International Journal of Evaluation and Research in Education (IJERE)
Vol. 14, No. 5, October 2025, pp. 3904~3916
ISSN: 2252-8822, DOI: 10.11591/ijere.v14i5.34333

Does cognitive load moderate students' learning engagement mechanism in blended learning?

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Article Info

Article history:

Received Dec 28, 2024
Revised May 9, 2025
Accepted Jun 17, 2025

Keywords:

Blended learning
Cognitive load
Learning engagement
Learning satisfaction
Moderating effect
Vocational students

ABSTRACT

With the popularity of technology-supported blended learning (BL) in vocational colleges, students' cognitive load (CL) caused by the increasing complexity of BL environments potentially impact the overall learning satisfaction (LS). In order to explore the effects of CL on students' BL, this study investigates how different dimensions of learning engagement (LE) (emotional, cognitive, and behavioral) impact on students' LS and whether CL can moderate these relationships. This quantitative study was conducted among 615 Chinese vocational students. Survey research was carried out by questionnaires that have been well-established that were taken and modified from previous studies. Structural equation modeling (SEM) was used to analyze the relationships among these variables. Findings revealed that emotional, cognitive, and behavioral engagement (BE) can positively predict LS. Additionally, BE mediates the relationship between psychological engagement (emotional and cognitive) and LS when CL is not at a low level. CL moderates the pathways from psychological engagement to BE and in turn changes the LE influence mechanism on LS. This study provides valuable insights for educators to stimulate students' engagement by satisfying their psychological needs, and optimize teaching design to balance CL in order to maintain active LE and satisfaction levels.

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1. INTRODUCTION

In recent years, the ongoing advancement of modern information and communication technologies (ICTs), internet of things (IoT) and social media have turn to be a catalyst for dramatic change in education, which also facilitating the new approaches for vocational teaching and learning [1], [2]. With this trend, the concept of blended learning (BL) has gained extensive attention, especially in the wake of the global COVID-19 pandemic [3], [4]. BL integrates traditional face-to-face classroom and online learning, which is crucial for fostering students' learning engagement (LE) [5] and learning outcomes [6]–[9], supporting various of learning preferences and styles [10], [11]. In addition to providing diversified learning materials and tools, BL also facilitates more targeted and customized instruction [12], [13]. Given that the learning activities take place without the constraints of space and time under BL context [14], it is students' initiative learning rather than the receptive learning that account for a large proportion [15], thus learning outcomes mainly depend on the extent to which the students devote to their study, that is, the actual LE, which also predict the overall learning satisfaction (LS) and efficiency [16]–[20].

LE can take on multiple forms in BL context. Newmann categorized LE into two types [21], namely psychological and behavioral engagement (BE). In detail, psychological engagement can be seen as the internal motivation and mental effort (ME). By contrast, BE is the external manifestation which is apparent to observe and measure, such as the amount of study time, participation, and persistence in study activities. With the continuous deepening of related research, Fredricks *et al.* [22] further divided the psychological engagement into two sub-dimensions, namely emotional engagement (EE) and cognitive engagement (CE). CE represents the learners' employment of various learning strategies and self-regulation during the learning process, which can range from simple memorization to the use of deep and reflective thinking to promote deep learning [23]. While EE focuses on students' affective experience during learning process, such as the interest, curiosity, and enthusiasm [24]. Early studies produced clear evidence that students' actual learning behaviors (BE) is largely governed by their learning motivation, attitude and cognitive structure, and to some extent, can reveal the students' cognitive and emotional status [25]. Besides, studies have testified that the psychological (cognitive and emotional) engagement can also impact LS and learning performance by way of students' BE [26], [27].

It is worth noting that the level of students' actual LE is limited by their cognitive load (CL), which represents the ME required to process information during learning [28]–[30]. Researchers have tried to investigate the function of CL and measure students' LE in different CL levels, some of them contended that the rich media and information technology environment of BL requires more cognitive resources and calls for higher capacity for processing and retrieving knowledge [31]–[33]. It is acknowledged that significantly increased complexity and CL will have an impact on students' actual LE and result in heterogeneous learning experiences. Some scholars posited that digital tools like immersive virtual reality (VR), augmented reality (AR) can enhance learning outcomes by effectively reducing students' CL [32], [34], [35] and fully develop students' intellectual potential, which can result in improved learning performance. However, some other scholars hold different viewpoints, they revealed that not all kinds of CL is detrimental, excessive simplification can result in boredom and disengagement [36]. Some degree of cognitive challenge is necessary to maintain learning motivation and engagement [37]–[39]. Given this, when designing blended courses, students' CL must be taken into account so that BL may proceed in line with the cognitive capacity of each learner [40]–[43].

However, few studies have focused on students' LE at sub-dimension level to deeply explore the influence of CL on these different kinds of engagement and corresponding outcomes. According to Szulewski *et al.* [42], not all CL is detrimental. Intrinsic CL relates to the inherent difficulty of the material, while extraneous CL stems from how information is presented. Reducing extraneous load can free up cognitive resources, but lowering intrinsic load too much may lead to under-stimulation. Instructional methods should account for this to maximize learning outcome [44]. Especially in BL context, controlling the difficulty of learning content as well as the total information to be processed help students to maintain a reasonable level of CL. In addition, most of the existing studies focus on the comprehensive university's scenarios, few attentions were paid to vocational schools. However, vocational students have their own particularities, such as higher goal-oriented study, more dependence on their teacher, and lower self-regulation ability compare to their college students' counterparts [2], [6], [7], [16], [25]. These characteristics may result in different situation of vocational students' LE and allocation of cognitive resource in BL context, which need to be further investigated.

To address this gap, it is urgent to conduct in-depth investigation on the LE mechanism towards LS under the influence of CL among vocational students, with a view to facilitating the blended course design and optimization of vocational students' learning performance in BL context. Towards this end, this study aims to identify:

- The influencing mechanism of vocational students' LE on LS in BL context.
- The moderating effect of CL on the influencing mechanism of LE towards LS in BL scenario among vocational students.

From the perspective of sub-dimension of LE, this study assumes that BE is not only an important carrier of psychological engagement, but also an important predictor of students' LS in BL environment. Besides, in addition to directly influence on students' LS, the psychological engagement (emotional and cognitive) can also affect LS through BE in BL context. Furthermore, in consideration of CL factor, this study hypothesizes that CL will play a moderating role in the influence mechanism of LE on LS of vocational students in BL context. The research model is shown in Figure 1. The research hypothesis includes i) EE can positively predict BE (H1); ii) CE can positively predict BE (H2); iii) EE can positively predict LS (H3); iv) CE can positively predict LS (H4); v) BE can positively predict LS (H5); vi) BE plays a mediating role between EE and LS (H6); vii) BE plays a mediating role between CE and LS (H7); and viii) CL plays a moderating role in the influence mechanism of LE on LS (H8).

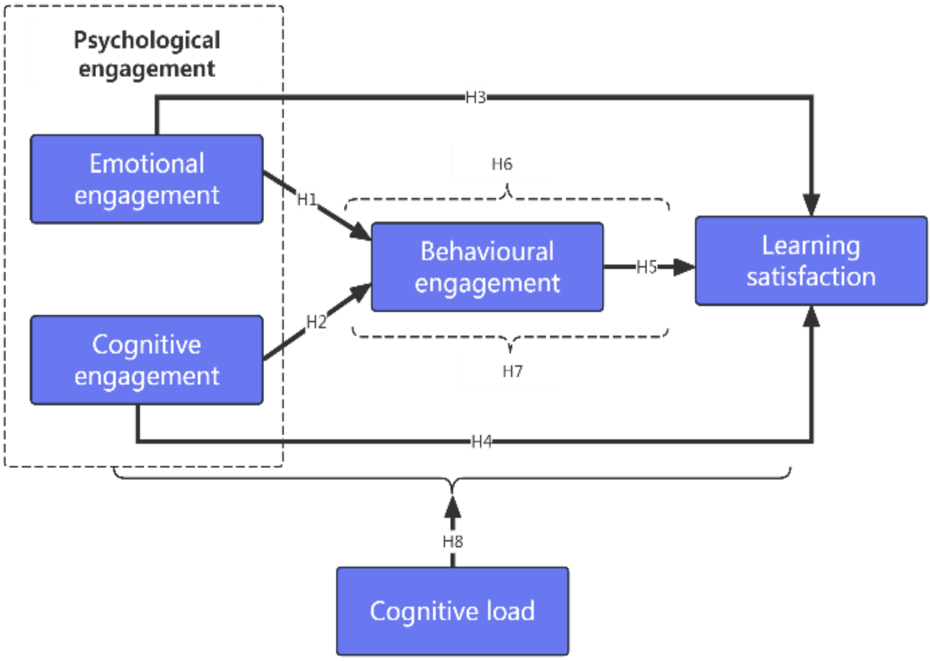

Figure 1. Research model and hypothesis of this study

2. METHOD

2.1. Research design

This study endeavors to investigate the influencing mechanism of vocational students' LE on LS and how CL moderates this influencing mechanism in BL context. Given the purpose of verifying hypotheses, it is important to obtain the real statistical data and employ reliable tools. Thus, this study employed a quantitative research approach, based on the data collected by online questionnaire survey on vocational students in China, this study constructs structural equation modeling (SEM) to examine the influencing paths among different forms of LE and LS under different CL level.

Key variables involved in this study including EE, CE, BE, CL, and LS were measured by corresponding measurement scale. Prior to conduct the SEM, this study applied Cronbach's alpha coefficient and confirmatory factor analysis (CFA) to check the reliability and validity of the instruments and structural model. Then, multi-group SEM analysis was conducted to test the difference in the influencing mechanism of LE on LS under different CL level.

2.2. Research context and participants

This study was conducted on the compulsory course "physical education" in the second semester of 2023-2024 in Hebei Sport University, a Chinese vocational college of sports. The course of "physical education" has begun to apply BL mode since 2020 due to the COVID-19 pandemic. The course process includes two parts, namely online and offline classroom, which makes it more representative and targeted for this study. The super star learning management system (LMS) incorporated e-books, lesson presentations, recorded videos, and weekly tasks for individuals and groups were applied in this blended course. Besides, students are able to discuss problems with each other in a shared learning space supported by WeChat App and discussion conference.

The sample size was determined based on SEM requirements, a sample size of at least 200 to 300 is typically recommended for SEM. A random sampling procedure was conducted after being approved by Research and Ethics Committee of Hebei Sport University. Staff members were given a 20-minute anonymous digital questionnaire created by Wenjuanxing online questionnaire platform (https://www.wjx.cn/), which they subsequently gave to students who took "physical education" course in the first semester of 2023-2024 (689 students in total). The online questionnaires were disseminated to every voluntary participant via a QR code. As a result, a total of 615 questionnaires were filled out, which was meet the requirement for carrying out SEM, accounting for 89% of the total questionnaires distributed. After data screening, 609 responses were remained for further analysis.

2.3. Measurement instruments

The instruments utilized in this study were measurement scales adopted from precious research with both reliability and validity. As showed in Table 1, the questionnaire with a total of 30 items was constructed, in which 3 items for demographic information (gender, age, and major), 8 items for CL, 15 items for LE and 4 items for LS. Since all these questionnaires were first created in English, they were translated by two translators who were familiar with pedagogy knowledge and an English linguistics teacher. The forward and backward translation procedures were used to guarantee the accuracy of the translation of all items. All scale measured with Likert scale with 5-point ranging from 1 to 5. In addition, this study also uses the CFA as a way to test the validity and reliability of the measurement instrument.

Table 1. Measurement instruments

Variables	Sub-dimension	Items	Source	Scales
CL	ML	5	[45]	5-point Likert scale
	ME	3		
LE	BE	4	[46]	
	EE	6		
	CE	5		
LS	—	4	[47]	

Note: ML=mental load

2.4. Data analysis procedure

AMOS v24.0 and SPSS v29.0 software were used to analyze the data. Firstly, the preliminary analysis was conducted to obtain the mean, correlation, standard deviation and distribution of the data. Secondly, confirmatory factors analysis (CFA) was employed to confirm the reliability and validity of the measurement model. The goodness-of-fit indexes for SEM ($\chi 2$/df, comparative fit index (CFI), goodness of fit index (GFI), and root mean square error of approximation (RMSEA)) were calculated to make sure the structural model was suitable for further examination.

Then, the SEM and bootstrapping with 2,000 resamples were carried out to investigate the causal relationships among psychological engagement (EE and CE), BE and LS in BL, and further test the mediating effects of BE between psychological engagement (EE and CE) and LS. Finally, in order to test the moderating role of CL in the influencing mechanism of LE on LS, this study conducted multi-group SEM analysis to examine the difference between the low and high CL group. According to research by Schoemann and Jorgensen [48], dividing the total sample into several sub-samples according to the moderating variable, and test the moderating effect by examining the difference of the SEM of the sub-sample groups respectively is one of the typical methods to analyze the moderating effect. In this study, a total of 609 eligible respondents were divided into a high CL group (n=273) and a low CL group (n=336) based on the mean score of the CL scale.

2.4.1. Descriptive analysis

In this preliminary stage, after eliminating outliers and missing data, the Mahalanobis distance was calculated by SPSS to discern extreme value; skewness and kurtosis values were used to verify normality [49]; and variance inflation factor (VIF) value was used to test multicollinearity (VIF<5 means the multicollinearity is not exist). Thus, after data screening, 609 responses were eligible for following analysis. The demographic information of respondents is presented in Table 2.

Table 2. Demographic information of respondents

Demographic information	Categories	Numbers	Proportions (%)
Gender	Male	408	67
	Female	201	33
Grade	Freshmen	171	28.1
	Sophomores	182	30.0
	Juniors	181	29.6
	Seniors	75	12.3
Major	Athletic training	172	28.3
	Physical education	259	42.5
	Sports dance	84	13.8
	Martial art	94	15.4

Table 3 displays the means, standard deviations, correlation matrix, skewness, kurtosis, and Cronbach's alpha coefficient for each construct. The results show that the values of kurtosis and skewness range from -1.544 to 1.737, implying the normal distribution of constructs. Besides, correlation coefficient of emotional, cognitive, BE and LS are lower than .9, indicating that there is no multicollinearity problem. As indicated by the mean values, all types of students' LE reach a relatively high level (score above 4.1), but the LS and CL witness a medium degree, with the mean score 3.64 and 2.97 respectively. All five constructs had Cronbach's alpha values ranging from .830 to .936, which are much higher than the recommended range suggested by Hair *et al.* [50].

Table 3. Results of preliminary analysis

Variables	BE	EE	CE	LS	CL
BE	1				
EE	.776**	1			
CE	.712**	.802**	1		
LS	.496**	.749**	.722**	1	
Mean	4.3549	4.2751	4.1620	3.6463	2.9734
Std. Deviations	.80788	.84116	.85969	.83034	.87263
Skewness	-1.544	-1.255	-.859	-.034	-.090
Kurtosis	1.320	1.737	.589	-.022	.286
Cronbach's alpha	.849	.926	.936	.830	.907

Note: **p<.01; n=609

2.4.2. Measurement model

The measurement model for each construct was evaluated by examination of the reliability, discriminant and convergent validity. Composite reliability (CR) (>.7) was used to confirm the reliability of the constructs. We computed CR and average variance extracted (AVE) in order to determine the convergent validity. According to Fornell and Larcker [51], the CFA findings verified that the factor loading, AVE (>.5), and CR values (>.7) of the data are appropriate, as shown in Table 4. The measurement model's discriminant validity was judged to be achieved as the square root of AVE value for each latent variable was higher than the correlation coefficient with any other construct in this model, as shown in Table 5.

Table 4. Results of CFA

Constructs	Items	Factor loading (>.5)	AVE (>.5)	CR (>.7)
BE	BE1	.881	.67	.89
	BE2	.622		
	BE3	.872		
	BE4	.902		
EE	EE1	.882	.68	.92
	EE2	.744		
	EE3	.903		
	EE4	.724		
	EE5	.884		
	EE6	.721		
CE	CE1	.890	.72	.93
	CE2	.811		
	CE3	.903		
	CE4	.818		
	CE5	.718		
CL	CL1	.629	.62	.92
	CL2	.758		
	CL3	.823		
	CL4	.735		
	CL5	.858		
	CL6	.885		
	CL7	.840		
	CL8	.724		
LS	LS1	.722	.56	.82
	LS2	.681		
	LS3	.781		
	LS4	.750		

Table 5. Discriminant validity for the measurement model

Constructs	BE	EE	CE	LS	Square root of AVE
BE	_	.78	.71	.50	.82
EE		_	.80	.75	.82
CE			_	.72	.85
LS				_	.75

2.4.3. Structural model

According to Collier [52], for an acceptable degree of model fit, the value of χ2/df should be between 2 to 5 (better for lower than 3). At the same time, both of the value of GFI and CFI should above .9, and RMSEA should not greater than .08. After the verification, the final structural model's results show χ2=338.337, df=121, χ2/df=2.797, GFI=.945, adjusted goodness of fit index (AGFI)=.914, CFI=.977, and RMSEA=.054, indicating a good model fit. In total, the model explained 62% and 61% of the variance in BE and LS respectively.

3. RESULTS AND DISCUSSION

3.1. The mediating role of behavioral engagement

The results of the SEM analysis, as in Table 6 and Figure 2 show that research hypothesis H1, H2, H3, H4, and H5 are supported. To be specific, both vocational students' EE (β=.585, p<.001) and CE (β=.233, p<.001) positively impact on their BE. Referring to H3 and H4, vocational students' EE and CE can positively impact on their LS, with standardized estimate β=.360 and β=.282 at the significant level P<.001. Besides, BE can positively influence on LS in BL context (β=.204, p<.01). The influencing paths among EE, CE, BE, and LS are displayed in Figure 3.

Table 6. The examination of research hypotheses

Hypotheses	Paths	Standardized Estimate (β)	Estimate (B)	S.E.	C.R.	P	Results
H1	EE–>BE	.585	.585	.055	10.670	***	Supported
H2	CE–>BE	.233	.237	.053	4.460	***	Supported
H3	EE–>LS	.360	.303	.066	4.584	***	Supported
H4	CE–>LS	.282	.240	.057	4.222	***	Supported
H5	BE–>LS	.204	.172	.054	3.170	**	Supported

Note: **p<.01, ***p<.001 (two-tailed); n=609

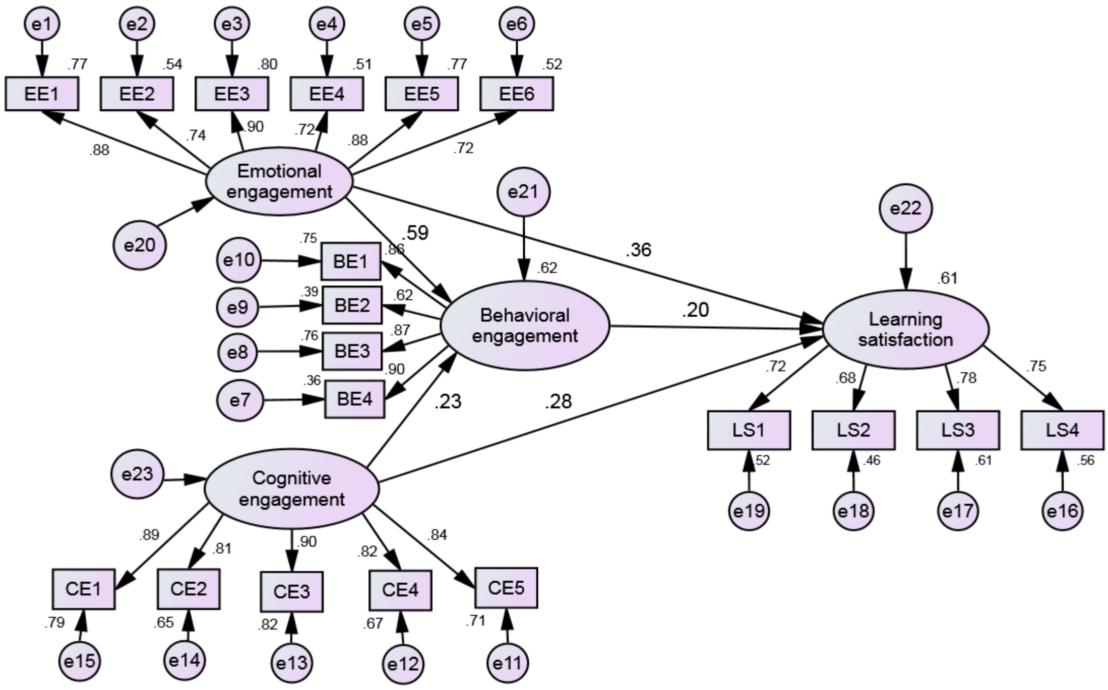

Figure 2. Results of structural model

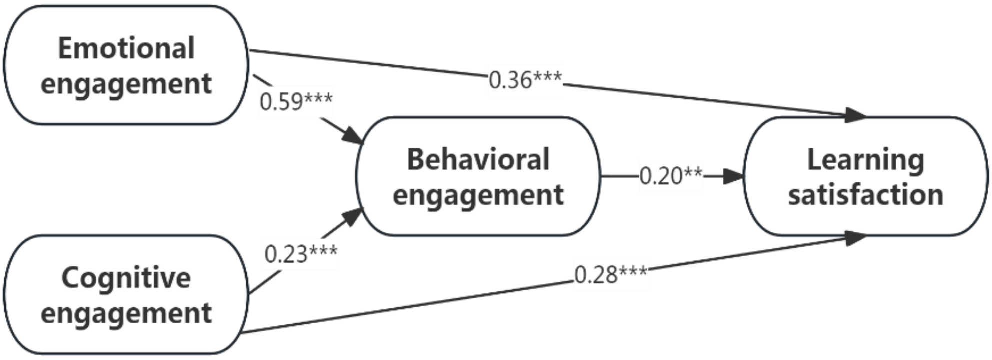

Figure 3. Influencing paths among LE and LS

This study used bootstrapping method with a sample size of 2,000 and a confidence interval (CI) of 95% to test the mediating effect of BE in the relationship between EE and LS as well as between CE and LS. This study carefully examined the CI of the lower and upper boundaries. Seeing from Table 7, the bootstrapping results confirm that BE has a positive mediating effect between EE and LS (standardized indirect effect=.120) as well as between CE and LS (standardized indirect effect=.047). As a result, H6 and H7 are accepted.

Table 7. The test of research hypotheses H6 and H7

Standardized effects	Estimates	Bias-corrected 95%CI Lower	Upper
Standardized total effects			
EE–>LS	.480	.366	.604
CE–>LS	.329	.211	.445
Standardized direct effects			
EE–>LS	.360	.200	.520
CE–>LS	.282	.166	.397
Standardized indirect effects			
EE–>BE–>LS	.120	.040	.211
CE–>BE–>LS	.047	.015	.097

3.2. The moderating role of cognitive load

In this study, multi-group analysis method was used to test the difference of the model between low CL group and high CL group. From the model fit indices, the χ2/df of each model is lower than 5; RMSEA ranges from .07 to .08, which is less than .08, while GFI and CFI are all greater than .9. These indexes showed that the multi-group SEM is relatively fit with the observed data.

The comparison of the two models shows that there were significant differences in the model of the high and low CL group, as in Table 8 and Figure 4. Specifically, in the model of the low CL group, research hypothesis H1 and H2 are rejected (p>.05); H3, H4, and H5 are still accepted, that is, both the EE and CE of low CL students has no significant impact on their BE, but only can predict their LS in a medium degree (influencing coefficient .309 and .268 respectively). Furthermore, students' BE still significantly and positively predicting their LS (β=.214).

Table 8. Comparison of multi-group analysis

Hypotheses	Low-cognitive-load group Standardized estimate (β)	P	High-cognitive-load group Standardized Estimate (β)	P	Z
H1	.104	.061	.676	***	4.671
H2	.089	.461	.332	***	2.472
H3	.297	**	.436	***	2.073
H4	.268	**	.292	**	.037
H5	.214	**	.209	**	.013

Note: **p<.01, ***p<.001 (two-tailed)

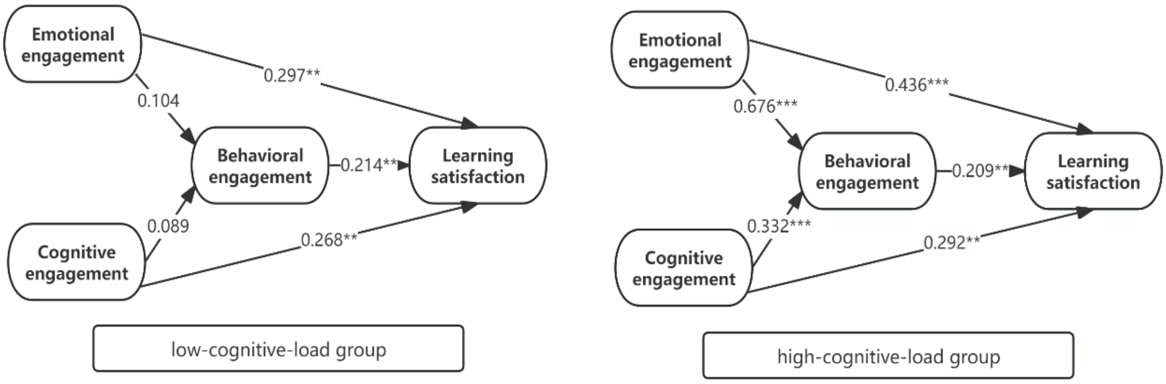

Figure 4. Influencing mechanism of LE and LS in different levels of CL group

By contrast, in the model of the high CL group, research hypothesis H1, H2, H3, H4, and H5 are all approved. Specifically, the path coefficients of H1, H2, H3, and H4 in the high CL group are greater than the low CL group. However, as for the influencing path from BE to LS (H5), the β value is .209, which is slightly lower than that in low CL group. That may be indicates that although students have enough interest and motivation to explore problems and devote cognitive resources to learning tasks, but in view of the limited cognitive resources, the actual satisfaction that can be generated from hardworking is also limited.

Referring to the significance of differences between low and high CL group, Table 9 shows the comparison of structural weights between the low and high CL group, when assuming the measurement weights to be correct. The comparison results show that the P value is .035, which is lower than the threshold of .05, implying the significant difference in structural weights between the two groups. To be specific, the parameter comparison Z value of H1, H2, and H3 in two groups is 4.671, 2.472, and 2.073 respectively, which are both greater than 1.96, indicating that there is significant difference between the two groups in path H1, H2, and H3. The results indicate that there are significant differences in the influencing paths from LE to LS under different CL level, especially in the paths relate to the psychological (emotional and cognitive) engagement towards BE as well as the effect of EE on LS.

Table 9. Results of multi-group analysis

Assuming model measurement weights to be correct							
Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho2
Structural weights	5	10.372	.035	.001	.002	.002	.001
Structural residuals	10	28.391	.002	.004	.004	.003	.002
Measurement residuals	54	580.895	.000	.074	.076	.067	.070

The test results of the multi-group SEM show that, the mediating effect of BE in the relationship between psychology engagement (EE and CE) and LS is not existed in the low CL group. That means, the EE and CE of vocational students in the low CL group fail to impact on their LS by way of BE. While in high CL group, the influence of EE and CE both flow through BE to impact on LS, the indirect effects is .099 and .040 respectively, as in Table 10. By comparison with the initial model, these two indirect influences all witness a slight descend. A reasonable explanation might be that in the high CL context, students still maintain a high level of psychological engagement, such as learning motivation and proactive learning strategies, but the required total amount of cognitive resources exceeds students' cognitive ability, which may not lead to higher BE. Additionally, high CL could cause a certain burden on students, affecting their positive learning behavior and LS. Thus, H8 is accepted.

Table 10. High CL group bootstrapping test of mediating effect

Standardized indirect effects		Estimates	Bias-corrected 95% CI		P
			Lower	Upper	
High CL	EE–>BE–>LS	.099	.021	.146	**
	CE–>BE–>LS	.040	.018	.219	.02

Note: **p<.01; n=273

3.3. Discussion

Firstly, the results indicate that in BL context, without considering the influence of CL, vocational students' psychological engagement (emotional and cognitive) can positively predict their BE. This result confirms the viewpoint that BE is the carrier and external representation of psychological engagement, which is consistent with the conclusions in the field of higher education based on intelligent classroom and BL scenarios [24], [25], [27], [53]. Similarly, Tang and Hew [54] also highlight the important role of emotional aspect in engagement mechanism, and regarded the cognitive and behavioral factors as antecedents of emotions in online contexts. In contrast to the findings, Joshi *et al.* [55] showed that CE has significant impact on both behavioral and EE.

The above debate reflects the reciprocal nature of LE, particularly in blended contexts. The relationship between cognitive, emotional, and BE is not strictly linear but interactive and context-dependent. Seeing from contemporary vocational education field, this study testified that psychological engagement has an impact on BE in a sub-dimension level, which can be seen in the influencing coefficient of emotional and CE on BE in the initial model, but these significant effects have not been found in the low CL group. This indicates that the students with low CL have limited psychological engagement's function in BL. A plausible explanation may be that, in case of low CL circumstances, the learning content and assignments may not arouse students' interest and desire to learn, so that they will not trigger the corresponding learning behavior. An implication of this finding is the possibility that, rather than blindly reduce the richness and difficulties of learning content and tasks to reduce the CL, a certain level of CL is necessary to maintain students' psychological engagement. In view of this, the quality of discourse and learning materials need to be well-designed in order to meet the students' real need. Besides, teaching activities and methods need to be enriched and innovated with the view of stimulating students' interest and initiative, maintaining a proper level of intrinsic CL in order to sustain an appropriate level of students EE and CE.

Secondly, the results also show that students' LS can be influenced by emotional, cognitive and BE in BL process. In addition to the direct positive impact of EE and CE, they also have an indirect effect on LS by way of BE. Furthermore, these effects are moderated by CL. These findings are consistent with the research results from several studies [56]–[59]. That is, LE can positively predict LS. Besides, this study further revealed the influencing mechanism of all types of LE on LS in BL situations. That is, the higher the psychological engagement of students, the higher their learning effort and involvement, and the higher the satisfaction of BL. This result is also in line with the self-determination theory [60], when learners' psychological needs are satisfied, this internal motivation will be triggered and in turn boost active learning behaviors, leading to higher satisfaction as a result. Otherwise, it will show burnout. Thus, in order to improve students' LE and LS, it is important to identify the students' real learning demands, psychological needs and intrinsic learning motivation, especially for vocational students, who have a strong learning purpose for their future career.

Lastly, the results further revealed that CL in BL situations can moderate the influence of LE on LS by affecting the interactions between psychological and BE. That means, only when students' CL reaches a certain level, can the BE will be driven by psychological engagement, and become one of the paths that psychological engagement affects LS. A plausible explanation seems to be that in the context of BL, when the learning tasks are challenging and diverse to a certain extent, they give rise to students' interest and desire to achievement, and this kind of motivation will induce more proactive LE. But it is worth noting that, an excessive high CL places burden on students and negatively impact on their LS, even though they have an active willingness to fulfillment, but they fail to gain an ideal learning result due to the high CL which is beyond their ability. Therefore, in teaching practice, when educators design blended courses, the goal should be to balance CL. Learning content and tasks should be designed in suitable level of challenge and complexity, so that students can generate appropriate CL, effectively stimulate their psychological engagement, drive the real and proactive learning behaviors, and thus maximize the value of BL mode. For instance, simplifying instructions and using clear, concise materials to prevent unnecessary ME. At the same time, maintain optimal intrinsic load by designing tasks that are challenging yet achievable, promoting deeper engagement and learning.

Based on the discussions, this study puts forward the following suggestions. Practitioners can stimulate the vocational students' intrinsic learning motivation and improve their psychological LE by satisfying their learning needs, interest and career expectation. Meanwhile, optimizing the design of BL tasks and resources, providing timely support based on dynamic learning situations, and ensuring that students' CL is at an appropriate level, so as to guarantee substantive LE and satisfaction, and achieve the most effective BL mode.

4. CONCLUSION

Based on the investigation of BL in vocational schools, this study developed a structural model of the relationship among EE, CE, BE, and LS under different levels of CL. Multi-group SEM analysis was employed to verify that CL has a moderating effect on the influencing mechanism of LE towards LS. It is found that, without considering CL, all types of LE (EE, CE, and BE) have a significant positive predictive effect on LS. Besides, BE has a mediating effect between EE and LS as well as between CE and LS. However, if the CL does not reach a certain level, this mediating role will disappear, that means, CL can moderate the influencing mechanism of LE on LS by adjusting the interaction between psychological engagement (EE and CE) and BE.

To summarize, this study introduces a novel perspective on how CL moderates the relationship between LE and LS in a BL environment, particularly among vocational students. Unlike previous studies that primarily consider CL as a challenge or barrier, this study examines its role in transferring the impact of LE on satisfaction. Besides, by distinguishing between emotional, cognitive, and BE, this study provides a deeper understanding of how each sub-dimension contributes to LS and how CL influences their relationships. The study offers empirical evidence that contributes to the theoretical and practical understanding of BL engagement mechanisms, filling the gap by addressing how vocational students experience engagement in BL and how CL affects their learning outcomes, providing practical insights for vocational education practitioners in course design and organization. However, this study was based on cross-sectional survey data and single course supported by a certain LMS, thus the conclusion may have limitations due to the influence of disciplines, choice of LMS, teachers' ability and other environmental factors. In considering the influencing factors will affect students' LE, LS, and the relationship between them, the conclusions of this study need to be verified in more various educational scenarios in the future studies.

FUNDING INFORMATION

Authors state that there is no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state that there are no conflicts of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author [NAJ]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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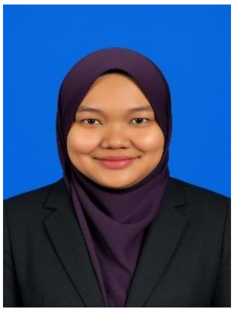

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