & Saljo, 1976; Saljo, 1981). Through a serial of text comprehension experiments, Marton and colleagues found that students adopted different approaches when reading texts and these different approaches led to qualitatively different learning outcomes. These approaches were later identified as surface and deep approaches. An approach to learning is a combination of students' learning motives and strategies. A surface approach is characterized in extrinsic interest and surface strategies (e.g., memorizing, rote learning, reproducing), and is linked to lower-quality learning outcomes. In contrast, a deep approach is featured in intrinsic interest and deep strategies (e.g., using evidence, relating, ideas, seeking meaning), and is related to higher-quality learning outcomes. The dichotomy between a surface and a deep approach to student learning has stimulated considerable research in higher education. Several instruments have been developed to measure students' approaches to learning, and their effects on learning have been confirmed by a large number of studies (e.g., Entwistle & McCune, 2004; Richardson, 2004). In particular, approaches to learning have been found to mediate the effects of personal and contextual factors on learning outcomes (Baeten, Kyndt, Struyven, & Dochy, 2010; Diseth et al., 2010; Guo, Yang, & Shi, 2017; Lizzio, Wilson, & Simons, 2002). This relationship has been nicely explained by the presage-process-product (3P) model proposed by Biggs (2001): The presage personal and contextual factors influence how students approach a particular task, which in turn determines the learning outcome obtained.

Different from SAL research that is prominent in Europe and Australia, the SRL research is rooted in North America. Substantial empirical research on SRL has shown that self-regulated learners who actively plan, monitor, control, and reflect their learning are more likely to obtain positive learning outcomes than those who do not (Dent & Koenka, 2016; Pintrich & Zusho, 2007). A number of models have been proposed to account for the effectiveness of SRL. Among these models, Pintrich and Zusho (2007) suggested a general framework of motivation and SRL that can be applied to higher education learning. This model consists of five categories of learning variables: personal characteristics, classroom context, motivational processes, self-regulatory processes, and outcomes. According to this model, motivational processes are positively correlated with self-regulatory processes, both of which lead to learning outcomes. Students with higher levels of value, efficacy beliefs and interest are likely to adopt deeper cognitive and metacognitive strategies, which will help them to achieve better outcomes. In addition, this process is moderated by personal and contextual factors such as age, gender, and instructional methods.

It is surprising to find that studies on engagement, SAL, and SRL have been conducted independently and separately by different researchers, which inhibits communications and development in this area. As Zusho (2017) argued, the three research traditions share a considerable amount of overlap, including learning assumption, learning process, constitutive structure, and measurement. Wolters and Taylor (2012) also claimed that researchers of one tradition often use terminology or ideas from another tradition. Zusho (2017) therefore recommended integrating these models to develop a coherent understanding of student learning. Given that engagement is salient, substantial, easy for understanding, and critical to college success (Fredricks, Filsecker, & Lawson, 2016), Guo and his colleagues (Guo, 2018; Guo et al., 2022) recommended adopting student engagement as the fundamental framework to integrate the other two perspectives of SAL and SRL. As shown in their studies, engagement was found to mediate the effects of academic self-concept and perceptions of the learning environment on generic skills development and learning satisfaction.

3. Relationship among students' perceptions of the learning environment, engagement, and learning outcomes

Related to the research that investigates how students learn in higher education, another strand of research focuses on how students perceive and experience their learning environment and how this affects their learning in college. Students' perceptions of the learning environment have been intensively investigated and shown to be crucial factors affecting student learning. How students learn is not only related to their personal traits but also affected by the context within which the learning happens. The simultaneous interactive relationships of the learner, the task, and the context ultimately determine how students learn (Baeten et al., 2010; Entwistle & McCune, 2004). Researchers further argue that it is students' perceptions of their learning environment that predict their learning, rather than the objective context in and of itself (Asikainen & Gijbels, 2017; Ramsden, 1991). In general, as shown in the engagement, SAL, and SRL literature previously introduced, positive perceptions of one's learning environment are related to more engagement, deeper cognitive and metacognitive strategies, as well as better learning outcomes (Guo et al., 2017; Kahu, 2013; Zusho, 2017).

Students' perceptions of the learning environment reflect their overall learning experience and are thus often used to evaluate educational effectiveness of a department or university (Ramsden, 1991). This is in comparison to the traditional approach to students' evaluation of teaching that focuses the teaching effectiveness of a specific teacher in a specific class. As Ramsden (1991) claimed, students' perceptions of the learning environment are aggregated ratings across students within an academic unit and thus can reflect differences between departments and universities. Marsh and colleagues further noticed the hierarchical nested structure of the data and suggested using a multilevel model with three levels of students, departments, and universities to address this nestedness (Cheng & Marsh, 2010; Marsh, Ginns, Morin, & Nagengast, 2011). Results of their studies, however, showed that students' perceptions of their learning environment are unable to discriminate between departments or universities; very little variance in individual students' responses is explained by departmental or university differences. As they concluded, major proportion of variance in students' perceptions is at the individual student level and should be explained by other student learning variables.

A considerable number of studies have explored the structural relationships among perceptions of the learning environment, learning behaviors, and learning outcomes. The results have generally shown that students' perceptions of the learning environment predict their learning behaviors, which in turn predict their learning outcomes (e.g., Dent & Koenka, 2016; Diseth, 2007; Guo et al., 2017; Trigwell, Ashwin, & Millan, 2013). Two types of learning outcomes are generally evaluated in the literature: cognitive and non-cognitive. Cognitive achievement is usually assessed by grade point average (GPA), while non-cognitive learning outcome is often measured by students' self-report generic skills development, including key competencies and higher order skills such as critical thinking, problem-solving, oral presentation skills, written communication, analytic skills, teamwork, etc. (Douglass, Thomson, & Zhao, 2012; Lizzio et al., 2002). For instance, Dent and Koenka (2016) claimed that self-regulated learning strategies mediate how an academic context affects achievement. Lizzio et al. (2002) showed that students' perceptions influence their academic achievement, satisfaction levels, and development of key skills both directly and indirectly through their approaches to learning. Diseth and colleagues found that students' course experiences and level of effort indirectly predict their academic achievement via the surface approach to learning (Diseth, 2007) and the strategic approach to learning (Diseth et al., 2010). Guo and colleagues (Guo, 2018; Guo et al., 2022) found the mediating effects of engagement on the relationship between perceptions of the learning environment and generic skills development.

Researchers have suggested that these variables are interconnected to and dependent on each other, and that the influences are dynamic and bidirectional (Guo, 2018; Zusho, 2017). Increased engagement promotes learning outcomes, which in turn spirals up to better levels of perception and engagement (Kahu, 2013; Llorens et al., 2007). Richardson (2006) found that students who perceive a positive learning environment are likely to engage more in learning, which in turn fosters their positive perceptions. Ben-Eliyahu and Bernacki (2015) also claimed the iterative and cyclical nature of most SRL models in which "any activity that occurs within one cycle can affect activities that follow within that cycle, and any activities within subsequent cycles" (p. 3).

These reciprocal relationships, however, should be interpreted with caution because of the cross-sectional design adopted by previous studies. To the best of our knowledge, there are no studies adopting a longitudinal research design to effectively test this hypothesized relationship and determine the order of change. The present study was thereby conducted with a large sample of university students and used an auto-/cross-lagged simultaneous regression model across a lag of 2.5 years between data collections. Its aims were to test the reciprocal interplay among perceptions of the learning environment, engagement, and learning outcomes.

4. The present study

Following the student engagement framework adopted in Guo's studies (Guo, 2018; Guo et al., 2022), the present study used a longitudinal design to explore the reciprocal effects among engagement, its antecedents and consequences. As suggested by previous studies, antecedents were measured by students' perceptions of their learning environment which were conceptualized through in-class course experience and out-of-class cocurricular experience. Consequences were measured by learning outcomes of academic achievement and self-report generic skills development.

Students' learning was measured at two time points with a 2.5-year interval, namely, the end of the first semester of their sophomore year (Time-1, T1) and the end of their senior year (Time-2, T2). To this end, a nonrecursive model of perceptions of the learning environment, engagement, and learning outcomes was developed and tested. As shown in Fig. 1, an auto-/cross-lagged reciprocal model was hypothesized to fit the present study's data. For this model, auto-lagged relationships between all Time-1 and Time-2 variables were hypothesized. T1 perceptions were expected to positively predict T2 perceptions, T1 engagement was expected to positively predict T2 engagement, and T1 learning outcomes were expected to positively predict T2 learning outcomes. In addition to the auto-lagged relationships, all Time-1 constructs were modeled as predicting all Time-2 variables. T1 perceptions were expected to positively predict T2 engagement and learning outcomes, T1 engagement was expected to positively predict T2 perceptions and outcomes, and T1 outcomes were expected to positively predict T2 perceptions and engagement.

5. Methods

5.1. Participants

The present study was carried out at a full-time research-intensive university in mainland China. The longitudinal sample comprised 966

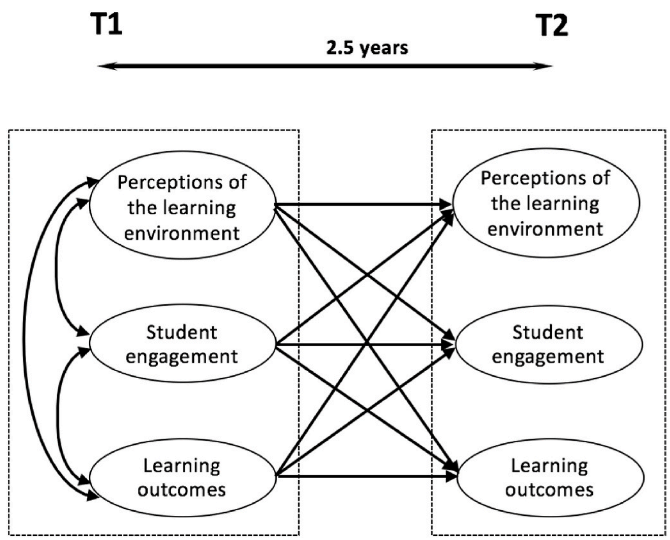

Fig. 1. The hypothesized model depicting the reciprocal relationship of perceptions of the learning environment, engagement, and learning outcomes.

university students who completed the survey at both T1 and T2. Within the sample, the participants' mean age was 22.31 years (range 18.47–27.21, SD = 0.80) at T2. Approximately 45.2% of the participants were males and 54.8% were females. With respect to discipline, approximately 35% of the participants were humanities/social science majors, and 65% were science/engineering majors. The gender and discipline balance presented in the present study broadly represented the overall population at the university.

At T1 and T2, convenient sampling was used and students at this university were invited to participate in the study. The invitation containing the linkage to the online survey platform was sent to students through emails, and was posted on the website and social media of the university. Participants could use their university ID and password to log on to the online system containing the inventories of this study. They were allowed as much time as they needed to complete the inventories, which was typically approximately 10 min. There was a preface given before the survey that introduced the purpose of the study and explained that participation was voluntary. The participants were also clearly instructed that the survey had no impact on their grades and that all data were saved anonymously and kept confidential. Only after answering all the questions required could the participants click the "submit" button to finish the survey. However, they were allowed to quit the study anytime.

5.2. Measures

Except for academic achievement, which was measured by student's GPA and obtained from university records, other variables were measured by inventories developed by Guo and colleagues, which are based on existing measures and Chinese culture. Prior studies have shown that each of these scales has strong psychometric properties and is suitable for evaluating Chinese university students' learning (Guo, 2018; Guo et al., 2017, 2022).

Course experience. Two four-item scales, namely, *good teaching* ("The teacher often encourages us to share our ideas") and *teaching organization* ("The teacher clearly explains course goals and requirements"), were used to measure the students' overall evaluation of the teaching quality in the university. The items were rated on a scale ranging from 1 (strongly disagree) to 5 (strongly agree) scale. The Cronbach's α coefficients of this scale were 0.89 at T1 and 0.92 at T2.

Cocurricular experience. Two four-item scales, namely, *university resource* ("The university has sufficient teaching space") and *university support* ("The university provides support for communicating with peers from diverse backgrounds"), were used to assess the students' perceptions of the university's campus environment. The items were rated on a scale ranging from 1 (strongly disagree) to 5 (strongly agree) scale. The Cronbach's α coefficients of this scale were 0.88 at T1 and 0.89 at T2.

Student engagement. A 25-item inventory was employed to measure student engagement in the university. Four scales were extracted from this inventory, including *deep learning approach* ("When studying, I often try to understand the author's intention"), *student-faculty interaction* ("I talk to the lecturer my ideas about learning in the classroom"), *peer interaction* ("I actively participate in group or team collaborative learning"), and *course study* ("I listen carefully and think actively in class"). The items were rated on a scale ranging from 1 (never) to 5 (very often) scale. The Cronbach's α coefficients of this scale were 0.96 at both T1 and T2.

Generic skill developments. An eight-item scale was used to assess the students' generic skills development. Students were asked to self-evaluate their ability in oral presentation, written communication, problem-solving skills, analytic skills, etc. An example item is "The development of my writing skills". The items were rated on a scale ranging from 1 (very poor) to 5 (excellent) scale. The Cronbach's α coefficients of this scale were 0.92 at T1 and 0.88 at T2.

Academic achievement. Academic achievement was measured by calculating students' first year and last year GPA using a 4-point scale. Higher GPA scores indicate better academic achievement. For instance, 4 points of GPA mean that an individual's average course grade is within the range of 90–100. Students' GPA scores were available from official university records.

5.3. Hypothesized model

A SEM model was developed to examine the reciprocal relationship among perceptions of the learning environment, engagement, generic skills, and academic achievement. A cross-lagged relationship between the T1 and T2 variables was hypothesized: T1 perceptions predicting T2 engagement, generic skills, and academic achievement; T1 engagement predicting T2 perceptions, generic skills, and academic achievement; T1 generic skills and academic achievement predicting T2 perceptions and engagement. In addition to the cross-lagged relationship, the auto-lagged relationship between all T1 and T2 variables was added into the model. The predictive effects of T1 variables on T2 variables were thus examined when controlling for the effects of prior T1 parallel variables.

5.4. Data analysis

Analyses were conducted in two phases. In the first stage, a longitudinal confirmatory factor analyses (CFA) were used to assess the reliability and validity of the measurement models. Specifically, a longitudinal measurement invariance approach (Little, Preacher, Selig, & Card, 2007) was used to examine the statistical equivalence of the test scores across the two time points. In the second stage, the hypothesized relationships between course experience, cocurricular experience, engagement, generic skills development, and GPA were examined using the SEM method. We modeled the covariances among all predictors at T1 and allowed the residuals of the T2 variables to covary. We also included correlated measurement errors for parallel T1 and T2 items in the model to avoid systematically biased estimates of relations between the latent constructs (Marsh, Roche, Pajares, & Miller, 1997). Gender, major, birthplace, high school performance, parental education, and family income were entered into the model to control for the effects of demographics on dependent variables.

Participants studied within 26 different departments from one university which constituted the hierarchical nested structure of the data for the present study. To address this nestedness, we used the command "type = complex" and "estimator = MLR" in Mplus and analyzed department as a clustering variable to deal with nonindependence of data. 984 students participated in the survey at T1, but 18 of them did not finish the survey at T2. We compared participants with both waves of data ($N = 966$) against those with only the first wave ($N = 18$) on the perceptions of the learning environment, engagement, and learning outcomes and did not find any significant differences on these variables. This indicates that the missing data were not missing systematically.

Tests for convergent and discriminant validity were performed to assure the validity of the constructs. Convergent validity is confirmed when indicator factor loadings are statistically significant at the 0.01 level and above the acceptable value of 0.5 on their corresponding constructs (Hair, Black, Babin, Anderson, & Tatham, 2006), and when the average variances extracted (AVEs) for constructs are greater than 0.5. The discriminant validity of the construct is assured by the square root of the AVEs being greater than the interconstruct correlations in the model (Fornell & Larcker, 1981). Cronbach's alpha and composite reliability were used to examine the internal consistency of each construct with the recommended 0.7 parameter value. We used a number of indices to evaluate the robustness of fit in the CFA and SEM analyses, including the chi-square statistic, the Root Mean Square Error of Approximation (RMSEA), the Confirmatory Fit Index (CFI), and Non-Normed Fit Index (NNFI). As suggested by literature (Marsh, Balla, & McDonald, 1988; Schreiber, Stage, King, Nora, & Barlow, 2006), data fit is excellent when the NNFI and CFI are larger than 0.95, and the RMSEA is under 0.06. Data fit is acceptable when the NNFI and CFI are larger than 0.90, and the RMSEA is under 0.08. We also calculated the R^2 for the proportion of variance explained by each variable.

6. Results

6.1. Descriptive statistics and grade differences

Table 1 presents the descriptive statistics, reliability, and validity information of the measures. The results showed that students generally reported positive course experience, cocurricular experience, engagement, and generic skills development. Specifically, they reported relatively high levels of university support (T1: $M = 4.32$, SD = 0.62; T2: $M = 4.32$, SD = 0.62), university resource (T1: $M = 4.10$, SD = 0.84; T2: $M = 4.32$, SD = 0.69), teaching organization (T1: $M = 4.21$, SD = 0.65; T2: $M = 4.24$, SD = 0.59), and course study (T1: $M = 4.16$, SD = 0.68; T2: $M = 4.25$, SD = 0.63). In contrast, students were less engaged in student-faculty interaction (T1: $M = 2.98$, SD = 1.21; T2: $M = 3.33$, SD = 1.05), peer interaction (T1: $M = 3.71$, SD = 0.85; T2: $M = 4.03$, SD = 0.74), and deep learning approach (T1: $M = 3.95$, SD = 0.75; T2: $M = 4.08$, SD = 0.65). They also reported a lower level of generic skills development (T1: $M = 3.48$, SD = 0.75; T2: $M = 3.80$, SD = 0.74). These results indicated that students perceived more positive learning experience but there was still room for their engagement and generic skills development to be improved.

6.2. Measurement invariance testing

Before conducting the longitudinal modelling, we tested the measurement invariance for Time-1 to Time-2 constructs to make inferences about changes in constructs over time (Chen, 2007). Measurement invariance was established if CFI does not change larger than 0.01 and the RMSEA does not change larger than 0.015 for the invariant model (Chen, 2007). The baseline configural model provided an acceptable fit ($x^2[420] = 1244.43, p < .001,$ RMSEA = 0.05, CFI = 0.95) showing a similar factor structure over time. The summary of factor loadings is reported in Table 1. We found that all of the factor loadings were no less than 0.60 (all significant at $p < .001$). All of the average variance extracted (AVE) were above 0.50 and the square root of the AVEs was larger than the correlation between this construct and other constructs, suggesting acceptable discriminant validity. The constructs' composite reliability (CR) and Cronbach's α coefficients were all above 0.70, showing acceptable internal reliability.

In addition, the metric invariance model with equal factor loadings over time did not show a meaningful deterioration in model fit (ΔCFI = 0.003, ΔRMSEA <0.001). The scalar invariance model with equal thresholds was not supported with CFI change larger than 0.01 (ΔCFI = 0.019). As suggested by Putnick and Bornstein (2016), we further tested a partial scalar invariance model by releasing intercept constraints of four items from the scales of course experience and generic skills development. As indicated in Table 2, the partial scalar invariance was supported as its overall model fit was not significantly worse than the metric invariance model (ΔCFI = 0.010, ΔRMSEA = 0.004). Taken together, the results support the longitudinal measurement invariance of the constructs across time.

6.3. Preliminary correlations

The Pearson product-moment correlation matrix in Table 3 shows the expected significant correlations between the variables. Students' course experience, cocurricular experience, engagement, and generic skills development had moderate and positive correlations with each other at both Time-1 and Time-2 (T1: r ranging from 0.24 to 0.67, $ps < .001$; T2: r ranging from 0.25 to 0.68, $ps < .001$). Apart from the within-time correlations, the between-time correlations also generated a similar pattern of variables over time. Students' learning at Time-1 was significantly correlated with their subsequent learning at Time-2 in a positive way ($ps < .05$). Due to the lag between data points, however, the overall between-time correlation coefficients were smaller. The test-retest correlations of these variables were moderate and significant (r ranging from 0.29 to 0.40, $p < .001$). The within-time and between-time

Table 1
Descriptive statistics, reliabilities, and validities ($N = 966$).

Scale	Time 1 Mean	SD	Cronbach's α	CR	AVE	CFA loadings range (mean)	Time 2 Mean	SD	Cronbach's α	CR	AVE	CFA loadings range (mean)
Course experience	4.08	.67	.89	.81	.68	.80-.85(.83)	4.18	.59	.92	.80	.66	.79-.84(.82)
Teaching organization	4.21	.65	.86	.87	.62	.74-.82(.79)	4.24	.59	.92	.92	.74	.79-.91(.86)
Good teaching	3.94	.81	.84	.85	.58	.68-.84(.76)	4.13	.70	.88	.88	.64	.70-.87(.80)
Cocurricular experience	4.21	.66	.88	.76	.62	.72-.85(.79)	4.32	.59	.89	.79	.65	.74-.87(.81)
University resource	4.10	.84	.85	.85	.59	.70-.80(.77)	4.32	.69	.85	.85	.59	.71-.82(.77)
University support	4.32	.62	.83	.84	.57	.67-.81(.75)	4.32	.62	.87	.88	.64	.74-.85(.80)
Student engagement	3.75	.73	.96	.84	.58	.67-.88(.76)	3.95	.62	.96	.83	.55	.62-.87(.74)
Deep learning approach	3.95	.75	.95	.95	.61	.68-.83(.78)	4.08	.65	.95	.95	.61	.71-.81(.78)
Student-faculty interaction	2.98	1.21	.96	.96	.83	.85-.94(.91)	3.33	1.05	.95	.95	.81	.84-.92(.90)
Peer interaction	3.71	.85	.87	.87	.63	.71-.88(.79)	4.03	.74	.85	.85	.60	.63-.92(.77)
Course study	4.16	.68	.77	.79	.50	.60-.86(.69)	4.25	.63	.82	.83	.56	.61-.89(.74)
Generic skills	3.48	.75	.92	.92	.60	.70-.84(.77)	3.80	.74	.88	.88	.50	.61-.79(.70)
GPA	3.07	.65	–	–	–	–	3.14	.70	–	–	–	–

Note. $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$ (2-tailed).

Table 2
Statistics of measurement invariant models.

Model description	χ2	*df*	CFI	RMSEA	Δχ2	Δdf	ΔCFI	ΔRMSEA
Configural invariance	1244.426	420	.945	.045				
Metric invariance	1293.650	432	.942	.045	49.224	12	.003	<.001
Partial scalar invariance	1460.687	440	.932	.049	167.037	8	.010	.004

Table 3
Within- and between-time longitudinal correlations between variables ($N = 966$).

Scale	CE	TO	GT	CC	UR	US	SE	DL	SI	PI	CS	GS	GPA
CE	**.32**	.90/.90	.93/.93	.64/.58	.51/.46	.67/.59	.62/.62	.58/.59	.49/.48	.47/.49	.50/.46	.39/.47	.04[a]/.03[a]
TO	.26/.30	**.29**	.67/.66	.62/.56	.50/.47	.63/.55	.55/.53	.54/.51	.41/.38	.41/.42	.47/.41	.35/.40	.04[a]/.03[a]
GT	.32/.28	.26/.18	**.31**	.56/.50	.44/.39	.59/.52	.58/.60	.54/.56	.48/.49	.45/.48	.46/.43	.36/.46	.04[a]/.03[a]
CC	.27/.23	.26/.23	.23/.20	**.40**	.93/.92	.86/.90	.50/.47	.48/.44	.37/.36	.44/.41	.40/.33	.31/.43	−.07[b]/-.04[a]
UR	.21/.18	.22/.21	.17/.13	.38/.37	**.38**	.62/.64	.39/.37	.36/.34	.31/.30	.35/.33	.29/.25	.24/.36	−.11/-.03[a]
US	.29/.24	.27/.22	.26/.23	.34/.36	.27/.31	**.35**	.53/.48	.52/.46	.36/.35	.45/.41	.45/.35	.33/.42	−.01[a]/-.04[a]
SE	.24/.25	.22/.19	.22/.26	.20/.20	.17/.15	.20/.22	**.38**	.93/.93	.84/.84	.80/.73	.72/.73	.63/.68	.04[a]/.09
DL	.25/.24	.23/.19	.23/.24	.20/.19	.17/.13	.19/.22	.38/.36	**.39**	.64/.64	.65/.57	.62/.63	.58/.63	.05[a]/.11
SI	.15/.18	.13/.12	.15/.20	.13/.15	.10/.13	.13/.15	.29/.30	.24/.26	**.32**	.64/.54	.48/.48	.56/.60	−.02[a]/.02[a]
PI	.20/.18	.17/.14	.19/.19	.19/.16	.17/.12	.18/.18	.28/.27	.24/.25	.22/.19	**.30**	.52/.47	.52/.51	−.02[a]/.03[a]
CS	.19/.23	.19/.19	.17/.23	.16/.15	.14/.10[b]	.16/.18	.27/.30	.25/.29	.15/.18	.19/.20	**.38**	.40/.39	.16/.16
GS	.17/.17	.16/.13	.15/.17	.18/.14	.15/.09[b]	.17/.17	.30/.28	.30/.28	.23/.25	.24/.21	.17/.13	**.39**	−.01[a]/.04[a]
GPA	.03[a]/.01[a]	.03[a]/.03[a]	.02[a]/-.03[a]	−.08[b]/-.07[b]	−.10[b]/-.09[b]	−.05[a]/-.02[a]	.08[b]/.03[a]	.09[b]/.04[a]	−.02[a]/-.01[a]	.03[a]/-.02[a]	.19/.12	.01[a]/-.01[a]	**.76**

Note. CE = Course experience, TO = Teaching organization, GT = Good teaching, CC = Cocurricular experience, UR = University resource, US = University support, SE = Student engagement, DL = Deep learning approach, SI = Student-faculty interaction, PI = Peer interaction, CS = Course study, GS = Generic skills. Within-Time 1/within-Time 2 correlations are reported in the upper diagonal, whereas between-time (Time 1-Time 2/Time 2-Time 1) correlations are reported in the lower diagonal. Test-retest correlations are bolded in diagonal. [a]$p > .05$, [b]$p < .05$, others $p < .001$ (2-tailed).

correlations between GPA and other variables were generally weak (*r* ranging from 0.01 to 0.19 with a mean of 0.05). In summary, students with positive learning experience were likely to engage more in learning and to report greater levels of generic skills development. Positive correlations existed within and across the sophomore and senior years. The correlation results provide support for testing the hypothesized relationships in the hypothesized model that takes into account shared variances among the variables.

6.4. Longitudinal structural equation modeling

This model showed an acceptable fit to the data ($x^2[646] = 2044.05$ $p < .001$, RMSEA = 0.05, CFI = 0.91, NNFI = 0.90). As shown in Fig. 2, regarding the auto-lagged effects, each T1 variable positively predicted its parallel T2 variable at a significant level: T1 course experience predicted T2 course experience ($\beta = 0.33$, $p < .001$), T1 cocurricular experience predicted T2 cocurricular experience ($\beta = 0.44$, $p < .001$), T1 engagement predicted T2 engagement ($\beta = 0.27$, $p < .001$), T1 generic skills predicted T2 generic skills ($\beta = 0.28$, $p < .001$), and T1 GPA predicted T2 GPA ($\beta = 0.77$, $p < .001$).

As expected, the cross-lagged effects were much smaller than the auto-lagged effects, suggesting strong stability of the variables over the 2.5-year period. As shown in Fig. 2, the cross-lagged effects were only partially consistent with the research hypotheses. Regarding the relationship between perceptions of the learning environment and engagement, T1 course experience ($\beta = 0.18$, $p < .05$) and T2 cocurricular experience ($\beta = -0.12$, $p < .05$) were found to significantly predict subsequent T2 engagement respectively, after accounting for initial levels of other variables. The reverse, however, was not found in the model. Prior engagement was not a significant predictor of subsequent course experience and cocurricular experience (*ps* > .05), partialing out effects of prior variables.

Regarding the relationship between student engagement and generic skills development, the model showed a reciprocal relationship between these two variables. After accounting for prior variables, students' prior engagement positively predicted subsequent generic skills ($\beta = .10$, $p < .01$), and prior generic skills positively predicted subsequent engagement ($\beta = 0.09$, $p < .05$).

Except for the effects reported above, no other significant cross-lagged relationships were found among perceptions of the learning environment, generic skills, and GPA (*ps* > .05). That is, students' prior perceptions did not directly predict their subsequent generic skills development, and conversely, students' prior generic skills did not predict their subsequent perceptions. GPA did not have any significant cross-lagged relationship with other variables.

All regression coefficients and standard errors are presented in Table 4. The amount of variance of the T2 variables accounted for by the T1 predictor variables in this model were $R^2 = 0.15$ for course experience, $R^2 = 0.20$ for cocurricular experience, $R^2 = 0.18$ for student engagement, $R^2 = 0.20$ for generic skills development, and $R^2 = 0.60$ for GPA.

7. Discussion

Although prior research has documented the bidirectional and reciprocal relationships between students' perceptions of the learning

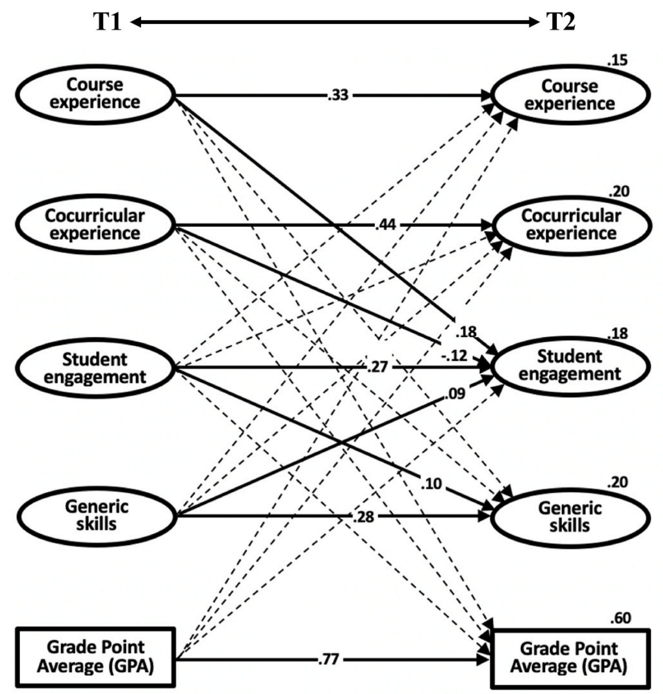

Fig. 2. Structural path coefficients of the reciprocal model (N = 966). Solid lines represent significant standardized coefficients; dotted lines are non-significant paths. The measurement model, the covariances among all T1 predictors, the covariances among the residuals of all T2 variables, and controlled variables are omitted in the figure to maintain the clarity of the model.

environment, engagement, and learning outcomes (Biggs, 1999; Kahu, 2013; Skinner et al., 2008), due to the limitations of a cross-sectional design, effective tests of this hypothesized relationship have been rare in previous studies. To the best of our knowledge, the present study is the first to examine the reciprocal relationships among these variables from a longitudinal reciprocal modeling perspective. Students' data were collected at two time waves (Time-1: sophomore year; Time-2: senior year), and a latent, nonrecursive, regressive structural model was developed to test these relationships. In totality, results from the study provide partial support for this theoretical reciprocal assertion, and, importantly, extend previous findings in theoretical meaningful ways.

The correlational results indicated that students' course experience, cocurricular experience, engagement, and generic skills development were significantly and positively correlated with each other at both within and between the two time waves, although the between-time correlation coefficients were smaller due to the time lag. These results are consistent with previous studies showing that students' perceptions of the learning environment, engagement, and outcomes are interconnected (e.g., Dent & Koenka, 2016; Guo et al., 2017; Kahu, 2013). The moderate positive Time-1–Time-2 test-retest correlations of all the variables supported the stabilities of the factors over time, indicating that students' learning is relatively dependent on their previous performance. It is noted that the magnitude of the correlational coefficient between the variables generally decreased from the cross-sectional within-time correlation to longitudinal parallel test-retest correlation and then to between-time correlation. This result provided support for conducting longitudinal SEM models to further explore the reciprocal relationships of these variables at the two time waves. The results are discussed below in comparison with theory and prior evidence.

The SEM results first showed the stronger auto-lagged effects over the cross-lagged effects, suggesting the overwhelming long-termed effects of student learning variables. It seems that the variance of the learning variables is substantially accounted for by their previous parallel variables. Students with positive learning experience, high levels of engagement and learning outcomes are likely to do so in subsequent years.

Compared with the auto-lagged effects of prior variables, the cross-lagged effects were smaller and some are insignificant. Regarding the relationship between students' perceptions of the learning environment and engagement, the model showed significant direct effects of prior perceptions on later engagement. Specifically, this longitudinal work provides stronger evidence for the assertion that students with positive in-class course learning experience are likely to put forth more effort in academic related activities. This finding converges with previous cross-sectional evidence showing the direct effect of course experience on engagement (Diseth et al., 2010; Guo et al., 2017, 2022; Lizzio et al., 2002).

Unexpectedly, the effect of prior cocurricular experience on subsequent engagement was negative, which is contrary to previous cross-sectional evidence showing that cocurricular experience can positively predict student engagement (Guo, 2018; Guo et al., 2022). Considering the significant and positive within-time and between-time correlations between these two variables, it is surprising to find this negative path, after controlling for effects of prior variables. It is possible that items in the inventory of engagement largely assess students' academic involvement in course study, deep learning, and interpersonal interaction. These are largely academic related activities and are different from cocurricular activities. Therefore, engagement was negatively predicted by prior cocurricular experience and positively predicted by prior course experience.

Although students' perceptions of the learning environment were found to predict their subsequent engagement, the reverse links from T1 engagement to T2 perceptions were not supported. This is inconsistent with the theoretical assertion that perceptions and engagement were reciprocally connected (Biggs, Kember, & Leung, 2001; Skinner et al., 2008). It is somewhat surprising to find that students who engaged more in learning did not subsequently have more positive perceptions towards their learning environment. Instead, students' prior learning experience was a more important factor predicting changes in later experience. Nevertheless, the results showed that perceptions of the learning environment should be considered presage predicting variables rather than process or outcome variables in student learning model.

A noteworthy set of results in the present study is the significant and positive reciprocal links between engagement and generic skills. Prior engagement was a significant and positive predictor of changes in generic skills, and reciprocally, prior generic skills development was a

Table 4
Regression results for the longitudinal model.

Variables	T2 Course experience			T2 Cocurricular experience			T2 Student engagement			T2 Generic skills			T2 GPA		
	b	*SE*	β	*b*	*SE*	β	*b*	*SE*	β	*b*	*SE*	β	*b*	*SE*	β
T1 Course experience	.298	.081	.334***	–	–	–	.165	.080	.178*	.047	.085	.044	−.068	.088	−.051
T1 Cocurricular experience	–	–	–	.360	.051	.438***	−.110	.052	−.123*	−.025	.062	−.026	−.022	.047	−.018
T1 Student engagement	.015	.079	.021	−.071	.074	−.094	.238	.076	.272***	.090	.035	.098**	.062	.044	.056
T1 Generic skills	.014	.056	.021	.071	.048	.104	.075	.037	.090*	.213	.032	.280***	–	–	–
T1 GPA	.003	.029	.004	−.023	.023	−.030	.030	.020	.038	–	–	–	.845	.043	.766***

Note. b = unstandardized coefficient, *SE* = standard error, β = standardized coefficient, T1 = Time 1, T2 = Time 2. *$p < .05$, **$p < .01$, ***$p < .001$.

significant and positive predictor of subsequent engagement. This finding is consistent with previous research demonstrating positive predicting effects of engagement on generic skills (Guo, 2018; Guo et al., 2022; Lizzio et al., 2002; Pascarella & Terenzini, 2005), and aligns with theories claiming that students who obtain better outcomes are more likely to put forth more effort in academic related activities (Kahu, 2013; Llorens et al., 2007).

Regarding the relationship between students' perceptions of the learning environment and their generic skills development, no cross-lagged effects were found between these variables. That is, prior learning experience did not directly lead to increase of later generic skills, and prior generic skills development did not directly lead to subsequent positive experience. Previous studies have reported contradictory findings on the predicting effects of students' perceptions on their generic skills development. Some studies reported both direct and indirect effects of students' perceptions on their generic skills (Guo et al., 2017; Lizzio et al., 2002), whilst some did not find the direct predicting path from perceptions to generic skills (Guo et al., 2018; 2022). Given the longitudinal nature of the present study and that prior variables have been controlled in the model, the study may serve as a more convincing evidence on these inconsistent findings.

Together with the findings discussed above, it could be concluded that engagement serves as a crucial variable in the process of college student learning. Students' engagement was predicted by their prior learning experiences, engagement, and generic skills, but also predicted their subsequent generic skills development. It is clear that the students' changing generic skills hinge more heavily on their engagement and initial levels of generic skills, rather than on their perceptions of the learning environment. In addition, the predicting paths from prior engagement and generic skills to later perceptions were not supported. This is in line with Kahu's (2013) claim that "there is a dominant direction of influence from the antecedents to engagement, and from engagement to the consequences" (p. 768) despite the reciprocal hypotheses of these variables. Students' perceptions of the learning environment are presage and contextual factors that predict engagement, which in turn shapes learning outcomes (Biggs et al., 2001; Skinner et al., 2008).

The results also showed that students' GPA did not correlate with other variables at both within and between the two time waves; they were developmentally relatively independent. Students with positive learning experience or high levels of engagement did not subsequently achieve high GPA. Likewise, those with good GPA did not subsequently report high levels of perceptions or engagement. This is consistent with previous findings reported by Guo and colleagues (Guo, 2018; Guo et al., 2022), showing that students' university GPA was largely predicted by their prior GPA, rather than their learning experience or engagement. As they explained, Chinese university GPA might reflect students' memorization of domain knowledge rather than critical competency, and thus were uncorrelated with deep learning experience and engagement.

To sum up, the findings of the present study provide partial evidence for the longstanding theoretical assertion that perceptions of the learning environment, engagement, and learning outcomes are bidirectional and reciprocal. Despite the significant and positive within-time and between-time correlations, after simultaneously controlling for the effects of prior variables in the model, especially for the significant auto-lagged effects, some cross-lagged effects unexpectedly disappeared or inversed. The significant and positive reciprocal links between student engagement and generic skills is the only set of reciprocal relationship revealed in the present study. Especially, the predicting direction from perceptions to engagement and from engagement to generic skills was confirmed. Perceptions of the learning environment mainly served as antecedent variables that predict engagement which leads to outcome variable of generic skills. Other theoretical predicting paths from prior engagement to subsequent perceptions, between perceptions and learning outcomes, and between engagement and GPA, however, were not supported in the model.

8. Limitations and future directions

There are several limitations to consider when interpreting the findings and which point out the directions for future research. First, although the present study examined the reciprocal relationship among perceptions of the learning environment, engagement, and learning outcomes based on longitudinal data, the 2.5-year interval of data collection may be too long to connect the variables at two time points. This may explain the small cross-lagged effects in the model. Marsh and Martin (2011) suggested three waves of data collection with a 1-year interval between each measurement time for studying reciprocal effects, which would examine indirect effects in a more systematic way and provide more rigorous evidence of causality. This method should be considered in future research. Second, the present study was carried out at one research-intensive university in China, which limits the external validity of the findings reported by the study. Students from other types of universities or other countries might exhibit different patterns of learning. For instance, university students in China are less stressful to get course credits, read less outside of class (Loyalka et al., 2021), and adopt more surface learning approaches (e.g., rote-learning, exam-oriented strategies) to obtain higher grades (Guo, 2018), which are largely different from their counterparts in western countries. Future research is therefore strongly encouraged to use a similar longitudinal design to replicate the study in other national and international populations. Third, it is important to be aware that the study relied heavily on student self-report data which are only indirect indicators of student learning. The results should therefore be interpreted with suitable care. Additional data sources, such as interviews with students, teacher reports, paper-and-pencil assessments, and observations, are suggested to supplement the self-report data in future studies.

9. Educational implications

It is important to compare the findings of the present study to those reported by previous cross-sectional studies. Some existing findings were confirmed by the present study. Some findings, however, were inconsistent and even contradictory. The longitudinal results of the present study first support the existing findings claiming that college students' perceptions of the learning environment, engagement, and learning outcomes are connected with each other. Different from the previous cross-sectional studies that drew this conclusion based on concurrent correlations, the longitudinal nature of this study confirms these relationships with a stronger methodological foundation. In addition to the within-time correlations, variables were also found to correlate with each other across different time slots. More importantly, the present study further tests the longstanding theoretical assertion that the relationship of these variables is both reciprocal and dynamic. The auto-lagged and cross-lagged effects reported in the model hold important educational implications for the existing research on student learning in higher education.

First, the presence of significant auto-lagged effects suggests the important long-term influence of factors over time. The auto-lagged effects of prior parallel variables are much stronger than the cross-lagged effects, indicating that the variance of the learning variables is largely explained by their previous parallel variables. These results reveal the importance of students' early college experience. Students with positive learning experience, engagement, and high levels of learning outcomes tend to perform similarly in future. It is thus suggested to promote student's learning as early as possible. Institutions are advised to deploy more resources and programs to build a strong foundation for enhancing early-year undergraduate experience. This is especially important for students' academic achievement given the strong auto-lagged effect of GPA. It should be aware that, apart from GPA, other auto-lagged effects were moderate and only explained a limited amount of variance of T2 variables. Early-intervention seems insufficient to enhance these learning variables. It is possible that important variables contributing to student learning were not investigated in the current study. For instance, factors such as intelligence and self-concept that students have developed prior to university entry might significantly influence their college learning. Future research examining effects of these variables would provide additional important educational implications for higher education.

Second, the cross-lagged effects suggest the importance of engagement in college learning, as well as ways to promote students' engagement. Positive course experience enhances student engagement, which in turn fosters subsequent engagement and generic skills development. It is therefore important for teachers to create a learning environment that is perceived by students as positive. For instance, teachers are suggested to well organize their lessons, clearly explain curriculum objectives and requirements, and use student-centered teaching approaches. By doing this, students are likely to devote more time and effort to academic related activities, which would lead to high levels of subsequent engagement and generic skills development.

Author statement

Jian-Peng Guo: Conceptualization, Methodology, Writing- Original draft preparation, Formal analysis. **Shuai Lv:** Data Curation Formal analysis. **Shi-Chao Wang:** Software. **Si-Mei Wei:** Investigation. **Yi-Rong Guo:** Software. **Ling-Yan Yang:** Conceptualization, Investigation, Writing - Review & Editing.

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Appendix. The scales used in the study (translated from Chinese)

Course experience

(Items were scored on a five-point Likert scale from "strongly disagree" to "strongly agree")

Good teaching

The teacher's instruction relates theory to practice
In class, the teacher emphasizes inspiring our thinking
The teacher often encourages us to share our ideas
The teacher often asks us to discuss in groups

Teaching organization

The teacher clearly explains course goals and requirements
The course delivered by the teacher is logical and clear
The teacher well prepares the course
The teacher's assessment criteria are fair to students

Cocurricular experience

(Items were scored on a five-point Likert scale from "strongly disagree" to "strongly agree")

University resource

The university has sufficient teaching space (e.g., classroom, lab)
The university has sufficient learning space and public area (e.g., library, study room)
The IT resources are numerous
The library resources (including electronic resources) are numerous

University support

The university provides support for communicating with peers from diverse backgrounds
The university provides opportunities for attending campus activities or competition (giving speeches, performing arts, athletic events, etc.)
The university provides seminars, lectures, or other relevant events that address important social, economic, or political issues
The university provides appropriate support for English as a second language learning

Student engagement

(Items were scored on a five-point Likert scale from "never" to "very often")

Deep learning approach

I am strongly fulfilled when learning
I can easily generate interests on what I am learning
I study hard because I am interested in learning
I have broad interests and often spend a lot of time to study new things
I relate what the teacher conveys to my previous learning to deepen my understanding
When reading, I often try to understand the author's intention
When studying, I often try to generate my own opinions
I often question what I am studying
I apply what I learn from courses to practical problems or new situations
I evaluate a point of view, decision, or information source
I often read lots of relevant materials to deepen my understanding of the course
I combine ideas from different courses when completing assignments

Course study

I carefully take notes in class
I come to class after completing readings or homework
I follow classroom rules, no being late, leaving early, or being absent
I listen carefully and think actively in class

Student-faculty interaction

I talk to the lecturer or the tutor after class
I discuss my academic performance with a faculty member
I discuss assessment scoring or assignments with a faculty member
I discuss study plan with a faculty member
I talk to the lecturer my ideas about learning in the classroom

Peer interaction

I ask another student to help me understand course material
I work with other students on course projects or assignments
I actively participate in group or team collaborative learning
I prepare for examination with other students

Generic skills development

(Items were scored on a five-point Likert scale from "very poor" to "excellent")

Oral communication skills

Writing skills
Problem-solving skills
Cross-disciplinary knowledge
Ability to appreciate art (painting, music, comedy, dancing, etc.)
Analytical skills
Working as a team member
Innovation ability

References

Asikainen, H., & Gijbels, D. (2017). Do students develop towards more deep approaches to learning during studies? A systematic review on the development of students' deep and surface approaches to learning in higher education. *Educational Psychology Review, 29*, 1–30.

Baeten, M., Kyndt, E., Struyven, K., & Dochy, F. (2010). Using student-centered learning environments to stimulate deep approaches to learning: Factors encouraging or discouraging their effectiveness. *Educational Research Review, 5*(3), 243–260.

Ben-Eliyahu, A., & Bernacki, M. (2015). Addressing complexities in self-regulated learning: A focus on contextual factors, contingencies, and dynamic relations. *Metacognition and Learning, 10*, 1–13.

Biggs, J. B. (1993). What do inventories of students' learning processes really measure? A theoretical review and clarification. *British Journal of Educational Psychology, 63*, 3–19.

Biggs, J. B. (1999). *Teaching for quality learning at university*. Buckingham: Open University Press.

Biggs, J. B., Kember, D., & Leung, D. Y. P. (2001). The revised two-factor study process questionnaire: R-SPQ-2F. *British Journal of Educational Psychology, 71*, 133–149.

Bowen, H. R. (1977). *Investment in learning: The individual and social value of American higher education*. San Francisco: Jossey-Bass.

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling, 14*, 464–504.

Cheng, J. H. S., & Marsh, H. W. (2010). National Student Survey: are differences between universities and courses reliable and meaningful? *Oxford Review of Education, 36*, 693–712.

Christenson, S. C., Reschly, A. C., & Wylie, C. (Eds.). (2012). *The handbook of research on student engagement*. New York: NY: Springer Science.

Coates, H. (2007). A model of online and general campus-based student engagement. *Assessment & Evaluation in Higher Education, 32*, 121–141.

Dent, A. L., & Koenka, A. C. (2016). The relation between self-regulated learning and academic achievement across childhood and adolescence: A meta-analysis. *Educational Psychology Review, 28*, 425–474.

Diseth, A. (2007). Approaches to learning: Course experience and examination grade among undergraduate psychology students: Testing of mediator effects and construct validity. *Studies in Higher Education, 32*, 373–388.

Diseth, A., Pallesen, S., Brunborg, G. S., & Larsen, S. (2010). Academic achievement among first semester undergraduate psychology students: The role of course experience, effort, motives and learning strategies. *Higher Education, 59*, 335–352.

Douglass, J. A., Thomson, G., & Zhao, C. M. (2012). The learning outcome race: The value of self-reported gains in large research universities. *Higher Education, 64*, 317–335.

Entwistle, N., & McCune, V. (2004). The conceptual bases of study strategy inventories. *Educational Psychology Review, 16*, 325–345.

Filsecker, M., & Kerres, M. (2014). Engagement as a volitional construct: A frame- work for evidence-based research on educational games. *Simulation & Gaming, 45*, 450–470.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research, 74*, 59–109.

Fredricks, J. A., Filsecker, M., & Lawson, M. (2016). Student engagement, context, and adjustment: Addressing definitional, measurement, and methodological issues. *Learning and Instruction, 43*, 1–4.

Fredricks, J. A., & McColskey, W. (2012). The measurement of student engagement: A comparative analysis of various methods and student self-report instruments. In S. Christenson, A. L. Reschy, & C. Wylie (Eds.), *Handbook of research on student engagement* (p. 319e339). New York: Springer.

Guo, J. P. (2018). Building bridges to student learning: Perceptions of the learning environment, engagement, and learning outcomes among Chinese undergraduates. *Studies In Educational Evaluation, 59*, 195–208.

Guo, J. P., Yang, L. Y., & Shi, Q. H. (2017). Effects of perceptions of the learning environment and approaches to learning on Chinese undergraduates' learning. *Studies In Educational Evaluation, 55*, 125–134.

Guo, J. P., Yang, L. Y., Zhang, J., & Gan, Y. J. (2022). Academic self-concept, perceptions of the learning environment, engagement, and learning outcomes of university students: Relationships and causal ordering. *Higher Education, 83*, 809–828.

Hair, J., Black, B., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate data analysis*. Prentice-Hall.

Kahu, E. (2013). Framing student engagement in higher education. *Studies in Higher Education, 38*, 758–773.

Linnenbrink-Garcia, L., Rogat, T., & Koskey, K. (2011). Affect and engagement during small group instruction. *Contemporary Educational Psychology, 36*, 13–24.

Little, T. D., Preacher, K. J., Selig, J. P., & Card, N. A. (2007). New developments in latent variable panel analyses of longitudinal data. *International Journal of Behavioral Development, 31*, 357–365.

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*, 27–52.

Llorens, S., Schaufeli, W., Bakker, A., & Salanova, M. (2007). Does a positive gain spiral of resources, efficacy beliefs and engagement exist? *Computers in Human Behavior, 23*, 825–841.

Loes, C., Pascarella, E., & Umbach, P. (2012). Effects of diversity experiences on critical thinking skills: Who benefits? *Journal of Higher Education, 83*, 1–25.

Loyalka, P., Liu, O., Li, G., Kardanova, E., et al. (2021). Skill levels and gains in university STEM education in China, India, Russia and the United States. *Nature Human Behavior, 5*, 892–904.

Marsh, H. W., Balla, J. R., & McDonald, R. P. (1988). Goodness-of-it indexes in confirmatory factor-analysis: The effect of sample size. *Psychological Bulletin, 103*, 391–410.

Marsh, H. W., Ginns, P., Morin, A. J. S., & Nagengast, B. (2011). Use of student ratings to benchmark universities: Multilevel modeling of responses to the Australian Course Experience Questionnaire (CEQ). *Journal of Educational Psychology, 103*, 733–748.

Marsh, H. W., & Martin, A. J. (2011). Academic self-concept and academic achievement: Relations and causal ordering. *British Journal of Educational Psychology, 81*, 59–77.

Marsh, H. W., Roche, L. A., Pajares, F., & Miller, D. (1997). Item-specific efficacy judgments in mathematical problem solving: The downside of standing too close to trees in a forest. *Contemporary Educational Psychology, 22*, 363–377.

Marton, F., & SäljÖ, R. (1976). On qualitative differences in learning. I: Outcome and process. *British Journal of Educational Psychology, 46*, 4–11.

Pace, C. R. (1998). Recollections and reflections. In J. C. Smart (Ed.), *Higher education: Handbook of theory and research* (Vol. 13, pp. 1–34). New York: Agathon.

Pascarella, E. T., & Terenzini, P. T. (2005). *How college affects students: A third decade of research*. Jossey-Bass.

Pintrich, P. R., & Zusho, A. (2007). Motivation and self-regulated learning in the college classroom. In R. Perry, & J. Smart (Eds.), *Handbook on teaching and learning in higher education*. Dordrecht: Springer Publishers.

Prosser, M., & Trigwell, K. (1999). *Understanding learning and teaching: The experience in higher education*. Buckingham: SRHE and Open University Press.

Putnick, D., & Bornstein, M. (2016). Measurement invariance conventions and reporting: The state of the art and future directions for psychological research. *Developmental Review, 41*, 71–90.

Ramsden, P. (1991). A performance indicator of teaching quality in higher education: The Course Experience Questionnaire. *Studies in Higher Education, 16*, 129–150.

Ramsden, P. (1997). The context of learning in academic departments. In F. Marton, D. Hounsell, & N. Entwistle (Eds.), *The experience of learning. Implications for teaching and studying in higher education*. Edinburgh: Scottish Academic Press.

Reeve, J., & Tseng, C. M. (2011). Agency as a fourth aspect of students' engagement during learning activities. *Contemporary Educational Psychology, 36*, 257–267.

Reschly, A. L., & Christenson, S. L. (2006). Prediction of dropout among students with mild disabilities: A case for inclusion of student engagement variables. *Remedial and Special Education, 27*, 276–292.

Richardson, J. T. E. (2004). Methodological issues in questionnaire-based research on student learning in higher education. *Educational Psychology Review, 16*, 347–358.

Richardson, J. T. E. (2006). Investigating the relationship between variations in students' perceptions of their academic environment and variations in study behaviour in distance education. *British Journal of Educational Psychology, 76*, 867–893.

Saljo, R. (1981). Learning approach and outcome: Some empirical observations. *Instructional Science, 10*, 47–65.

Schreiber, J. B., Stage, F. K., King, J., Nora, A., & Barlow, E. A. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *Journal of Educational Research, 99*, 323–338.

Skinner, E. A., Furrer, C., Marchand, G., & Kinderman, T. (2008). Engagement and disaffection in the classroom: Part of a larger motivational dynamic? *Journal of Educational Psychology, 100*, 765–781.

Thomas, L. (2012). *Building student engagement and belonging in higher education at a time of change: Final report from the what works? Student retention and success programme*. London: Paul Hamlyn Foundation, Higher Education Funding Council for England, The Higher Education Academy and Action on Access.

Trigwell, K., Ashwin, P., & Millan, E. S. (2013). Evoked prior learning experience and approach to learning as predictors of academic achievement. *British Journal of Educational Psychology, 83*, 363–378.

Wolters, C. A., & Taylor, D. J. (2012). A self-regulated learning perspective on student engagement. In S. Christenson, A. Reschly, & C. Wylie (Eds.), *Handbook of research on student engagement*. New York: Springer.

Zepke, N. (2014). Student engagement research in higher education: Questioning an academic orthodoxy. *Teaching in Higher Education, 19*, 697–708.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*, 166–183.

Zusho, A. (2017). Toward an integrated model of student learning in the college classroom. *Educational Psychology Review, 29*, 301–324.