International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 26 August 2023 **Revised:** 20 October 2023 **Accepted:** 02 November 2023*

Research on the Influencing Factors of College Students' Deep and Meaningful Learning in Blended Learning Mode

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Abstract: This study explores the influencing factors of deep and meaningful learning in blended learning modes and their interrelationships. The sample comprises 397 college students from a university in Sichuan Province, selected through random sampling. Data collection utilized a questionnaire based on Bandura's ternary interaction theory, covering dimensions such as learners, helpers, environment, and interaction. Hypotheses were formulated based on literature research, and a survey was developed using established scales. Quantitative analysis was conducted using SPSS and AMOS software. The mean, standard deviation, variance, skewness, and kurtosis values were within reasonable ranges. The latent variables of the model exhibited sound convergent validity, with SFL ranging from 0.807 to 0.965, AVE from 0.697 to 0.946, and CR from 0.919 to 0.946. Model fit indices indicated acceptable fit (CMIN/DF: 2.303, NFI: 0.966, CFI: 0.980, RMSEA: 0.58, RMR: 0.008, PNFI: 0.789). Through path analysis, the study optimized the model, resulting in the final structural equation model (SEM). The findings suggest that (1) learner, environmental, and interaction factors positively influence deep and meaningful learning, while helper factors show a negative correlation; (2) learner, interaction, and helper factors mediate the environment's impact on deep and meaningful learning; and (3) environmental factors have the most significant influence on helper factors, followed by interaction and learner factors. Helpers play a significant role in enhancing deep understanding for learners. These insights guide effective strategies in promoting deep and meaningful learning in blended learning environments.

Keywords: Deep Meaningful Learning, Blended Learning Mode, College Student.

I. Introduction

Industry 4.0 necessitates individuals with deep meaningful learning capabilities (Zhong et al., 2017). In 2013, the German Federal Ministry of Education and Research and the Federal Ministry of Economics and Technology issued a publication titled "Safeguarding the Future of German Manufacturing: Suggestions for the Implementation of the 'Industry 4.0' Strategy," integrating emerging technologies such as the Internet, big data, cloud computing, and the Internet of Things into industrial production (Zhong et al., 2017). This initiative established interconnected resources, information, goods, and man-machine systems, ushering in a new era of intelligence and transitioning from traditional "manufacturing" to "intelligent manufacturing."

As a consequence, the demand for labor shifted towards innovative, versatile, and skilled high-end professionals, significantly reducing the need for low-skilled labor (Ojanperä et al., 2018).

In May 2015, the Chinese State Council released a notice titled "Made in China 2025," acknowledging the profound amalgamation of information technology and manufacturing as a catalyst for industrial transformation (Broo et al., 2022). The document prioritized innovation-driven growth as the foundational policy and emphasized the importance of enhancing innovation capabilities within the national manufacturing industry (Levine, 2020). It highlighted the strategic requirement of improving the multi-level talent development system, particularly focusing on the cultivation of high-level professionals and urgently needed and scarce technical and innovative talents (Lu & Li, 2023). The goal of talent training shifted from fostering individual literacy to cultivating compound talents (Anthonysamy et al., 2020).

As information technology advanced, the concept of school education evolved from nurturing individuals who could adapt to automated production to fostering intelligent individuals capable of lifelong learning. The educational landscape shifted from semi-open vocational education and general education to embracing open lifelong learning and vocational education rooted in general education. This transition entailed a shift from a "teaching" paradigm to a "learning" paradigm, focusing on learner-centered approaches (Mondol & Mohiuddin, 2020). It necessitated proactive and efficient learning, enabling the leap of knowledge across disciplines and ultimately nurturing compound talents with innovative capabilities (Reaves, 2019).

In January 2020, the World Economic Forum unveiled a report titled "The School of the Future: Defining a New Education Model for the Fourth Industrial Revolution," presenting a global framework with eight essential attributes (Penprase, 2018). These attributes include global citizenship skills, innovation and creativity skills, technology skills, interpersonal skills, accessible and inclusive learning, problem-based collaborative learning, personalized and self-paced learning, and lifelong and student-driven learning.

The development of information technology has transformed education, entering the era of big data with the advancement of communication technology (Mayer-Schönberger & Cukier, 2013). In 2008, the Computing Community Coalition published a report on "Big Data Computing: Creating Revolutionary Breakthrough Business," describing the context of data-driven research. According to McKinsey, the impact, key technologies, and application areas of Big Data have been analyzed in depth (Yuspiani & Wahyuddin, 2021). Big Data is widely recognized for its 3V characteristics—volume, variety, and real-time nature—making its value crucial (Silva et al., 2019). Authenticity is a key aspect of big data (Benjelloun & Lahcen, 2019).

As of June 2022, China has 1.051 billion Internet users, with an Internet penetration rate of 74.4%. The scale of instant messaging users is 1.027 billion, online video (including short video) users reach 995 million, and online news users number 788 million. While this scale of users has driven rapid information development, it has also led to trends of information overload and fragmentation (Lauri et al., 2021).

II. Literature Review

Blended Learning

Blended learning is an instructional method that combines conventional face-to-face teaching with online learning elements (Firmansyah et al., 2021). This educational approach offers students a flexible and personalized learning experience by integrating the advantages of in-person interaction and internet resources (Dorobăţ et al., 2019). Blended learning provides a dynamic environment where students can actively engage with course materials, collaborate with their peers, and receive individualized feedback from instructors, enhancing the overall quality of their educational experience (Buelow et al., 2018).

Deep Meaningful Learning

Deep Meaningful Learning is a concept that focuses on promoting a profound understanding of the subject matter, as opposed to surface-level memorization of facts. It involves engaging students in critical thinking, problem-solving, and the application of knowledge to real-world situations (Byrne, 2018). Deep Meaningful Learning goes beyond surface-level learning by encouraging students to connect new information with their existing knowledge and experiences, fostering a deeper understanding of the subject matter (Byrne, 2018). The current state of research on Deep Meaningful Learning suggests that it has a positive impact on students' academic achievement, motivation, and engagement in the learning process (Nuryanto, 2021). The research indicates that students who engage in deep meaningful learning are more likely to demonstrate higher levels of critical thinking skills, problem-solving abilities, and retention of information compared to those who engage in surface-level learning (Rahmatullah & Atika, 2021).

Influences on Deep Meaningful Learning in a Blended Learning Mode

Research on the factors influencing deep meaningful learning and the relationships between them is receiving extensive attention and exploration. Studies have shown that the educational environment, encompassing both physical and human aspects, significantly influences students' achievement, satisfaction, and success (Shah et al., 2019). This environment includes shared perceptions among students and, at times, teachers within that setting. The physical classroom environment, comprising layout, seating arrangement, and resource availability, can profoundly impact students' engagement and learning outcomes (Khaliq et al., 2018). A positive learning environment not only enhances teachers' motivation, job satisfaction, and effectiveness but also influences instructional strategies that create opportunities for deep and meaningful learning (Ghaffari et al., 2020; Jeronen et al., 2016).

A supportive, inclusive, and participative learning environment promotes deep processing of information, critical analysis of concepts, and connections between new and existing knowledge (Willems et al., 2018). Additionally, a positive learning atmosphere fosters students' autonomy and self-direction, promoting intrinsic motivation to explore new ideas (Linarsih, 2020). The interaction between learners and the learning environment is a crucial aspect influencing the depth and meaningfulness of the learning experience (Aziz et al., 2020). Learners who perceive the learning environment as supportive, respectful, and inclusive are more likely to actively participate in discussions, ask questions, and seek additional resources to deepen their understanding (Castro-Rodríguez et al., 2021).

Research has demonstrated that individual factors, such as students' learning interests and self-efficacy, significantly contribute to their engagement in deep meaningful learning in a blended learning mode (Vidić, 2021). Students with a high level of interest in the subject matter and confidence in their ability to succeed are more likely to engage in deep processing, seek additional resources, and actively participate in discussions and activities (Schiepe-Tiska, 2019). Learner factors, including motivation, prior knowledge, and learning strategies, also influence engagement in deep meaningful learning (Banegas & Lowe, 2021).

Interaction plays a significant role in promoting deep meaningful learning in a blended learning mode (Olufunke et al., 2022). Additionally, interaction in a blended learning mode provides opportunities for collaborative learning and the development of critical social skills (Jaya et al., 2022). Student-to-student interactions in a blended learning mode have been shown to effectively facilitate deep and meaningful learning (Puspaningtyas & Ulfa, 2020). Teachers and teaching assistants can utilize various instructional strategies, such as small group discussions, collaborative projects, and online forums, to promote student-to-student interaction and engagement (Hassan et al., 2018).

The leadership style, level of support, and instructional approach of teachers and teaching assistants can impact students' readiness for change and their innovative work behavior (Rahmatullah & Atika, 2021). Educators who are supportive, motivating and foster a positive learning environment inspire students to engage in deep meaningful learning actively (Tachie et al., 2022). Additionally, teachers and teaching assistants play a vital role in promoting active learning strategies and self-directed adaptive learning, which are key components of deep meaningful learning in a blended learning mode (Dewi & Alam, 2021).

III. Method

Research Background

In recent years, the integration of traditional face-to-face instruction with online learning activities, known as blended learning, has emerged as a unique educational approach. Blended learning offers students the advantages of both synchronous and asynchronous interactions, providing greater flexibility and access to course materials. Meanwhile, deep meaningful learning strives to foster profound comprehension and meaningful engagement with subject knowledge by cultivating critical thinking skills and problem-solving abilities that can be applied in real-world scenarios. By combining these two approaches, learners can construct their knowledge more effectively. This study aims to examine the factors that have the most significant influence on deep meaningful learning within a blended learning mode. It will explore whether these factors interact with each other and assess the effectiveness of their impact.

Participant

The research object selected for this study was a university in Sichuan Province, China, with a total of 46,951 undergraduate college students. The sample size, determined through random sampling, was calculated using Yamane's (1967) finite aggregate formula. A questionnaire survey was then conducted on 397 college students to investigate the influencing factors of deep meaningful learning under the blended learning mode.

Instrument

A questionnaire was developed based on the Likert scale, titled "In the Blended Learning Mode, Deep Learning Influencing Factors Questionnaire," featuring five levels of rating scales. Four level 1 dimensions were designed, encompassing learner, helper, environment, and interaction. Within these, 18 level 2 dimensions were included, such as self-efficacy, metacognitive ability, course perception, interest in learning, satisfaction, instructor professional competence and support, helper professional competence and support, teacher-student relationship, resource environment, virtual environment, classroom climate, student-student interaction, teacher-student interaction, content interaction, deep meaningful learning motivation, deep meaningful learning strategies.

Additionally, the questionnaire was constructed based on the Maturity Scale, incorporating 18 secondary dimensions, which included deep meaningful learning motivation, deep meaningful learning strategies, and deep meaningful learning inputs and outcomes. The questionnaire was designed in consideration of the maturity scale.

Research Design

The purpose of this study is to explore the influencing factors of deep meaningful learning in the blended learning mode and the interrelationships among these factors. The study utilizes a questionnaire survey method and a quantitative research approach. Drawing on the ternary interaction theory, the theoretical model of the influencing factors of deep meaningful learning ability is constructed. This model considers the impact of four influencing factors, namely learner, helper, interaction, and environment, on deep meaningful learning, as well as the relationships between these variables.

Hypotheses are formulated based on a thorough literature review regarding the influencing factors of deep meaningful learning and their interrelationships. The following hypotheses are proposed:

H1: Environmental factors have a positive influence on learner factors.

H2: Environmental factors have a positive influence on interaction factors.

H3: Environmental factors have a positive influence on helper factors.

H4: Environmental factors have a positive influence on deep meaningful learning.

H5: Learner factors have a positive influence on interaction factors.

H6: Learner factors have a positive influence on deep meaningful learning.

H7: Interaction factors have a positive influence on deeper meaningful learning.

H8: Helper factors have a positive influence on interaction factors.

H9: Helper factors have a positive influence on learner factors.

H10: Helper factors have a positive influence on deep meaningful learning.

Based on these research hypotheses, a theoretical model of the factors influencing deep meaningful learning was constructed,

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as illustrated in Figure 1.

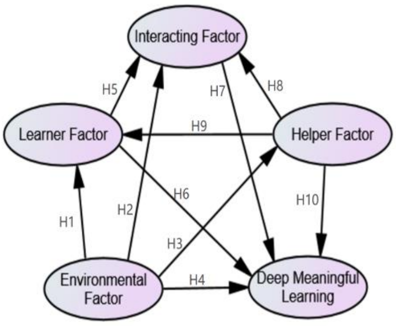

Figure 1. Theoretical Framework Diagram of Deep Meaningful Learning Influences

The components influencing deep meaningful learning were scrutinized, leading to the development of an open-ended questionnaire named "In the Blended Learning Mode, Deep Learning Influencing Factors Questionnaire Expert Evaluation Form" for experts. Nine experts were invited to evaluate the questionnaire, including three experts in instructional design, three in educational technology, and three in assessment education. All experts held the title of Associate Professor or above and had a minimum of five years of experience as Associate Professors. The purpose was to solicit their opinions on the Index of Consistency of Program Objectives (IOC).

Based on the theoretical model of influencing factors for deep meaningful learning in blended learning mode and utilizing data collected from the questionnaire, learner factors, helper factors, environmental factors, and interaction factors were categorized as latent variables. Meanwhile, self-efficacy, metacognitive ability, course perception, learning interest, satisfaction, instructor professional competence and support, helper professional competence and support, teacher-student relationship, resource environment, virtual environment, classroom atmosphere, student-student interaction, teacher-student interaction, content interaction, deep meaningful learning motivation, deep meaningful learning strategy, deep meaningful learning input, and deep meaningful learning outcome were classified as observational variables. Structural equation modeling was then constructed based on the relationships between these variables (see Figure 2).

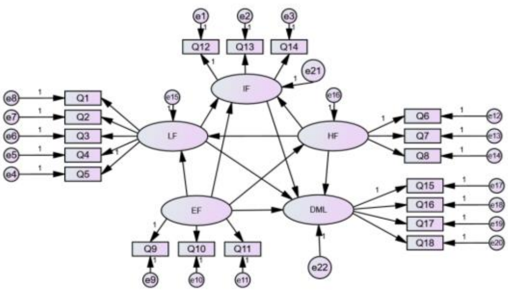

Figure 2. Structural Equation Modeling Diagram of Deep Meaningful Learning Influential Factors

After coding the quantitative data obtained from the questionnaires, the study underwent a validated Confirmatory Factor Analysis (CFA) using AMOS software (IBM SPSS Amos 24.0) to assess parameter estimation, convergent validity, and fitness metrics for the influencing factor model of deep learning capability. The hypotheses were evaluated based on the P-value and the path coefficients of each variable. Hypotheses deemed untenable were subsequently removed to obtain the final influence factor model diagram.

Data Collection Analysis

Recovering the results of the expert IOC assessment. The criteria for evaluation were to revise items with scores below 0.5 and to retain items with scores above or equal to 0.5. Before starting the formal survey, 30 university students were selected for pre-testing. The questionnaire dimensions were assessed to have Kaiser-Meyer-Olkin (KMO) values ranging from 0.7 to 0.891, Bartlett's test of sphericity with significance less than 0.001, and Cronbach's alpha data of 0.986, and the questionnaire was ready to be used for the formal test.

After the quantitative data from the questionnaires were coded, the study was subjected to a validated factor analysis (CFA) using AMOS software (IBM SPSS Amos 24.0) to assess the parameter estimation, convergent validity, and fitness metrics of the influencing factor model of the deep learning capability. The hypotheses were evaluated based on the P-value and the path coefficients of each variable, and the untenable hypotheses were deleted to obtain the final influence factor model diagram. The specific validation parameter criteria are as follows: 1) Model parameter estimation: the probability of significance value is required to be P>0.05. If the P-value is greater than 0.05, the null hypothesis can be accepted, indicating that the hypothesized model can be fitted to the sample data. However, it should be noted that when the sample size is larger, the chi-square value may become larger, resulting in a smaller probability of significance value P. It is easy to reject the null hypothesis, which is the hypothesis that the model cannot be fitted to the sample data.2) Convergent validity: five values were used for assessment: standardized item reliability (STD), correlation sum of squares loading (SMC), 1-SMC, composite reliability (CR), and average variance extracted (AVE). First, STD and SMC values are standardized item reliabilities, with STD values greater than 0.7 being the ideal level and greater than 0.6 being the acceptable range. SMC values greater than 0.5 are the ideal level, and greater than 0.36 is the acceptable range. Second, the CR value is a combination of the reliabilities of all measurement items and indicates the internal consistency of the construct. Similar to Cronbach's alpha, the larger the CR value, the higher the internal consistency of the construct, and a value greater than 0.7 is a more desirable criterion (Hair, 1997). Fornell and Lacker (1981) suggested that a CR value of 0.6 or higher is considered a criterion. AVE is used to calculate the magnitude of the explanatory power of the variance of the measured variables in the conceptualization and the higher the AVE value. The better the reliability of the conceptualization and the better the convergence, in general, more than 0.5 is the desirable range. More than 0.3 is the acceptable level.3) Model Fitness Indicator: It is used to measure the optimization of each measurement model or structural model, including the bigger and better the CMIN (chi-square value), the smaller and better the DF (degree of freedom). The ratio of CMIN to DF is perfect between 0 and 3, and between 0 and 5 is an acceptable level; GFI (generalized fit index) is greater than 0.8 as an acceptable range; AGFI (adjusted generalized fit index) is greater than 0.9 as an acceptable range; and RMSEA (root-mean-square error approximation) is less than 0.08. By following the above specific validation parameter criteria, we can comprehensively assess the model's fit and validity, ensuring the consistency of the established model of influencing factors of deep learning ability with the actual data and providing reliable support for the scientific reliability of the research results.

IV. Results and Discussion

Descriptive Data Statistic

SPSS 27.0 software was employed to process the collected formal survey data. A total of 414 questionnaires were distributed, and after data sorting, 391 questionnaires were deemed valid, resulting in a recovery rate of 94.44%. These questionnaires were then sorted and analyzed to calculate the mean, standard deviation, variance, skewness, and kurtosis for the 18 indices of the observed variables. The values of the variables fall within reasonable limits and the distributions exhibit normality.

Analysis Results

Assessment of Model Convergent Validity: Convergent validity serves as an indicator to evaluate the effectiveness of the relationship between latent variables and observed variables in the measurement model, reflecting the extent to which each observed variable effectively represents the corresponding latent variable. As per the AMOS software analysis, the Standardized Factor Loadings (SFL) between each observed variable and its corresponding latent variable ranged from 0.807 to 0.965, all-surpassing 0.5. This indicates a high explanatory power of the latent variable for its observed variable. The Average Variance Extracted (AVE) falls within the range of 0.697 to 0.840, exceeding 0.5, indicating substantial explanatory power of the latent variables for their observed variables. Additionally, the Composite Reliability (CR) ranges from 0.919 to 0.946, surpassing 0.7, suggesting strong internal consistency among the latent variables. These findings signify that the model exhibits good convergent validity, and the relationship between observed and latent variables is highly reliable.

Table 1. Latent Variable AVE and CR Values

	AVE	**CR**
EF	0.793	0.920
LF	0.697	0.920
HF	0.791	0.919
IF	0.840	0.940
DML	0.814	0.946

Quality of Model Fit and Fitness: In the absolute fitness index, the chi-square degrees of freedom ratio (CMIN/DF) is 2.303, falling within the favorable range of 1 to 3. The NFI value is 0.966, aligning with the index requirements within the range of 0.9 to 1. In the incremental fitness index, CFI represents the relative fit index of the model, ranging from 0.9 to 1, with a higher value indicating better model fit. The CFI value of 0.980 on this scale meets the specified requirements.

RMSEA, representing the root mean square and square of standardized residuals, has a value of .058, indicating a reasonable model fit as it is less than .08. The RMR value, indicating the mean square and square root of residuals, is 0.008, meeting the index requirements. A lower RMR, closer to 0, signifies a better fit.

In the PNFI, which gauges the degree of model streamlining, a value between 0.5 and 1 is desirable, with a value closer to 1 indicating better model streamlining. The scale validates that the model has a PNFI of .789, meeting the specified requirements. Refer to Table 2 for details.

Table 2. Structural Equation Fit and Fitness Indicators

	CMIN/DF	**NFI**	**CFI**	**RMSEA**	**RMR**	**PNFI**
Value	2.303	.966	.980	.058	.008	.789
Standard	≤3	≥0.90	≥0.90	≤0.05, ≤0.08	≤0.05	≥0.50
Findings	favorable	favorable	favorable	reasonably	favorable	favorable

Path Analysis and Scenario Evaluation: According to the path coefficient analysis conducted using AMOS on the relevant influencing factors, the learner factor emerges as the most significant influencer on deeper meaning, with a path coefficient of 0.55 and a p-value of <0.05, indicating a positive impact of the learner factor on deeper meaning learning. Environmental and interaction factors follow closely with path coefficients of 0.50 and 0.49, respectively, both with p-values <0.05, signifying positive influences on deep meaning learning. In contrast, the learner-assistant factor exhibits a path coefficient of -0.53, a p-value < 0.05, and an absolute Z value greater than 1.96, indicating a negative influence on deep meaningful learning.

Regarding the factors affecting the learner factor, the environmental and learner-assistant factors show path coefficients of 0.34 and 0.56, respectively, with p-values < 0.05, suggesting significant effects on the learner factor. For the interaction factor, the environmental factor exerts the most substantial influence with a path coefficient of 0.84 and a p-value < 0.05, signifying a positive and significant impact on the interaction factor. However, the learner factor and helper factor do not exhibit a significant effect on the interaction factor.

Environmental factors significantly impact helper factors in a positive direction, with a path coefficient of 0.92. Detailed values are presented in the table. Based on the Z-value, the Z-values of the two paths LF→IF and HF→IF are less than 1.96, and the p-value is greater than 0.05. This indicates that the difference between the sample mean and the overall mean is not significant, leading to the rejection of the null hypothesis at the 95% confidence level. Simultaneously, H5 and H8 are not considered valid.

Table 3. Path Analysis and Scenario Evaluation Data

Research Hypothesis	Trails	Path Factor	Estimate	S.E.	Z-value	p	Valid or not
H1	EF→LF	.34	.360	.109	3.303	***	YES
H2	EF→IF	.84	.924	.108	8.556	***	YES
H3	EF→HF	.92	1.025	.045	22.778	***	YES
H4	EF→DML	.50	.556	.117	4.752	***	YES
H5	LF→IF	.03	.028	.069	0.406	0.681	NO
H6	LF→DML	.55	.576	.060	9.600	***	YES
H7	IF→DML	.49	.490	.073	6.712	***	YES
H8	HF→IF	.07	.067	.099	0.677	0.499	NO
H9	HF→LF	.56	.526	.099	5.313	***	YES
H10	HF→DML	-.53	-.529	.085	-6.224	***	YES

Final structural equation model: After path optimization, the final structural equation model of the influencing factors of deep meaningful learning is shown in Figure 3.

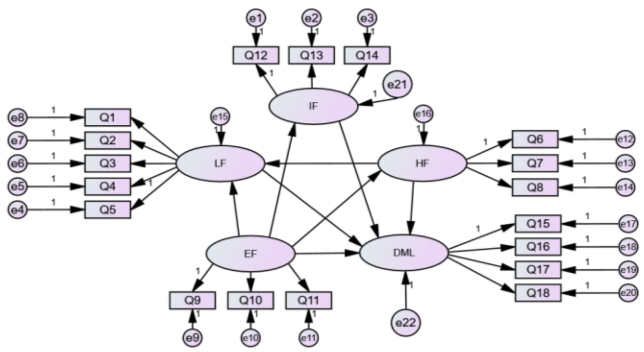

Figure 3. Structural Equation Modeling of Influences on Deep Meaningful Learning

The study results revealed that student factors, environmental factors, and interaction factors positively influenced deep meaningful learning in a blended learning model. Notably, the student factor exerted the most significant influence, followed by the environmental factor and interaction factor. Concurrently, it was observed that the helper factor had a negatively directed influence on deep meaningful learning. This highlights the importance for educators to be cautious in not over-assisting learners but guiding them to foster the development of deep meaningful learning abilities. Additionally, it underscores the need for learners to actively engage in the learning process, explore, and think independently rather than relying solely on the assistance of educators.

The learner factor, interaction factor, and helper factor all functioned as mediating variables in the impact of environmental factors on the ability to learn deep meaning. Environmental factors should be conveyed to learners, educators, and interaction sessions to facilitate their influence on deep meaningful learning. In a blended learning environment, the quality and richness of learning resources, the appropriateness of instructional design, and the encouragement and guidance provided by teachers are all considered environmental factors. The direct relationship between these factors and students' deep meaningful learning may not be significantly profound. However, through the mediation of interaction factors, these environmental factors can more effectively influence students' deep meaningful learning.

Regarding the relationships between latent variables, environmental factors positively affected learner factors and helper factors, with the most substantial impact on helper factors. Helper factors, in turn, had a positive influence on learner factors. Notably, the learner factor and learner helper factor exhibited no influence on the interaction factor. Helper factors were identified as playing a crucial role in the teaching and learning process, positively impacting students' motivation, learning attitudes, and behaviors.

V. Conclusion

Based on the findings, the study proposes several recommendations to enhance the cultivation of deep meaningful learning abilities in a blended learning model.

Firstly, there is a need to balance student and educator factors. Student factors were identified as having the most significant influence on deep meaningful learning. To address this, educators should prioritize fostering students' active engagement and independent exploration. This involves encouraging independent thinking developing problem identification and solution skills. Additionally, educators should tailor their teaching approaches to individual students' needs, guiding them to actively participate in learning within the blended learning environment.

Secondly, optimizing interaction design is crucial. Interaction factors play a vital role in facilitating the impact of environmental factors on deep meaningful learning. Therefore, educators should focus on designing interactive elements that promote collaborative learning and discussions among students. This approach fosters the collision of thoughts to stimulate inspiration and enhances comprehension and mastery. Concurrently, active interaction and guidance from teachers can ignite students' interest and motivation for learning.

Another important recommendation is to avoid over-assistance. Research suggests that excessive assistance may negatively impact deep meaningful learning. Educators should be mindful of refraining from excessive intervention in students' learning processes. Instead, through guidance and motivation, educators can empower students to develop autonomous learning abilities through exploration. This requires a conscious effort to cultivate students' autonomy and problem-solving skills, offering moderate support.

Furthermore, there is a need to optimize environmental factors. These factors need to be integrated into learners, educators, and interactive sessions. Educators should focus on delivering high-quality and diverse learning resources, designing instructional content and activities thoughtfully, and actively encouraging student participation. Through these enhancements, a learning environment conducive to deep meaningful learning can be established.

Lastly, educators should cultivate learning motivation. There is a need to stimulate students' interest and motivation for learning, encouraging them to engage in the learning process willingly. Students should be encouraged to pursue deep understanding rather than merely surface knowledge acquisition, fostering enduring enthusiasm and self-driven learning.

In summary, these recommendations underscore that cultivating deep meaningful learning abilities in a blended learning setting necessitates educators' attention to student autonomy, active involvement, optimization of interaction design, balanced assistance, enhanced environmental factors, and motivation cultivation. These efforts collectively contribute to enhancing students' deep meaningful learning capabilities.

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