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# Deepening Self-Efficacy and Emotional Expectation in Learning through Interpersonal Interaction: An IEEP Perspective

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**ABSTRACT**

This study explores the potential for deep learning among students participating in the Innovation and Entrepreneurship Education Program (IEEP). Drawing on ecosystem theory and expected value theory, this research investigates how teacher-student and peer interactions can influence students' willingness to engage in deep learning, as determined by their self-efficacy and emotional value expectations. The study examines the relationships between perceived teacher-student and peer interactions, self-efficacy, emotional value expectations, and deep learning. A sample of 265 students from a Chinese university participated in the study. Research tools were developed using exploratory factor analysis (EFA) and partial least squares structural equation modeling (PLS-SEM) to test the research hypotheses. The results indicate that perceived teacher-student and peer interactions have a significant impact on students' self-efficacy and emotional value expectations, which in turn, influence deep learning behavior. Self-efficacy and emotional value expectations mediate the relationship between perceived teacher-student and peer interactions and deep learning. The findings suggest that micro-ecosystems can influence individuals' intrinsic belief values, which can, in turn, affect their behavior. The study highlights the significant impact that activities promoting such interactions can have on enhancing students' deep learning and innovation and creativity abilities.

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## 1. Introduction

### *1.1 Fourth Industrial Revolution*

According to Liu and Zhang (2020), the State Council of China has been actively promoting mass entrepreneurship and innovation since 2015, and higher education institutions have been implementing policies to support this initiative. The 18th National Congress of the Communist Party of China has also emphasized the need to improve the quality of talent training and cultivate top-notch innovative talents. The cultivation of students' deep thinking and independent innovation ability is essential for talent training in higher education and is in line to improve students' deep learning ability.

Deep learning involves intrinsic motivation and learning intention for learning tasks, as well as the integration of previous knowledge and experience to form a systematic understanding of new knowledge (Marton & Saljo, 1997; Biggs, 1987). It is a key strategy for meaningful learning and represents students' comprehensive learning ability of integration, synthesis, and reflection (Laird et al., 2008). Furthermore, in the context of sustainable development education, deep learning represents the interdisciplinary thinking, innovation, and insight necessary for comprehensive ability (Warburton, 2003). Therefore, deep learning ability is strongly related to innovation and creativity.

According to PCSD (1994), environmental education and a sustainable educational environment are important for developing students' critical thinking, creative thinking, problem-solving, and decision-making skills. Providing a good teaching environment, learning support, and appropriate content methods can help students adopt deep learning abilities (Ramsden, 1997). The current research on the Innovation and Entrepreneurship Education Program (IEEP) was conducted in a Chinese university, where students from different professional backgrounds and grade levels volunteered to sign up for the project. The organizing committee assigned a guiding teacher to each group of students, and a total of 20 teams participated in the competition. The success criteria for the project competition were decided by the project organizing committee, and the theme of the competition was related to innovation and entrepreneurship.

The study verified a model of students' perception of external teacher and peer environments, their internal mental state, and actual deep learning ability, based on the Microsystem in Ecosystem Theory (Bronfebrenner et al., 2007). The study hypothesized that students' perceived teacher-student interaction and peer support have an impact on their psychology. Additionally, based on the theory of expected value (Atkinson, 1957), the study posited that students' high levels of self-efficacy and emotional value expectations have a significant impact on their deep learning level, and play a role in improving their deep innovation and creativity abilities.

## 2. Literature Review

### *2.1 The Mediating Role of Self-efficacy between Perceived Teacher-student Interaction and Peer Interaction and Deep Learning*

Self-efficacy refers to an individual's belief in their ability to achieve a specific task, which is directly related to their motivation and belief level and is proportional to the effort and time they invest in the task (Bandura, 1988, 1997). In the Innovation and Entrepreneurship Education Program (IEEP), self-efficacy is a critical inner motivation and belief that supports students in completing project creation.

Teacher-student interaction in the IEEP program encompasses three dimensions: emotional support, classroom organization, and teaching support. Each of these dimensions is related to students' academic achievements (Curby et al., 2009; Rimm-Kaufman et al., 2009). Affective support includes a positive atmosphere, a negative atmosphere, teacher sensitivity, and a student-concern perspective. Classroom organization includes behavior management, productivity, and teaching-learning forms. Teaching support includes concept development, feedback quality, and language modeling (Pianta et al., 2008). In the IEEP program, students require innovative guidance from teachers, and the perceived degree of teacher-student interaction is an important factor in completing the project.

The micro-system theory of ecosystem theory posits that the relationship between teachers and students is a crucial factor influencing students' short-term and long-term development (Pianta, 1999). Studies have demonstrated that students who receive more care and support from teachers exhibit more positive attitudes toward their studies and themselves (Wentzel et al., 2010). They also report higher levels of satisfaction with their studies (Solomon et al., 2000) and greater academic engagement (Ryan & Patrick, 2001; Solomon et al., 2000). Students' assessment of the intimacy between themselves and their teachers is significantly correlated with their social and learning skills (Pianta & Stuhlman, 2004). Additionally, there is a significant positive correlation between the quality of teacher-student relationships and student performance (O'Connor & McCartney, 2006). Positive teacher-student relationships are significantly associated with increased student participation (Hughes, 2011; Wu et al., 2010), which also contributes to improved student motivation and achievement (Hughes, 2011). Hence, numerous relevant studies have demonstrated that the degree of teacher-student interaction perceived by students has an impact on their individual academic and psychological development.

According to Johnson (1981), peer interaction, which involves cooperation and communication between peers, plays a crucial role in students' development and the achievement of educational goals. Peers belong to the micro-system in the ecosystem theory, which is a key factor influencing students (Pianta, 1999). The dialogue form of peer assistance can improve students' sense of belonging and connection (McFarlane et al., 2017), develop friendships, and enhance students' learning motivation. Effective cooperation with others can also promote students' academic challenges (Borup et al., 2020). Lacey et al. (2020) found that the form of peer interaction in the laboratory environment had an impact on students' personal achievement and work experience. Kamarainen et al. (2019) found that group cooperation helps regulate the cognitive imbalance of each member in the group, and members in the group can self-regulate to reach a cognitive balance state. Therefore, peer interaction has an impact on students' learning motivation, academic achievement, personal performance, and other aspects.

The current research background is mainly based on the IEEP program. In the program, students who participate in the competition form different groups, where peer cooperation is the form of peer interaction within one group, and peer competition is the form of peer interaction among different groups. Therefore, the perceived peer interaction is divided into two variable forms peer cooperation and peer competition.

According to Zhan et al. (2020), an individual is highly motivated when they can complete a task. The IEEP is a competition based on the development of students' innovative abilities, and the success of the competition is the goal of every participant. Relevant studies have found that in a mixed teaching environment, students' self-efficacy is correlated with academic performance (Warren et al., 2020), and self-efficacy is positively correlated with self-regulated learning strategies (Lee et al., 2020). Career decision-making self-efficacy is also correlated with students' learning styles (Farhang et al., 2020). Akamatsu et al. (2019) demonstrated that self-efficacy played a mediating role in the process of metacognitive strategies and self-regulated learning and illustrated the correlation between self-efficacy and learning strategies.

Therefore, the choice of academic self-efficacy and learning strategies, academic performance, and students' self-adjustment are correlated. In the current study based on the IEEP program, students' self-efficacy represents their confidence level in implementing the project competition, and deep learning represents the growth of students' innovative ability during the competition process.

Although some articles have demonstrated that teacher-student relationships and peer relationships are related to students' psychological and learning states, as well as the correlation between self-efficacy and students' learning state, no study has investigated whether self-efficacy can mediate the relationship between perceived teacher-student interaction, peer support, and deep learning. Therefore, we propose the following hypotheses: H1: perceived teacher-student interaction can significantly predict students' self-efficacy; H2 and H3: perceived peer support, cooperative interaction, and competitive interaction can significantly predict students' self-efficacy; H4: students' self-efficacy can significantly predict their level of deep learning.

*2.2 The mediating role of emotional value expectation among perceived teacher-student interaction, peer interaction, and deep learning*

According to Atkinson's (1957) expected value theory, human behavior can be predicted by expectation and value beliefs. Expectation refers to a cognitive expectation, which is triggered by cues in the situation, and indicates the likelihood of a specific behavior leading to a particular outcome. In this study, students' emotional value expectation for project success is the positive emotional expectation resulting from the achievement of the project, such as satisfaction and joy. This research aims to investigate whether positive emotional value belief significantly predicts students' deep learning behavior and whether it can serve as a dependent variable of students' perceived teacher and peer interaction in the microenvironment system, thereby mediating students' deep learning behavior.

Students' perception of teacher-student interaction involves the interaction of teaching, emotion, and classroom situational organization (Curby et al., 2009; Rimm-Kaufman et al., 2009). Based on the ecosystem theory (Pianta, 1999), students' perception of teacher-student interaction can affect their systems. Studies have also shown that teacher-student interactions can affect students' emotional states and behavior. For example, Poulou (2015) found that there is a significant correlation between teachers' interpersonal behaviors and students' emotions and behaviors, while LoCasale-Crouch et al. (2018) demonstrated that high-quality teacher-student interactions are more likely to contribute to positive emotions in school and better math and reading skills. The quality of teacher-student interaction is also correlated with students' perception of emotional and social engagement in class (Martin & Rimm-Kaufman, 2015), and the emotional involvement tends to be stable over time (Ulmanen et al., 2016). However, most relevant studies focus on middle and primary school students, and there is a lack of related studies on college students. In addition, these studies mainly focus on the correlation of emotional engagement, and there is no study on the emotional state of a certain task.

By ecosystem theory, students' perception of their relationships with peers has a direct impact on their emotional state. This study considers cooperative interaction between peers within the same group as cooperative interaction and competitive interaction between different groups. Prior research has shown that students' ability to regulate their emotions is linked to various indicators of social interaction quality such as interpersonal sensitivity, prosocial tendencies, and the proportion of positive and negative peer nominations (Lopes et al., 2005). Moreover, peer relationships have a stronger correlation with students' emotions and behaviors than teachers' interpersonal behaviors (Poulou, 2015). In addition, students' emotional engagement in learning is highly linked to peer relationships in addition to teacher-student relationships (Ulmanen et al., 2016). Therefore, previous research has demonstrated that peer relationships do have an impact on students. This study focuses on students' perceived peer interactions, specifically their perceived cooperative and competitive interactions, and examines the correlation between these variables and students' expectations of emotional value within the current project.

To Atkinson's expected value theory (1957), this study defines emotional value expectation as the satisfaction and joy that students derive from the success of the project. This value belief is derived from students' inner emotional value expectations and is an important factor in their emotional level. Prior research has shown that emotions have a significant impact on critical thinking (Leasa, 2018) and that emotional state plays a critical role in the learning process, especially in computer learning environments where students' psychological state can affect their interaction with the environment (Megahed et al., 2019). Additionally, emotions are correlated with language learning strategies and learning styles (Taheri et al., 2019). Therefore, students' emotional state is related to various factors such as their thinking, learning style, and interaction state in the learning environment. However, there has been no prior research on whether emotional value expectation is related to students' deep learning state in projects or learning tasks.

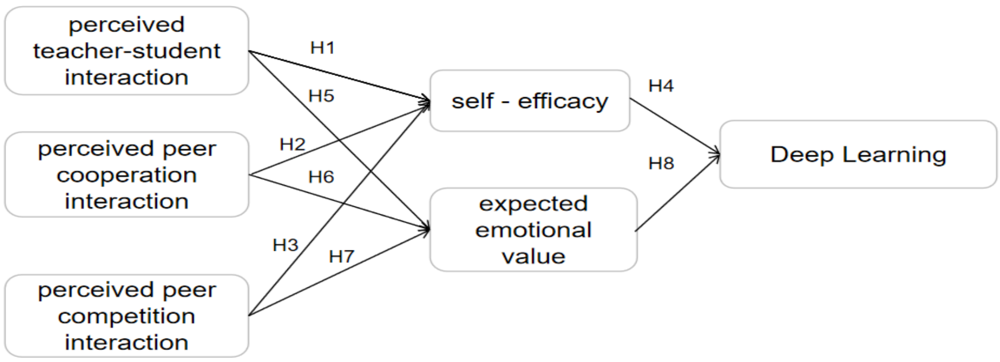
Although previous studies have demonstrated that teacher-student and peer relationships are related to students' emotional and learning states, no research has examined whether emotional value expectation plays a mediating role in the relationship between perceived peer support in teacher-student interaction and deep learning. Thus, this study proposes Hypothesis H5, which posits that perceived teacher-student interaction can significantly predict students' expectation of emotional value; Hypotheses H6 and H7, which suggest that perceived peer cooperative and competitive interaction can significantly predict students' expectation of emotional value; and Hypothesis H8, which postulates that students' emotional value expectations can significantly predict their level of deep learning (Zhan et al., 2020).

## 3. Method

*3.1 Sample and Procedure*

To test the study model in Figure 1., data was collected from 265 students who voluntarily participated in the Innovation and Entrepreneurship Education Program (IEEP) at a local undergraduate university in China. The participants were from different majors and grades and formed 10 groups with a total of 265 participants. The participants completed an online questionnaire using a 5-point Likert Scale (1= Strongly Disagree; 5= Strongly Agree). The questionnaire was reviewed, and 265 valid questionnaires were used to analyze and verify the conceptual framework through the structural equation model (Hair et al., 2006).

Figure 1. Conceptual Framework




*2.2 Instruments*

The instruments used in this study were developed based on previous research and adapted to fit the specific situation of the Innovation and Entrepreneurship Education Program (IEEP). The instruments included:

2.2.1 Perceived teacher-student interaction instrument

Consists of 10 items adapted from the Classroom Assessment Scoring System (Pianta et al., 2008) and tailored to the project implementation context, such as "I think the instructor can provide me with sufficient and timely interaction and help."

2.2.2 Perceived peer cooperation and peer competition interaction instrument

Consisting of 10 questions, with 5 items on perceived peer cooperation interaction and 5 on perceived peer competitive interactions. The questions were tailored to the project implementation context, such as "I think cooperation is more efficient for project innovation and project completion."

2.2.3 Self-efficacy instrument

Consisting of 10 questions adapted from the Academic Milestone self-efficacy Scale (Lent et al., 1986) and tailored to the project implementation context, such as "I think I can complete the project well."

2.2.4 Emotional value expectation instrument

Consists of 10 questions adapted from the expected value theory and tailored to the project implementation context, such as "I think the project to succeed in the competition can bring me happiness and a sense of accomplishment."

2.2.5 Deep learning instrument

Consists of 10 questions adapted from the Revised Two-Factor Study Process Questionnaire: R-SPQ-2F (Biggs et al., 2001) and tailored to the project implementation context, such as "During the process of the project, I can generate innovative ideas and concepts in the process of deep thinking."

*2.3 Data Analysis*

The collected data was analyzed using SPSS and Partial Least Squares (PLS). The measurements underwent Exploratory Factor Analysis (EFA) using various criteria such as Sphericity Bartlett Test ($p < 0.500$), Factor Loading, Kaiser-Meyer-Olkin, Communalities, and Eigenvalue, which were recommended by Hair et al. (2010) and Pallant (2011). The PLS method was used for structural equation modeling (SEM) to evaluate the measurement and structural model. To test the hypotheses, a standard PLS algorithm was implemented based on 5000 bootstrap procedures, following the recommendations of Hair et al. (2011).

## 4. Results and Discussion

*4.1 Assessment of the measurement model*

The current study adopted a two-step approach following Anderson and Gerbing (1988) to evaluate the convergent validity and reliability of the model. Convergent validity is achieved when the model satisfies the following criteria. Firstly, the indicators should reach a recommended value greater than 0.7 (Hair et al., 2019). As shown in Figure 2, all indicators have maintained a value above 0.7. Secondly, the composite reliability should exceed 0.70 (Gefen et al., 2000). Finally, Fornell and Lacker (1981) suggested that the average variance extracted (AVE) should be greater than 0.5. Additionally, Cronbach's Alpha and rho_A values should be higher than 0.7 (Hair et al., 2019). The values of these criteria are presented in Table 1.

Figure 2. PLS-Path analysis of R-square values (n=265).

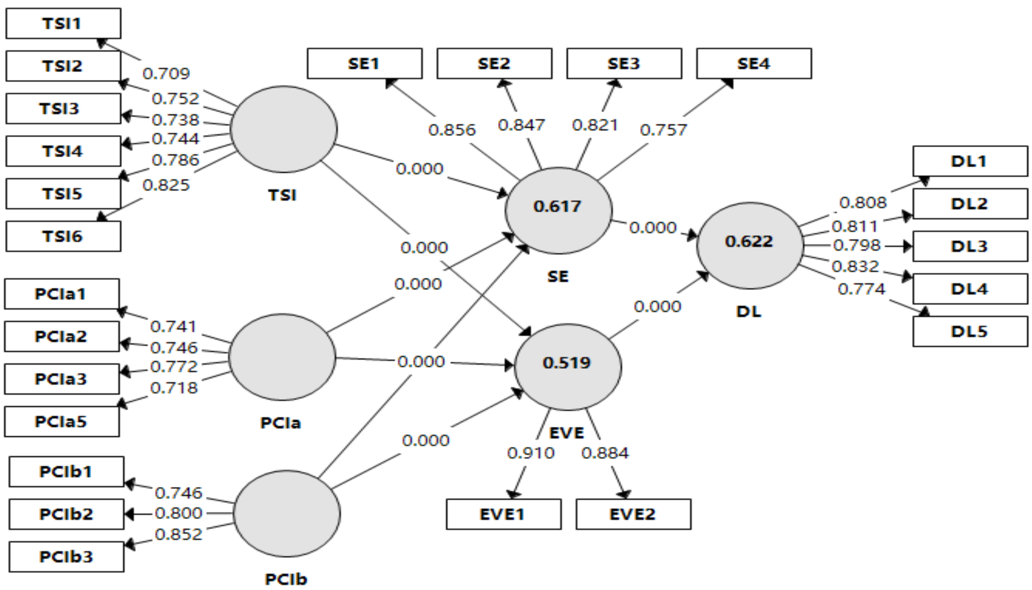


Table 1. Measurement model of PLS

| Latent variable | Items | Loading | Cronbach's Alpha | rho_A | Average Variance Extracted (AVE) | Composite reliability |
|---|---|---|---|---|---|---|
| Perceived teacher-student interaction | TSI1 | 0.709 | 0.854 | 0.867 | 0.577 | 0.891 |
| | TSI2 | 0.752 | | | | |
| | TSI3 | 0.738 | | | | |
| | TSI4 | 0.744 | | | | |
| | TSI5 | 0.786 | | | | |
| | TSI6 | 0.825 | | | | |
| Perceived peer cooperation interaction | PCIa1 | 0.741 | 0.732 | 0.732 | 0.554 | 0.832 |
| | PCIa2 | 0.746 | | | | |
| | PCIa3 | 0.772 | | | | |
| | PCIa4 | 0.718 | | | | |
| Perceived peer competition interaction | PCIb1 | 0.746 | 0.723 | 0.748 | 0.641 | 0.842 |
| | PCIb2 | 0.800 | | | | |
| | PCIb3 | 0.852 | | | | |
| Emotional value expectation | EVE1 | 0.910 | 0.758 | 0.766 | 0.805 | 0.892 |
| | EVE2 | 0.884 | | | | |
| Self-efficacy | SE1 | 0.856 | 0.839 | 0.845 | 0.674 | 0.892 |
| | SE2 | 0.847 | | | | |
| | SE3 | 0.821 | | | | |
| | SE4 | 0.757 | | | | |
| Deep learning | DL1 | 0.808 | 0.864 | 0.866 | 0.648 | 0.902 |
| | DL2 | 0.811 | | | | |
| | DL3 | 0.798 | | | | |
| | DL4 | 0.832 | | | | |
| | DL5 | 0.774 | | | | |

To ensure discriminant validity, the HTMT criterion was used and tested (Table 2). As per the recommended standard (Hair et al., 2019), the HTMT values should be less than 0.900.

Table 2. Heterotrait-Monotrait Ratio (HTMT)

| construct | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1. DL | | | | | | |
| 2. EVE | 0.826 | | | | | |
| 3.PCIa | 0.834 | 0.752 | | | | |
| 4.PCIb | 0.811 | 0.788 | 0.754 | | | |
| 5.SE | 0.863 | 0.770 | 0.790 | 0.816 | | |
| 6.TSI | 0.822 | 0.811 | 0.812 | 0.729 | 0.836 | |

### *4.2 Assessment of the structural model*

#### 4.2.1 Direct effects

To conduct hypothesis testing, this study utilized a bootstrap technique with 5000 bootstrap samples to examine the direct effects between each variable. The one-tailed t-test values used in this analysis were 1.645 (significant level = 0.05), 2.327 (significant level = 0.01), and 3.092 (significant level = 0.001), as recommended by Hair et al. (2017). The results of the bootstrap analysis, as shown in Table 3, indicate that there is evidence of direct influence based on the coefficient value and t-value. It is important to note that while this study only examined the indirect effects between variables based on theoretical assumptions, determining the direct effects was necessary before conducting the Smart PLS analysis and analyzing the indirect effects.

Table 3. Significance of direct effects-path coefficient(n=265)

| Path | Path Coefficient(β) | Sample Mean | Standard Deviation | T Statistics | P Values | Result |
|---|---|---|---|---|---|---|
| EVE -> DL | 0.348 | 0.350 | 0.068 | 5.098*** | 0.000 | Supported |
| PCIa -> EVE | 0.154 | 0.156 | 0.077 | 2.001* | 0.023 | Supported |
| PCIa -> SE | 0.180 | 0.182 | 0.067 | 2.661** | 0.004 | Supported |
| PCIb -> EVE | 0.271 | 0.270 | 0.075 | 3.610*** | 0.000 | Supported |
| PCIb -> SE | 0.296 | 0.294 | 0.064 | 4.626*** | 0.000 | Supported |
| SE -> DL | 0.525 | 0.525 | 0.063 | 8.339*** | 0.000 | Supported |
| TSI -> EVE | 0.405 | 0.406 | 0.082 | 4.932*** | 0.000 | Supported |
| TSI -> SE | 0.432 | 0.433 | 0.064 | 6.790*** | 0.000 | Supported |

*$p<0.05$, $t>1.645$; **$p<0.01$, $t>2.327$; ***$p<0.001$, $t>3.092$ (one-tailed)

4.2.2 Indirect effects

To examine the hypotheses, this study utilized a bootstrapping procedure with 5000 samples (Hair et al., 2017) to obtain the beta value, t-values, p-values, and bootstrapped confidence intervals. Since the hypotheses were based on theoretical assumptions, they were formulated to test the indirect relationships between variables. The results in Table 4 indicate that self-efficacy mediated the relationship between perceived teacher-student interaction and deep learning (β=0.227, t-value=2.512, $p<0.01$), as well as the relationship between perceived peer cooperative interaction and deep learning (β=0.094, t-value=4.930, $p<0.001$), and perceived peer competitive interaction and deep learning (β=0.155, t-value=4.092, $p<0.001$), supporting hypotheses H1, H2, H3, and H4. Furthermore, emotional value expectation mediated the relationship between perceived teacher-student interaction and deep learning (β=0.141, t-value=3.432, $p<0.01$), as well as the relationship between perceived peer cooperative interaction and deep learning (β=0.054, t-value=1.832, $p<0.05$) and perceived peer competitive interaction and deep learning (β=0.095, t-value=2.710, $p<0.01$), supporting hypotheses H5, H6, H7, and H8.

Table 4. Significance of specific indirect effects- Path coefficients(n=265)

| Path | Path Coefficient(β) | Sample Mean | Standard Deviation | T Statistics | P Values | Result |
|---|---|---|---|---|---|---|
| PCIa -> EVE -> DL | 0.054 | 0.054 | 0.029 | 1.831* | 0.034 | Supported |
| PCIb -> EVE -> DL | 0.095 | 0.096 | 0.035 | 2.71** | 0.003 | Supported |
| TSI -> EVE -> DL | 0.141 | 0.142 | 0.041 | 3.432*** | 0.000 | Supported |
| PCIa -> SE -> DL | 0.094 | 0.096 | 0.038 | 2.512** | 0.006 | Supported |
| PCIb -> SE -> DL | 0.155 | 0.154 | 0.038 | 4.092*** | 0.000 | Supported |
| TSI -> SE -> DL | 0.227 | 0.228 | 0.046 | 4.930*** | 0.000 | Supported |

*$p<0.05$, $t>1.645$; **$p<0.01$, $t>2.327$; ***$p<0.001$, $t>3.092$ (one-tailed)

4.2.3 R-square value and Q-square

To evaluate the predictive relevance of the research model, the size of the R-square and the predictive sample reuse procedure known as Stone-Geisser's Q2 were used as criteria. Henseler and Fassott (2009) recommended using Q2 to evaluate the predictive validity of a model, which is a measure of a model's ability to predict. Q2 values larger than zero indicate that exogenous constructs have predictive relevance for the endogenous construct (Hair et al., 2011). Additionally, the blindfold procedure was used to evaluate the predictive validity of the model via PLS. In this study, Table 6 indicated that the Q2 values of deep learning (Q2=0.392>0), expected emotional value (Q2=0.396>0), and self-efficacy (Q2=0.406>0) were greater than zero, suggesting that the research model has excellent predictive relevance.

Table 5. R-square value and Q-square value（n=265)

| Endogenous variable | R Square | Q-square |
|---|---|---|
| DL | 0.622 | 0.392 |
| EVE | 0.519 | 0.396 |
| SE | 0.617 | 0.406 |

*4.3 Discussion and Conclusion*

The purpose of this study was to examine the mediating role of self-efficacy and emotional value expectation in the relationship between students' perceived teacher-student interaction, peer interaction, and deep learning. The structural equation model was constructed and verified to test the relationship between variables. The study was conducted at a local undergraduate university in China, which focuses on cultivating students' innovative and technical abilities. This university represents the research status of most local applied undergraduate universities in China. The results of the study support the micro-ecosystem theory (Bronfebrenner et al., 2007) as students' perceived teacher-student interaction, peer cooperation, and peer competition significantly predict students' self-efficacy and emotional value expectation, which is consistent with related research (Martin & Rimm-Kaufman, 2015; LoCasale-Crouch et al., 2018; Kämäräinen et al., 2019; Lacey et al., 2020). The findings demonstrate the applicability of the micro-ecosystem theory in IEEP and highlight the significant impact of students' perceptions of teachers and peer interactions on their psychology.

## 5. Conclusion

The present study aimed to examine the mediating role of self-efficacy and emotional value expectation in the relationship between students' perceived teacher-student interaction, peer cooperation and competition, and their deep learning behavior. The study was conducted in a local undergraduate university that emphasizes the cultivation of students' innovative and technical application abilities, representing the research status of student quality and ability in most of the local applied undergraduate universities in China. The findings supported the micro-ecosystem theory, as perceived teacher-student interaction and peer support and competition all significantly predicted students' self-efficacy and emotional expectation value beliefs, demonstrating the impact of teacher-student and peer interactions on students' psychological states. The results also supported the theory of expected value, as students' internal self-efficacy and emotional value beliefs significantly predicted their deep learning ability. These findings are relevant for improving students' deep learning ability and innovation and creativity, particularly in the context of the current demand for innovative talents. The study provides empirical data for more schools to improve their innovation and entrepreneurship projects to cultivate students' internal creativity and innovation ability. Further research could include detailed observations and interviews with students to uncover their experiences and identify specific areas for improvement.

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