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Factors Influencing Deep Learning in Tourism Consumer Behavior Courses: A Study Based on Constructivism and Reciprocal Determinism

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The research aims to clarify the influencing factors of deep learning among students and improve their level of deep learning in tourism consumer behavior courses. The study takes questionnaire survey and statistical analysis methods to investigate and analyze the influencing factors of deep learning status among students in the tourism consumer behavior course. Based on constructivist theory, reciprocal determinism, and student participation theory, regression model assumptions and model variable selection are made. There were significant differences in the deep learning engagement among students of the Tourism Consumer Behavior course based on their gender and employment status as student cadres. Students' self-efficacy perception, interest in learning the course, and satisfaction level in the individual dimension had a significant positive impact on their deep learning status. The study innovatively conducts an internal logical analysis of students' deep learning states and their driving factors based on constructivist theory, reciprocal determinism, and student participation theory. Based on the actual situation of students in the tourism consumer behavior course, this research explores the driving factors of deep learning for undergraduate students in higher education institutions.

Keywords: tourism consumer behavior course, deep learning status, questionnaire survey method, driving factors, learning

INTRODUCTION

The tourism industry is rapidly transforming due to globalization and technological advancements, resulting in increasingly complex and unpredictable consumer behavior (Chandra et al., 2022; Rozhi et al., 2022; Manner-Beldeon et al., 2024). Consequently,

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the sector requires professionals capable of understanding and responding to consumer behaviors with high analytical skills and adaptability. Traditional education methods, which often rely on rote learning, fail to meet these demands (Biggs, 2011; Wu, 2019). To address this gap, Deep Learning (DL) has been recognized as an effective pedagogical approach.

DL emphasizes critical thinking, active engagement, and the practical application of knowledge—key competencies for tourism professionals dealing with diverse consumer behaviors (Liu et al., 2022; Fatimah et al., 2022). Unlike traditional approaches, DL fosters students' abilities to analyze, adapt, and apply concepts in real-world scenarios, which is crucial for effective tourism education (Nguyen et al., 2022; Anderson, 2016). However, fostering DL in educational settings presents challenges, largely due to the interplay between individual factors (e.g., self-efficacy, motivation) and environmental factors (e.g., teacher support, classroom atmosphere), which are vital in determining student engagement and learning outcomes (Bandura, 1986; Gratacós et al., 2023). Despite DL's potential, there is a gap in understanding how these factors specifically interact within tourism education.

Literature Review

Existing research identifies various factors that facilitate DL, ranging from technological innovations to human-centered approaches. Semerci and Goularas (2021) explored the role of neural networks and real-time feedback in enhancing learning, demonstrating the potential of constructivist principles in digital environments. However, applying these technologies in traditional, experiential contexts like tourism education presents challenges (Wu, 2019). Khamparia et al. (2021) also highlighted the limitations of implementing DL, particularly where computational resources are limited. Teacher support and interactive pedagogies are essential in fostering DL, yet scaling these practices in larger classes or digital environments poses difficulties (Sølvik & Glenna, 2022; Rodríguez-Díaz et al., 2018). Shrestha and Mahmood (2022) discussed the optimization of DL model parameters but also noted challenges in applying these techniques in diverse educational contexts. Anderson (2016) argued that resource-intensive, technology-centric approaches are often impractical in traditional settings.

Technologies such as AI and machine learning have been integrated into DL frameworks to enhance adaptability and personalized learning. For instance, Nguyen et al. (2022) showed how multi-agent reinforcement learning could improve educational engagement, while Yang et al. (2023) highlighted the importance of decision-making models in data-driven learning environments. Despite their promise, such interventions face challenges in tourism education, particularly due to infrastructure demands and the need for experiential, in-person learning (Eden et al., 2024).

Bandura's (1986) Reciprocal Determinism offers a valuable framework for understanding DL, highlighting the interaction between internal factors (e.g., motivation, self-efficacy) and external influences (e.g., peer and teacher support). An and Guo (2024) demonstrated that peer support can enhance self-efficacy and foster DL engagement, yet the literature lacks a nuanced understanding of how these dynamics unfold in tourism education, where adaptability is critical.

Addressing these gaps requires a deeper understanding of DL in tourism education. This study employs Constructivism and Reciprocal Determinism to explore DL in this context comprehensively. Constructivism, as articulated by Piaget (1954) and Vygotsky (1978), emphasizes active knowledge construction through interaction, aligning closely with DL's focus on experiential, student-driven learning (Fatimah et al., 2022). Reciprocal Determinism further explains how psychological factors (e.g., self-efficacy, motivation) and environmental influences (e.g., teacher support, peer interaction) shape DL outcomes (Siering et al., 2018). Together, these theoretical frameworks provide a holistic perspective on fostering DL in tourism consumer behavior education.

METHOD

To effectively analyze the factors influencing Deep Learning (DL) among students in tourism consumer behavior courses, a structured, three-stage process was employed: (1) selection and boundary determination of variables based on Reciprocal Determinism and Constructivist Theory, (2) establishing model constraints, and (3) constructing a conceptual model of DL and its influencing factors. This approach informed subsequent data sampling and research design.

Model Variables and Conceptualization

The selection of variables in this study is rooted in the theoretical frameworks of Reciprocal Determinism (Bandura, 1986) and Constructivism (Piaget, 1954; Vygotsky, 1978). These theories offer a robust lens for understanding how personal, behavioral, and environmental factors interact to shape students' deep Learning (DL) outcomes. The alignment of these frameworks with the specific context of tourism consumer behavior courses ensures that the variables selected for this study comprehensively capture the factors influencing DL.

In this study, DL serves as the dependent variable and is operationalized across four dimensions: motivation, engagement, strategy, and outcome. These dimensions reflect the depth of student learning and serve as critical indicators for evaluating the effectiveness of tourism consumer behavior courses in fostering meaningful and sustained learning outcomes. The independent variables were selected for their alignment with Reciprocal Determinism and Constructivism, and were divided into two primary dimensions: individual factors and learning environment factors. Each variable was rigorously defined to ensure both theoretical consistency and operational clarity. Therefore, the influencing factors and variables of DL among students in the tourism consumer behavior course can be shown in Figure 1.

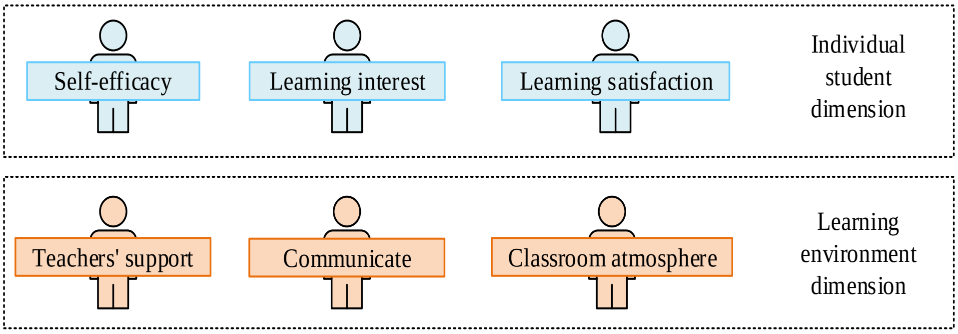

Figure 1
Conceptual framework of DL influencing factors

Figure 1 presents a conceptual framework illustrating key factors influencing Deep Learning (DL) by categorizing them into two dimensions: individual student factors and learning environment factors. Individual factors—self-efficacy, learning interest, and learning satisfaction—represent internal dynamics, reflecting how personal beliefs and attitudes influence the learning process, consistent with Reciprocal Determinism (Bandura, 1986). Learning environment factors—teacher support, teacher-student communication, and classroom atmosphere—highlight the role of social and contextual influences on learning (Sølvik & Glenna, 2022). These factors interact synergistically to shape students' motivation, engagement, learning strategies, and outcomes. Figure 1 illustrates this dynamic interplay between personal and environmental factors in fostering a deep learning state among students in tourism consumer behavior courses.

Individual Factors

Self-efficacy, as described by Bandura (1977), is an individual's belief in their capability to execute specific tasks, reflecting their sense of personal agency. In this study, it relates to students' confidence in mastering tourism consumer behavior concepts, influenced by direct experiences, observational learning, and external encouragement (Graham, 2022). High self-efficacy is linked to greater motivation to engage in deep learning activities (Kaufmann et al., 2022; Gratacós et al., 2023). Learning interest, based on Constructivist Theory, represents intrinsic motivation towards the course material, arising from perceived relevance and active engagement (Cayubit, 2022). This interest drives behaviors promoting deep learning both in and beyond classroom sessions. Self-learning satisfaction measures the gap between students' expectations and actual learning outcomes, predicting ongoing DL engagement when outcomes align positively with expectations.

Learning Environment Factors

Teacher support encompasses instructional, cognitive, and emotional assistance provided by instructors, including classroom instruction, emotional feedback, and post-class guidance—all of which affect student motivation and engagement (Islam et al., 2022). Effective teacher support nurtures both academic and emotional needs, creating an environment conducive to DL. Teacher-student communication involves the quality and frequency of interaction between instructors and students, enabling timely feedback, clarifying doubts, and encouraging active discussions—all critical for fostering deeper understanding of course material (Islam et al., 2022). Classroom atmosphere refers to the emotional and cognitive climate, where a supportive environment promotes collaboration and intellectual curiosity, directly influencing student motivation and adoption of DL strategies.

Model correlation assumptions and construction

The conceptual model developed in this study identifies six key influencing variables and applies Constructivism and Reciprocal Determinism as its theoretical foundation (Fatimah et al., 2022; Wong et al., 2022). These frameworks provide a comprehensive understanding of how personal, behavioral, and environmental factors influence DL among students in tourism consumer behavior courses. **Figure 2** outlines the assumed relationships between the six independent variables and DL, suggesting that each has a significant positive impact on DL, specifically on its dimensions of motivation, engagement, strategy, and outcomes.

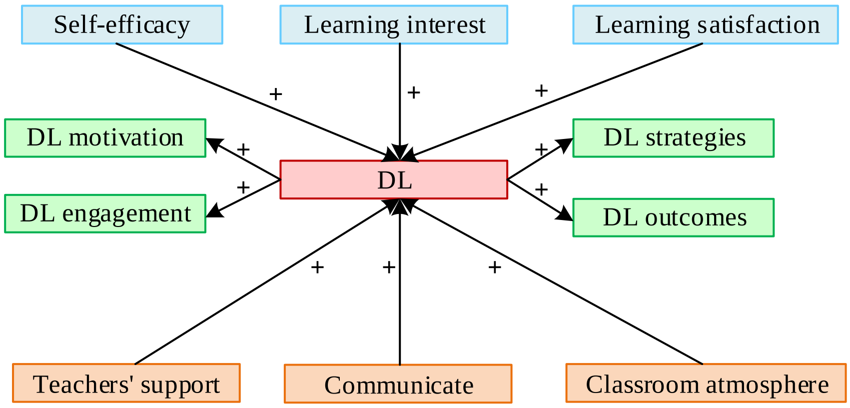

Figure 2
Assumptions related to impact factors

The model emphasizes the interaction between individual characteristics and environmental factors in fostering DL, consistent with Reciprocal Determinism. For instance, teacher support is posited to enhance students' self-efficacy, which subsequently boosts motivation and engagement. Constructivist principles further support this, suggesting that meaningful interactions with peers and instructors promote an active construction of knowledge. DL is therefore driven by student-centered engagement, with active problem-solving, collaboration, and inquiry-based activities. Variables such as learning interest and teacher-student communication are expected to encourage curiosity and engagement, thereby facilitating DL.

Based on these assumptions, the study proposes a conceptual model exploring the dynamic relationships between individual and environmental factors influencing DL among tourism consumer behavior students. Figure 3 illustrates this proposed model, depicting the relationships between the independent variables and the dependent variable, DL.

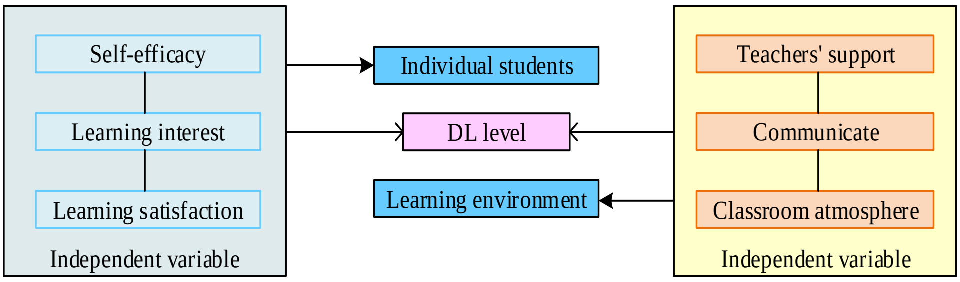

Figure 3
Conceptual model of deep learning and its influencing factors

The Figure 3 shows that the model is structured around two key dimensions: the individual dimension and Learning Environment Dimension. The individual dimension consists of self-efficacy, learning interest, and learning satisfaction. The learning environment dimension is composed of teacher support, teacher-student communication, and classroom atmosphere. The conceptual model assumes that the independent variables directly and indirectly impact the four dimensions of DL: Motivation is primarily influenced by personal factors such as self-efficacy and learning interest, while engagement is driven by both individual and environmental factors, including teacher support and classroom atmosphere. The model suggests that motivation leads to initial engagement, which is sustained by consistent support from the learning environment.

DL strategies refer to the specific methods and cognitive processes students use to deepen their understanding of course material. These strategies are influenced by learning satisfaction and the quality of teacher-student communication. DL outcomes are the result of successfully implementing these strategies, leading to the ability to apply learned knowledge in complex and novel situations. The study also formulates hypotheses regarding the influence of each independent variable on motivation, engagement, strategy, and outcomes. These hypotheses are grounded in Constructivism and Reciprocal Determinism, offering a comprehensive framework for examining the interactions that foster DL.

Data Collection and Sampling Strategy

To investigate the factors influencing Deep Learning (DL) among students in tourism consumer behavior courses, this study utilized a mixed-methods approach combining quantitative and qualitative analysis. The data collection was anchored by a structured questionnaire survey, followed by in-depth interviews. The survey design incorporated established instruments, namely the Deep Learning subscale of the National Survey of Student Engagement (NSSE) and Biggs' Learning Process Questionnaire (LPQ) (Winstone et al., 2022; Ashari et al., 2023). These instruments are well-aligned with the theoretical underpinnings of Constructivism and Reciprocal Determinism, which guided the research.

The questionnaire comprised three sections: demographic information, the DL Status Survey, and the DL Influencing Factor Scale. The DL Status Survey contained 22 items covering motivation, engagement, strategy, and outcomes, while the Influencing Factor Scale included 25 items evaluating self-efficacy, learning interest, teacher support, teacher-student communication, and classroom atmosphere. Responses were recorded using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Reliability and validity were ensured through a rigorous differentiation test involving F-value and T-value calculations. This process allowed the assessment of variance differences across items, ensuring that the questions effectively captured relevant distinctions among students. Items with non-significant differentiation were revised or excluded to enhance the overall validity of the instrument. A subsequent pre-test survey confirmed the reliability of the final questionnaire, yielding a Cronbach's Alpha coefficient exceeding 0.7 for all sections, indicating strong internal consistency.

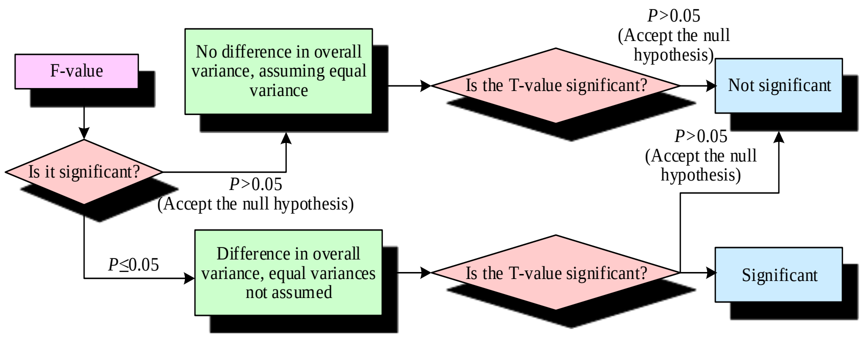

Figure 4
Verification process for distinguishing questionnaire question setting

After completing the differentiation verification process, a pre-test survey was conducted to further assess the reliability of the questionnaire. Cronbach's Alpha coefficient was used, and values exceeding $\alpha > 0.7$ indicated strong internal consistency, confirming the suitability of the instrument for subsequent data collection.

Data collection occurred in two phases: an initial quantitative survey followed by qualitative analysis. Utilizing a mixed-methods approach allowed for triangulation, thereby enhancing the validity and depth of the study results (Creswell & Creswell, 2018). Surveys were conducted both online and in-person to increase accessibility and yield a diverse sample. To specifically target students directly impacted by DL in tourism consumer behavior courses, purposive sampling was used. This strategy enabled the selection of participants with direct relevance to the study's objectives, which is a common and effective approach in educational research (Palinkas et al., 2015). However, purposive sampling may affect generalizability since the sample is not random, limiting the representativeness of findings to other educational settings (Etikan et al., 2016). Nevertheless, purposive sampling remains valuable in capturing detailed insights into specific phenomena (Gentles et al., 2015). Such an approach is particularly beneficial in understanding DL within diverse tourism education contexts and contributes to the broader applicability of the findings.

FINDINGS

To verify the proposed method, project analysis and validity verification are conducted before the questionnaire test to optimize the questionnaire. Secondly, based on the results of the questionnaire survey, an empirical analysis is conducted on the driving factors for students in the tourism consumer behavior course to enter the DL state.

Questionnaire pre-test and analysis

The study determines questions from different dimensions. Among them, the DL motivation corresponds to 4 problems (A1, A2, A3, and A4). The DL engagement corresponds to 5 questions (B1, B2, B3, B4, and B5). The DL strategy corresponds to 7 problems (C1, C2, C3, C4, C5, C6, and C7). The DL outcomes correspond to 6 problems (D1, D2, D3, D4, D5, and D6). There are 13 questions corresponding to the individual dimensions (E1, E2, E3, E4, E5, E6, E7, E8, E9, E10, E11, E12, and E13). There are 12 questions corresponding to the learning environment (F1, F2, F3, F4, F5, F6, F7, F8, F9, F10, F11, and F12). Firstly, the study conducts item analysis on the designed questionnaire using the problem discrimination test method. Table 1 displays the results of the Levine Variance Equivalence (LVE) test .

Table 1
The results of the Levine variance equivalence test

Question	*P*	Question	*P*	Question	*P*
A1	0.5	D1	0.22	E11	0.01
A2	0.05	D2	0.20	E12	0.77
A3	0.00	D3	0.00	E13	0.17
A4	0.43	D4	0.71	F1	0.27
B1	0.56	D5	0.00	F2	0.00
B2	0.92	D6	0.00	F3	0.02
B3	0.11	E1	0.38	F4	0.00
B4	0.64	E2	0.90	F5	0.00
B5	0.36	E3	0.00	F6	0.00
C1	0.26	E4	0.13	F7	0.02
C2	0.11	E5	0.50	F8	0.03
C3	0.95	E6	0.03	F9	0.00
C4	0.29	E7	0.00	F10	0.00
C5	0.14	E8	0.00	F11	0.00
C6	0.11	E9	0.47	F12	0.00
C7	0.14	E10	0.97	/	/

The results of the LVE test are closely related to subsequent variance analysis or t-test. If the significance (*P*-value) of the LVET test is greater than 0.05, it is considered that the variances of the two sets of data are equal. It can be assumed that the variances are equal for subsequent analysis. If the *P* is below 0.05, the variances of the two groups of data are not equal, and a corrected t-test needs to be used for analysis. Therefore, based on the results of the LVE for each question item shown in Table 1, the study further conducts a mean equivalence t-test. Figure 5 displays the results.

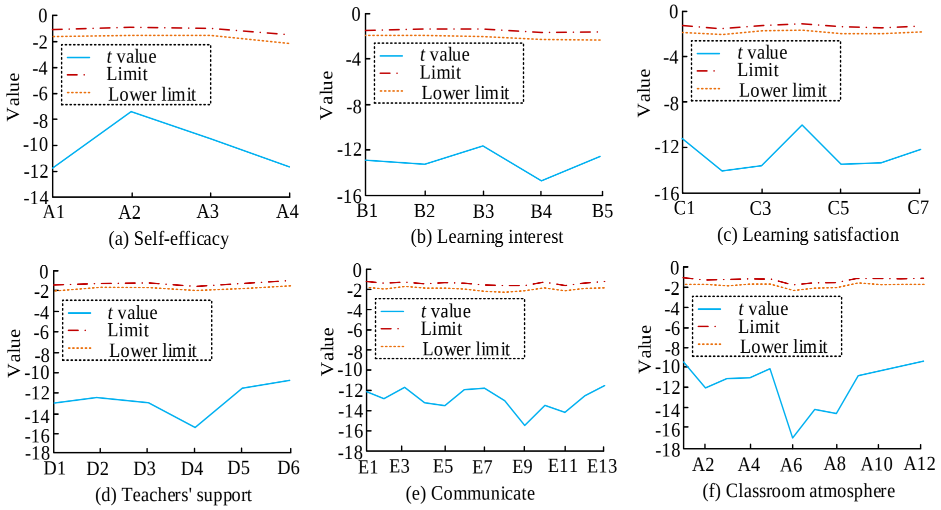

Figure 5
Mean equivalence t-test results

According to the changes in t-values in Figures 5 (a) - (f) and the corresponding 95% upper and lower limits of the confidence interval, the absolute values of t-values for all problem items were greater than the upper and lower limits. This indicates that there are significant differences among all problem items. All problem items have discriminative significance. On this basis, the Cronbach's Alpha coefficient validation is further conducted, as shown in Figure 6.

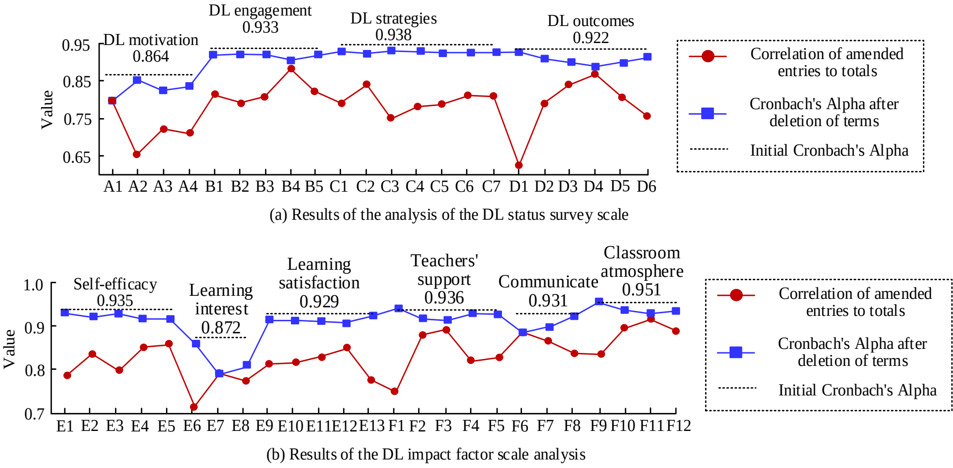

Figure 6
Cronbach's Alpha coefficient validation results

Figure 6 (a) shows the Cronbach's Alpha coefficient analysis results of the question items in the DL current situation survey scale. The Cronbach's Alpha of the D1 problem item after deletion was 0.93, exceeding the initial Cronbach's Alpha of the DL outcomes. Therefore, the study excluded question item D1 from the DL status survey scale. From Figure 6 (b), the Cronbach's Alpha value after deleting the F1 problem item exceeded the initial Cronbach's Alpha value, which should be deleted. The final DL status survey scale has 22 items and the DL influencing factor scale has 24 items. Among them, there are 4 problem items corresponding to DL motivation, 5 problem items corresponding to DL engagement, 7 problem items corresponding to DL strategy, 5 problem items corresponding to DL outcomes, 13 problem items corresponding to individual student learning dimension, and 12 problem items corresponding to learning environment dimension.

Empirical analysis

Based on the determined questionnaire survey items, a survey and analysis are conducted on the driving factors of students in the tourism consumer behavior course entering the DL state. Data analysis is conducted using the software SPSS22.0. The survey is conducted from October to November 2023, with a total of 500 electronic and paper questionnaires distributed and 451 valid questionnaires obtained. After confirming the reliability of the sample and following a normal distribution, the study conducts validity analysis on the obtained data sample. The samples are tested using Kaiser Meyer Olkin (KMO) test and Bartlett's sphericity test. Table 2 displays the specific results.

Table 2
Results of KMO test and Bartlett's sphericity test

Dimension	KMO	Approximate chi-square	df	Sig.
Questionnaire as a whole	0.97	15379.27	990.00	0.00
DL status questionnaire	0.95	6194.41	210.00	0.00
DL impact factor scale	0.96	7699.16	276.00	0.00

From Table 2, the KMO value of the entire questionnaire was 0.97, and the KMO values of the DL status survey scale and the DL influencing factors scale were 0.95 and 0.96, respectively. The validity of the data can be further confirmed according to the Bartlett sphericity test results. On this basis, the study conducts a differential analysis of basic information. The independent sample t-test results of gender on students' DL status are displayed in Figure 7.

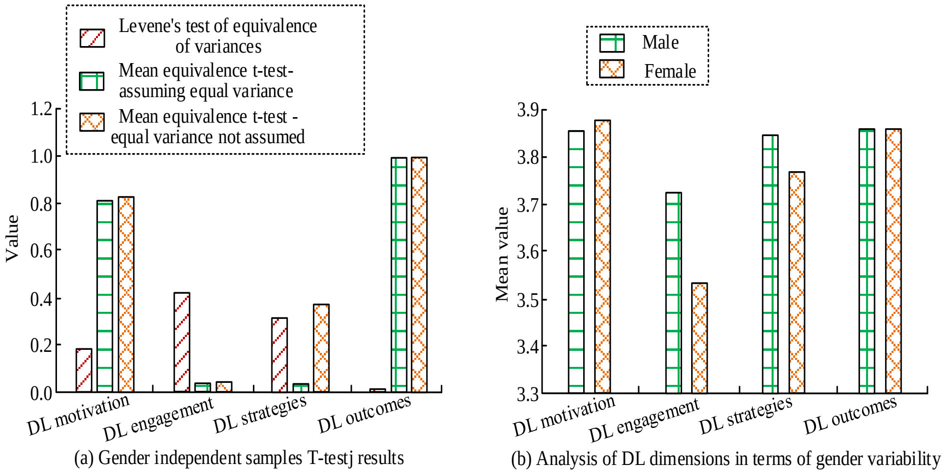

Figure 7
Independent sample t-test results of gender on students' DL status

From the results of Levene's variance equivalence test and mean equivalence t-test in Figure 7 (a), gender had a significant difference in the impact on the DL engagement dimension, satisfying the Levene's variance equivalence test P>0.05 and mean equivalence t-test P<0.05. Based on Figure 7 (b), in terms of DL engagement dimension, the average difference between males and females was 0.18. In other dimensions, no obvious difference existed in the average values between males and females. The independent sample t-test results of serving student cadres on students' DL status are shown in Figure 8.

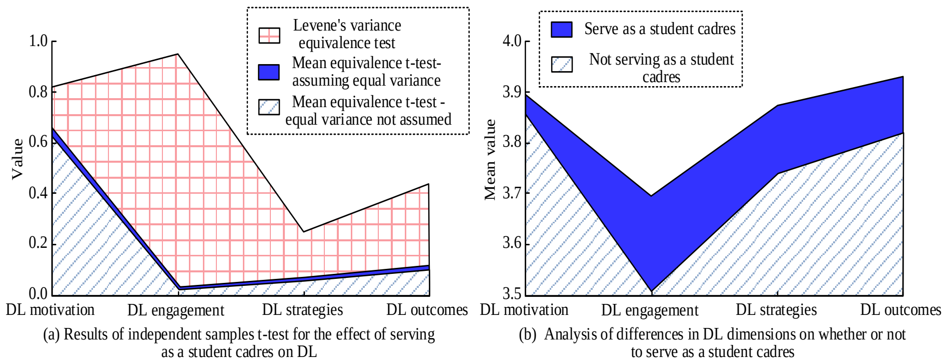

Figure 8
Independent samples t-test results of tenured student cadres on student DL status

From Figure 8 (a), the Levene's variance equivalence test for serving student cadres in the DL engagement dimension was P>0.05, and the mean equivalence t-test was P<0.05, indicating that there were differences in serving student cadres in the DL engagement dimension. Combined with Figure 8 (b), the average value of students who were employed was 3.70, significantly higher than the average value of students who were not employed. This indicates that students who serve as student cadres have a significantly higher level of DL engagement in tourism consumer behavior courses compared with those who do not serve. On this basis, the Pearson correlation coefficient is applied to analyze the relationship between DL and its influencing factors, as shown in Table 3.

Table 3
Pearson correlation analysis of DL and its influencing factors

/	DL motivation	DL engagement	DL strategies	DL outcomes	DL
Self-efficacy	0.68*	0.70*	0.78*	0.77*	0.82*
Learning interest	0.67*	0.67*	0.70*	0.58*	0.74*
Learning satisfaction	0.68*	0.73*	0.75*	0.65*	0.79*
Teachers' support	0.64*	0.61*	0.67*	0.63*	0.71*
Communicate	0.64*	0.72*	0.71*	0.61*	0.76*
Classroom atmosphere	0.62*	0.59*	0.66*	0.62*	0.70*

Note: * indicates that the correlation is significant at the 0.01 level (two-tailed).

The closer the Pearson coefficient is to 1, the stronger the correlation between two variables. From Table 3, there was a significant positive correlation between the four dimensions of DL and the six variables selected for the study. Therefore, further regression analysis is conducted on the DL strength and its influencing factors. Among them, the R^2 of the DL motivation was 0.58, the R^2 of the DL engagement was 0.64, the R-squared value of the DL strategy dimension was 0.70, and the R-squared value of the DL outcomes dimension was 0.62. The coefficient test results of the regression equation for four dimensions are shown in Table 4.

Table 4
Results of coefficient test of regression equation for 4 dimensions

Variant	DL motivation		DL engagement		DL strategies		DL outcomes	
	P value	VIF	*P*	VIF	*P*	VIF	*P*	VIF
Self-efficacy	0.00	2.59	0.00	2.59	0.00	2.59	0.00	2.59
Learning interest	0.00	2.76	0.02	2.76	0.02	2.76	0.28	2.76
Learning satisfaction	0.00	3.38	0.00	3.38	0.00	3.38	0.03	3.38
Teachers' support	0.28	3.98	0.24	3.98	0.72	3.98	0.28	3.98
Communicate	0.17	3.04	0.00	3.04	0.00	3.04	0.42	3.04
Classroom atmosphere	0.26	3.51	0.59	3.51	0.12	3.51	0.05	3.51

From Table 4, when the dependent variable was DL motivation, the P-values of the independent variables "self-efficacy perception", "interest in learning courses", and "learning satisfaction" were less than 0.05, indicating a high influence between the three dependent variables and DL motivation. Combined with the Variance Inflation Factor (VIF), the VIF of the six dependent variables was all greater than 1 and less than 5, indicating a certain degree of multi-collinearity between variables, but the linear correlation between independent variables was not severe. When the dependent variables were DL engagement and DL strategy, only the "teacher support level" and "classroom learning atmosphere" were greater than 0.05, indicating that these two dependent variables had a relatively small impact on DL engagement and DL strategy. In the DL outcomes, the *P*-values of the dependent variables "interest in learning the course", "teacher support level", "teacher-student communication", and "classroom learning atmosphere" were greater than or equal to 0.05. Therefore, students' self-efficacy perception and satisfaction with learning have a significant impact on DL outcomes.

DISCUSSION

The findings of this study underscore the complex interplay between individual and environmental factors in fostering Deep Learning (DL) in tourism consumer behavior courses. Individual characteristics, such as self-efficacy, learning interest, and satisfaction, were crucial in motivating students and driving DL engagement. Self-efficacy consistently emerged as a key predictor across all DL dimensions, aligning with Bandura's (1986) concept of personal agency, which is also supported by Gratacós et al. (2023), who found that higher self-efficacy significantly enhances students' willingness to tackle challenging tasks, facilitating deeper engagement.

Contrary to expectations, the influence of teacher support on DL outcomes was limited. This weak impact may stem from the challenges of providing personalized instruction in large classes, where individualized attention is often impractical (Rodríguez-Díaz et al., 2018). The effectiveness of teacher support may also suffer if it does not align with students' specific needs. Personalized support, focusing on individual requirements rather than generalized assistance, could better promote DL (Sølvik & Glenna, 2022). In larger or digital settings, traditional support mechanisms might be less effective, necessitating innovative solutions like peer mentoring or technology-enabled individualized feedback (Nguyen et al., 2022).

On the other hand, teacher-student communication significantly influenced DL engagement and learning strategies. This aligns with Sølvik and Glenna's (2022) findings that interactive environments foster deeper learning. Effective communication provides timely feedback, clarifies misunderstandings, and creates opportunities for meaningful discussion—key elements for enhancing student understanding and engagement. These findings suggest the importance of prioritizing regular, open dialogue to foster DL. The limited impact of classroom atmosphere on DL further emphasizes the bidirectional nature of Reciprocal Determinism (Bandura, 1986). A supportive learning environment alone is insufficient without students' intrinsic motivation and self-efficacy. Future research should explore mechanisms that better align environmental factors with individual motivational factors to optimize DL outcomes.

IMPLICATIONS

The study's findings have several practical implications for educators. Enhancing students' self-efficacy should be a priority, achieved through interventions like goal-setting workshops, self-reflection activities, and tailored feedback sessions to help students recognize their progress (Khamparia et al., 2021). Teachers should create structured opportunities for personalized feedback, potentially via digital platforms for asynchronous discussions that enable one-on-one support even in larger classes. Additionally, peer support systems could supplement teacher efforts, particularly when individual instructor attention is limited (Rodríguez-Díaz et al., 2018). To foster DL, educators could integrate context-rich experiences like simulations and problem-based learning activities to stimulate student interest and engagement (Nguyen et al., 2022).

CONCLUSION

This study enhances the theoretical understanding of DL by applying Constructivism and Reciprocal Determinism frameworks to tourism education. Constructivism emphasizes active, experiential learning—an approach particularly suitable for tourism education, where practical engagement is key. Reciprocal Determinism highlights how internal factors (e.g., self-efficacy, motivation) and external factors (e.g., teacher support, classroom environment) interact to shape learning outcomes, offering valuable insights into the dynamic nature of DL in this context.

The findings underscore the importance of individual factors—particularly self-efficacy, learning interest, and satisfaction—in promoting DL. However, environmental factors like teacher support require more nuanced approaches, especially in larger or digital classrooms. Teacher-student communication emerged as a critical element, emphasizing the need for interactive and responsive learning environments.

Future research should explore different methodologies to investigate DL mechanisms in tourism education further. Experimental studies could evaluate the efficacy of interventions aimed at enhancing student self-efficacy or optimizing teacher support in large classes. Additionally, research should examine DL in various learning contexts, such as online environments or across diverse student demographics, to improve the generalizability of findings. Investigating how peer support and technology-enhanced learning environments can complement teacher support in fostering DL is also a promising direction for future inquiry.

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