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Modeling the Effectiveness of Blended Learning Promotion with Artificial Intelligence Adaptive Learning System

Jun Xiang, Changsong Ma*

International College, Krirk University, Bangkok, Thailand, 10220

lss5241314@163.com (Corresponding author)

Abstract. Nowadays, big data and artificial intelligence are widely used in the field of education, effectively promoting the construction of teaching resources, teaching environment reform and teaching model innovation. This paper takes blended learning as the research object, relies on information-based teaching resources and environment, constructs a structural model of students' blended learning adaptation, collects data from 603 students through questionnaires, and analyses the influence relationships among blended learning adaptation, learning engagement and learning effectiveness. The study shows that blended learning adaptation and learning engagement have a significant positive impact on learning effectiveness, and learning engagement has a fully mediating role between learning adaptation and learning effectiveness. Therefore, to improve the learning effectiveness of online and offline blended courses, an artificial intelligence adaptive learning system can be used to strengthen students' self-management and enhance their blended learning adaptation and learning engagement.

Keywords: artificial intelligence; blended learning; learning adaptability; learning engagement; learning effectiveness.

1. Introduction

Artificial intelligence (AI) and virtual reality could only appear in science fiction in the past, but have become an integral part of people's lives today. With the rapid development of computer and communication technologies, artificial intelligence and big data technologies have triggered the era of education formalization, and smart education, digital education and mobile education have become the new trend (Liu Shu et al., 2020). The Futures of Education Briefing notes released by UNESCO (2022) suggest future trends in the development of digital transformation in education, with technology-driven teaching and learning models gaining more recognition. The analysis of student learning data as a basis for providing targeted intervention decisions, optimizing the allocation of teaching resources and providing students with personalized experiences and high-quality resources will become an important pathway to high-quality education. Following the explosion of COVID-19, student learning has generally shifted to online learning systems, MOOC learning platforms, and the completion of course assignments through distance learning and online learning modes (Khan & Jawaid, 2020; Manzoor, Isa & Dollmat, 2022). Although this approach solves the problem of learning during the suspension, the commitment and effectiveness of students' learning can only be assessed through online learning platforms, which have the problems of inconvenient process monitoring and single outcome assessment, and targeted instruction about students' needs more data and better platform support (Belhaj, Alothman, Hilal & Jibai 2022). Research on the development of teaching and learning platforms with artificial intelligence and big data technologies, learning process management, individual elements of adaptation influences, learning engagement, and online learning effectiveness for blended learning has been abundant, while some scholars have also analyzed the elements of learning motivation, self-efficacy, and social support in the context of the specialities of blended learning, combining the three elements of learning adaptation, learning engagement, and learning effectiveness The number of correlations between learning adaptation, learning engagement and learning effectiveness is still relatively small.

Specifically, this study aims to investigate and discuss the participation of students in blended online and offline learning in Chinese higher education schools. At the same time, it investigates whether this type of learning has a negative impact on learning engagement and learning effectiveness. By constructing a blended learning effectiveness promotion model using artificial intelligence tools to improve the effectiveness of online and offline blended learning, it is hoped that the findings and recommendations of this study will help universities to take effective measures to improve the quality of talent development.

2. Literature review

Advances in computers and ICT have brought about advances in artificial intelligence, which now gives machines and devices the ability to adapt to their environment and solve problems (Coppin, 2004), and is widely used in industries such as transportation, logistics, retail, and education. In the field of education, deep learning and data mining are used by many researchers to solve complex problems in the education process and carry out customized teaching and learning. Chen (2020), Zhang et al. (2020) constructed an online learning engagement problem to detect students through face data and mouse interaction, and Bhardwaj et al. (2021) used deep learning to analyse and record in real time student emotions, calculate learning engagement, and continue to explore the use of information technology in learning engagement monitoring. Smart devices and smart technologies are driving the development of intelligent learning environments. peng et al. (2019) build intelligent learning environments in terms of personal characteristics, personal performance, personal development and adaptive adjustments, which can provide support for the learning process, learning scenarios, physical environment, and learning communities, facilitating personalized adaptive learning and enhancing learner flexibility, effectiveness, and engagement (Su & Li, 2022), providing foundational support for exploring the issue of learning adaptability in blended learning environments. In addition, learning effectiveness, as an indicator of student engagement in learning, has become more diverse and faster with the addition of information technology. Data mining, statistical analysis, text analysis, social network analysis, data visualization, machine learning and signal processing provided by big data can help teachers to effectively manage teaching and learning and conduct scientific assessments (Sivarajah, 2017). Artificial intelligence, big data technologies, and communication technologies are being widely used in education to influence students' learning behaviour at different levels in space and time, and learners in the new era need to constantly adapt to technology, learn from it, and apply it to truly empower advanced technology for a happy life.

2.1. Blended learning adaptations and learning effectiveness

Blended learning adaptability is developed from a further clarification of the learning environment based on the concept of learning adaptability, i.e. the basic adaptability developed by students in the process of interacting with a blended learning environment (online environment merged with the offline face-to-face environment) (Qin Jinruo, 2019), by adapting to the blended environment in terms of learning attitudes, learning tasks, learning abilities, learning communication, learning environment, and physical and mental health needs, thus helping students to achieve better outcomes in their participation in blended learning. Learning effectiveness is a variable of the teaching and learning process, including factors such as learning achievement and learning satisfaction, and is influenced by learning approaches, self-regulation and external regulation (Fuente, Sander, Kauffman, & Yilmaz Soylu, 2020). Xie, Cao, Sun, & Yang (2019) concluded that learning adaptations have learning effectiveness and Liu (2022) concluded that learning adaptability has a significant positive impact on learning satisfaction. Can the learning adaptability of blended learning, a model that integrates online and offline learning, also affect learning effectiveness? Therefore, the following hypothesis was obtained:

H1: Blended learning adaptations have a positive impact on learning effectiveness.

2.2. Blended learning adaptation and learning engagement

Schaufeli (2002) argued that learning engagement is a continuous positive affective condition that individuals show during learning activities and is an important indicator of students' engagement and learning effectiveness. sun (2012) conducted a study on online learning engagement among American college students from three aspects: behavioral engagement, cognitive engagement and emotional engagement, and found that self-efficacy, self-regulation and learning Belhaj et al. (2022) concluded that adapting to environmental changes through self-regulation can change motivation and engagement in learning, and Meng Lina et al. (2012) found that learning adaptability was a good predictor of learning engagement. was a better predictor of learning engagement, and Li Fangjie (2018) also demonstrated that college students' learning adaptability was significantly and positively related to learning engagement. Therefore, the following hypotheses were obtained:

H2: Blended learning adaptations have a positive impact on learning engagement.

2.3. Learning engagement and learning effectiveness

Learning effectiveness is a proportional relationship between learning inputs and outputs, which mainly includes various aspects such as academic performance and course satisfaction. As an important indicator of students' engagement in learning, learning engagement is a good predictor of students' knowledge acquisition and skills training. Pascarella et al. (2010) and Kuh (2016) found that learning engagement is positively correlated with academic achievement, and teachers can assess learning outcomes through the level of engagement in learning scenarios and the degree of engagement in the learning process. As a result, the following hypotheses were obtained:

H3: Learning engagement has a positive impact on learning effectiveness.

2.4. Intermediary role

Learning adaptability, a necessary skill for a new era is well positioned to help students make the right choices and achieve desired goals in a new environment (Baker & Siryk, 1986), and Zhang (2020) found that adaptability directly predicted student engagement during the epidemic and could change students' self-efficacy, learning ability, mental health, learning environmental factors to support greater student engagement in learning. In recent years, big data and artificial intelligence have been widely used in learning and teaching psychology research (Starcic, 2019), where students use data recorded from learning behaviours as a basis for actively adapting to blended learning changes and actively engaging in online interactions between learners and teachers (Mekonnen & Muluye, 2020) in order to better enhance learning outcomes. As a result, the following hypotheses were obtained:

H4: Learning engagement mediates the relationship between blended learning adaptation and learning effectiveness.

2.5. Research model

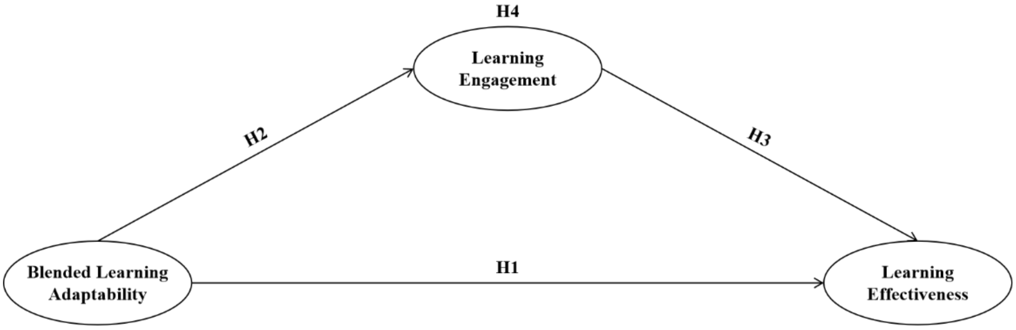

Fig.1: study framework

3. Research Method

3.1. Sampling method

In this study, a whole sample of students from five courses in managerial accounting, auditing fundamentals, financial management practices, corporate financial accounting and cost accounting in a higher education institution in Chongqing, China, was selected as the survey sample to investigate the actual status of adaptation, learning engagement and learning effectiveness of participation in online and offline blended learning courses. The course instructors acted as the main testers and used the same instructional language, asking the subjects to read carefully and fill in the questionnaires as required. A total of 603 questionnaires were distributed, including 135 on management accounting, 93 on auditing fundamentals, 121 on financial management practices, 107 on corporate financial accounting and 147 on cost accounting. 87 questionnaires that were not answered regularly or seriously were deleted, leaving 516 valid questionnaires (418 female and 98 male), with an efficiency rate of 85.57%.

3.2. Measuring tools

Based on the learning statistics in the Chongqing Higher Education Smart Education Platform, this study uses the Blended Learning Adaptability Questionnaire compiled by Qin Ruojin (2019), the Online Learning Engagement Scale revised by Hao Xiaojuan (2021) and the Learning Effectiveness Scale compiled by Long Chengzhi, Liu Zhimei and Wu Xiyan (2017) as measurement tools, which are divided into 4 sections with a total of 49 questions. Among them, the demographic questions include 3 items such as gender, place of origin and grade level; the blended learning adaptation questionnaire includes 6 dimensions of learning attitude, learning tasks, independent learning ability, learning communication, learning environment, and physical and mental health, with a total of 26 items (Qin, Ruojin, 2019); the online learning engagement scale is derived from a revision of the NSSE-CHINA classic scale, which includes behavioral engagement, cognitive (Hao, 2021); the Learning Effectiveness Scale includes knowledge, skills, and thinking skills, with five questions (Long, Chengzhi, Liu, Zhimei, and Wu, Xiyan, 2017). All except the demographic questions used Likert 5-point scale.

3.3. Data processing methods

This study used SPSS 27.0 and AMOS 26.0 software for reliability analysis and validity testing, as well as model fit and path analysis, to conduct an in-depth analysis of the impact of blended learning adaptation on learning engagement, learning effectiveness and the mediating role of learning engagement, and to summarise the findings based on the results of the data analysis.

4. Data Analysis

4.1. Reliability analysis

In this study, Cronbach's Alpha coefficient was used to test the internal consistency questions and the results are shown in Table 1. The Cronbach's Alpha coefficients for all variables of this questionnaire were greater than 0.9 and the overall reliability of this questionnaire was high.

Table 1: Reliability Analysis

Constructs	Cronbach's Alpha	Items No.
Blended learning adaptations	0.985	26
Learning engagement	0.985	15
Learning effectiveness	0.988	5
Total	0.972	46

4.2. Confirmatory factor analysis

This study used structural equation modelling (SEM) for data analysis and the standard factor loading (SFL) values for the constructs ranged from 0.884-0.954, which is above the judgement indicator of 0.7, and the study model was valid overall (Hair, 2019). The average variance extraction (AVE) for blended learning adaptation, learning engagement, and learning effectiveness were 0.858, 0.949, and 0.941, respectively, all greater than 0.5; the combined reliability (CR) values were 0.973, 0.987, and 0.988, respectively, all greater than 0.7. This indicates that the questionnaire in this study model has good convergent validity and combined reliability, as shown in Table 2（Bagozzi， Yi1988，Hair，2019）.

Table 2:Model AVE and CR metrics results（N=516）

		Std.	Unstd.	S.E.	T-value	P	SMC	CR	AVE
Blended Learning Adaptability	Attitude	0.916	1				0.839	0.973	0.858
	Task	0.904	1.083	0.041	26.317	***	0.817		
	Ability	0.955	1.169	0.041	28.549	***	0.912		
	Communication	0.941	1.162	0.043	26.978	***	0.885		
	Environment	0.954	1.17	0.041	28.696	***	0.910		
	Health	0.884	1.059	0.042	24.955	***	0.781		
Learning engagement	Behavioral	0.949	1				0.949	0.987	0.949
	Cognitive	0.983	1.032	0.024	43.517	***	0.980		
	Emotional	0.99	1.065	0.023	46.571	***	0.966		
	Social	0.974	1.022	0.023	45.094	***	0.901		
Learning effectiveness	CX01	0.973	1				0.947	0.988	0.941
	CX02	0.972	0.996	0.011	91.541	***	0.945		
	CX03	0.967	0.987	0.011	86.99	***	0.935		
	CX04	0.971	0.981	0.011	90.107	***	0.943		
	CX05	0.967	0.985	0.011	87.283	***	0.935		

The square root of AVE for each construct was taken as an indicator to verify the discriminant validity as suggested by Hair et al. (2019) et al. The values of the correlation coefficient matrix are shown in Table 3, and the square root of AVE for each dimension were 0.926, 0.974, and 0.970, respectively, which were all greater than the maximum absolute value of the correlation coefficients between the factors, showing that the measurement model in this study had good discriminant validity.

Table 3: Discriminant validity（N=516）

	AVE	Blended Learning Adaptability	Learning engagement	Learning effectiveness
Blended Learning Adaptability	0.858	0.926		
Learnling engagement	0.949	0.308**	0.974	
Learning effectiveness	0.941	0.119**	0.355**	0.970

Note: The diagonal values are the square roots of AVE and the numbers below are the coefficients of the relevant conformal surfaces. **P＜0.01.

Based on the results of the confirmatory factor analysis, as shown in Table 4, the Cmin/df value is 2.413, which is less than 3. This suggests that the fit between the hypothesized model and the sample data is acceptable. The Goodness of Fit Index (GFI) value is 0.901, the Adjusted Goodness of Fit Index (AGFI) value is 0.891, the Comparative Fit Index (CFI) value is 0.979, and the Tucker-Lewis Index (TLI) value is 0.978. These values are all within an acceptable range. Additionally, the Standardized Root Mean Square Residual (SRMR) is 0.022, and the Root Mean Square Error of Approximation (RMSEA) is 0.038, both of which are below 0.08. These results indicate a good fit of the model.Therefore, the fit indices of the research model meet the criteria for examination, indicating a good fit of the research model. Further hypothesis testing can be conducted based on these findings.

Table 4: Model fit metrics (N=516)

Fitting index	Cmin/DF	GFI	AGFI	CFI	NFI	TLI	SRMR	RMSEA
Acceptable range	<3	＞0.9	＞0.9	＞0.9	＞0.9	＞0.9	<0.08	<0.08
Measured value	2.413	0.901	0.891	0.979	0.965	0.978	0.022	0.038

4.3. Hypothesis testing

The significance and effect of the path coefficients between the potential constructs of the research model were analyzed as shown in Table 4. In terms of the effect of blended learning adaptation on learning effectiveness, the standardize coefficient (β) was 0.692, with a p-value less than 0.001, indicating that for each unit increase in blended learning adaptation score, learning effectiveness would increase by 0.692 units, and there was a significant positive correlation between the two, with research hypothesis H1 is supported. In terms of the effect of blended learning adaptability on learning engagement, the standardize coefficient (β) was 0.725, with a p-value less than 0.001, indicating that for every unit increase in blended learning adaptability score, learning engagement would increase by 0.725 units, with a significant positive correlation between the two, and the research hypothesis H2 is supported. In terms of the effect of learning engagement on learning effectiveness, the standardize coefficient (β) was 0.915, with a p-value less than 0.001. The more learning engagement, the better the learning effectiveness, and there was a significant positive correlation between the two, and the research hypothesis H3 is supported.

Table 5: Structural model path coefficients (N=516)

Independent variable	Dependent variable	B	SE_B	CR	β	P
Blended Learning Adaptability (BLA)	Learning Effectiveness (LEF)	0.953	0.064	14.966	0.692	***
Blended Learning Adaptability (BLA)	Learning Engagement (LEN)	0.796	0.058	13.796	0.725	***
Learning Engagement (LEN)	Learning Effectiveness (LEF)	1.168	0.057	20.408	0.915	***

Note: ***p<0.001

Using blended learning adaptation as the independent variable, learning engagement as the mediating variable, and learning effectiveness as the dependent variable,, Process selected Model 4 for the mediating effect analysis, and from the results, it can be seen that the main effect 95% CI (LLCI=0.0855, ULCI=1.2742) was significant under the condition that the number of Bootstrap was 5000, and The indirect effect 95% CI (LLCI=0.1062, ULCI=0.2375) was significant and the direct effect 95% CI (LLCI=-0.0768, ULCI=0.1100) was not significant, thus there was a fully mediated effect of learning engagement between blended learning adaptation and learning effectiveness. The mediating effect value of 90.56%, as seen through the percentage of indirect and total effects, is highly significant and research hypothesis H4 is supported.

Table 6: Intermediary Effect Statement

Model path Effect		Point estimate	Standard error	p	95% CI	
					LLCI	ULCI
BLA→LEN→ LEF	Total Effects	0.180	0.048	0.000	0.086	0.274
	Direct Effects	0.017	0.048	0.727	-0.077	0.110
	Indirect Effects	0.163	0.032	0.000	0.104	0.230

5. Conclusion

There are many ways for educators to use information technology in the era of artificial intelligence, such as developing artificial intelligence teaching systems, innovating teaching models, building intelligent teaching environments, expanding teaching resource channels, and increasing teaching interaction platforms (Khan, 2022), to continuously improve learning adaptation and learning engagement as a way to help students improve their learning effectiveness. Through the empirical analysis of online and offline blended learning adaptation, this study found that blended learning adaptation and learning engagement are both important factors affecting learning effectiveness, and that blended learning adaptation can also improve learning effectiveness through the mediating role of learning engagement, and these findings prove previous people's research conclusions from a new perspective.

Blended learning adaptability had a significant positive effect on learning effectiveness ($\beta = 0.692$, $p < 0.001$). This result is consistent with the findings of Xie et al. (2019) and Liu (2022), where learning adaptability positively predicted students' academic performance. According to previous studies, the better the learning adaptability of university students, the greater their interest in learning and the higher the academic outcomes achieved; if students are unable to adapt quickly to blended learning modes, they will perform poorly in terms of academic outcomes achieved in blended learning courses. Blended learning adaptation had a significant positive effect on learning engagement ($\beta = 0.725$, $p < 0.001$). This result further enriches the findings of Meng, Lina (2012) and Li, Fangjie (2018) that learning adaptability is still an effective predictor of learning engagement during online and offline blended learning, and the higher the student's learning adaptability, the better the learning engagement. Learning engagement had a significant positive effect on learning effectiveness ($\beta = 0.915$, $p < 0.001$). This result better enriches the findings of Pascarella et al. (2010), Kuh (2016) and others, where an increase in learning engagement in blended learning is associated with an increase in learning effectiveness. Learning engagement mediates between blended learning adaptation and learning effectiveness, and the results support the findings of previous studies by Zhang (2021), Mekonnen & Muluye (2020), and others that blended learning environments, learning styles, and learning communication are more convenient for students to access information and engage in interactions that facilitate students' behavioral, cognitive, emotional, and social aspects to increase engagement and ultimately achieve improved learning outcomes. In the blended learning process, students can be more engaged in the learning process according to their adaptability in order to improve learning outcomes and enhance learning effectiveness.

6. Limitations and Recommendations

However, the results of this study may not be extrapolated to all higher education students, as the sample of participating students in an online and offline blended first-class course at a higher education school in Chongqing, China, has a better resource profile and course quality compared to a typical blended professional course, and therefore the model validation can be further enhanced. In future research work, we can integrate resources to develop learning-assisted artificial intelligence systems based on blended learning management needs to support students' customized learning management in terms of interest, time, space and pace as a way to create an efficient learning environment.

In fact, this research model demonstrates the impact of hardware and software construction on learning effectiveness, such as learning adaptability and learning engagement, and provides a reference for promoting the development of intelligent management systems for learning behaviour, which can accelerate close cooperation between technology and teaching management, conduct interdisciplinary integration research and promote high-quality development of vocational education.

Finally, these research findings can help teachers in vocational institutions to continuously adjust adaptive factors in terms of learning attitudes, learning tasks, learning abilities, learning environment, learning communication and physical and mental health in future online and offline blended learning activities, enhance students' adaptation to the curriculum and increase their engagement in learning, so as to come to improve students' learning effectiveness. Students are supported to make full use of the online resource platform in the future blended learning process, to actively adapt to changes in learning modes and to actively integrate online learning and offline practice in order to meet the learning challenges brought about by new environments and technologies.

References

Baker, R. W., & Siryk, B. (1986). Exploratory intervention with a scale measuring adjustment to colle ge. *Journal of counseling psychology*, *33*(1), 31.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the acade my of marketing science*, 16, 74-94.

Bhardwaj, P., Gupta, P. K., Panwar, H., Siddiqui, M. K., Morales-Menendez, R., & Bhaik, A. (2021). Application of deep learning on student engagement in e-learning environments. *Computers & Electri cal Engineering*, 93, 107277.

Belhaj,F., Alothman,M., Hilal,N.,& Jibai,B.(2022).An Empirical Study on the Factors Affecting Stude nts' Motivation Toward Online Learning During Covid-19 Pandemic.*Journal of Logistics Informatics and Service Science*,10(1),141-168.

Coppin, B. (2004). Artificial intelligence illuminated. Jones & Bartlett Learning.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *Ieee Access, 8*, 75 264-75278.

De la Fuente, J., Sander, P., Kauffman, D. F., & Yilmaz Soylu, M. (2020). Differential Effects of Self- vs. External-Regulation on Learning Approaches, Academic Achievement, and Satisfaction in Under graduate Students. *Frontiers in psychology*, 11, 543884. https://doi.org/10.3389/fpsyg.2020.543884

Futures of Education: Briefing Notes [EB/OL]. (2022).https://en.unesco.org/futures of education/sites/ default/files/2022-04/tes-futures-education-briefing-notes-en.pdf.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. (2019). *Multivariate data analys is.*Cengage.

Hao X.J. (2021). Research on the influence of learning engagement on learning performance of physic al education college students, *Master's thesis, Shenyang Institute of Physical Education*: Liaoning.

Kuh,G.D.,Cruce,T. M.,Shoup, R.,Kinzie,J. & Gonyea,R.M.(2016).Unmasking the effects of student en gagement on first-year college grades and persistence.*The Journal of Higher Educatio*n, 79(5):540-56

3.

Khan, R. A., & Jawaid, M. (2020). Technology enhanced assessment (TEA) in COVID 19 pandemic. *Pakistan journal of medical sciences*, 36(COVID19-S4), S108.

Khan, M. A., & Khojah, M. (2022). Artificial intelligence and big data: The advent of new pedagogy in the adaptive e-learning system in the higher educational institutions of Saudi Arabia. *Education Research International*, *2022*, 1-10.

Long, C.C., Liu, C.M., & Wu, X.Y.. (2017). The effect of college students' self-directed learning strategies on learning performance: The moderating role of learning motivation. *Psychological Techniques and Applications*, 5(02), 89-98.

Li.F.J. (2018). The relationship between academic adjustment and proactive personality in university freshmen: The mediating role of future orientation and learning engagement ,*Master's thesis, Henan University*.

Liu S, Wang S, Liu X, Lin CT, Lv Z (2020) Fuzzy detection aided real-time and robust visual tracking under complex environments. *IEEE Trans Fuzzy Syst:1*. https://doi.org/10.1109/TFUZZ.2020.3006520

Li.J.X. (2021). Study on the relationship between digital learning ability, online learning engagement and learning performance of university students, *Master's thesis: Southwest University*, Chongqing.

Liu, G. (2022). Research on the Relationship between Students' Learning Adaptability and Learning Satisfaction under the Mobile Media Environment. *Int. J. Emerg. Technol. Learn.*, 17, 43-58.

Meng, L.N, Liu, Y.H, & Du, J.N. (2012). A study on the relationship between learning engagement and learning adaptability among undergraduate nursing students. *Journal of Nursing: A Comprehensive Edition*, 27(11), 69-71.

Mekonnen, S. T, & Muluye,W.（2020）. The Impact of COVID-19 Pademic on Education System in Developing Countries; a Review. *Open Journal of Social Sciences*, 8, 159-170.

Manzoor, S. R., Mohd Isa, W. N., & Dollmat, K. S. (2022).Predicting VARK Learning Styles from Five-Factor Personality of Computing Majors Studying Online.*Journal of Logistics, Informatics and Service Science,*Vol. 9 (2022) No. 4, pp. 331-345,DOI:10.33168/LISS.2022.0419

Pascarella, E. T., Seifert, T. A., & Blaich, C. (2010). How effective are the NSSE benchmarks in predicting important educational outcomes? Change: *The Magazine of Higher Learning*, 42(1), 16–22. doi: 10.1080/00091380903449060

Peng, H., Ma, S., & Spector, J. M. (2019). Personalized adaptive learning: an emerging pedagogical approach enabled by a smart learning environment. *Smart Learning Environments*, *6*(1), 1-14.

Qin J.R. (2019). Study on the influencing factors and interventions of MOOC-based blended learning adaptation of college students ,*Doctoral dissertation, Shaanxi Normal University*.

Schaufeli,W. B.,Martinez, I. M.,Pinto, A. M. ,Salanova, M. , & Bakker, A. B. (2002). Burnout and engagement in university students: a cross-national study. *Journal of Cross-Cultural Psychology*, 33(5), 464-481.

Sun,J.C.Y.,&Rueda,R.(2012).Situational interest,computer self-efficacy and self-regulation Their impact on student engagement in distance education.*British Journal of Educational Technology*,43(02):191-204.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of business research*, *70*, 263-286.

Starcic, A. I. (2019). Human learning and learning analytics in the age of artificial intelligence. *British journal of educational technology*, 50(6), 2974-2976.

Su,J.Y. ,& Li,Z.W.(2022)The Influencing Factors of School Environment on Student Sustainable Development.*Journal of Logistics Informatics and Service Science*,9(3),78-96.

Xie, Y. J., Cao, P., Sun, T., & Yang, L. B. (2019). The effects of academic adaptability on academic burnout, immersion in learning, and academic performance among Chinese medical students: a cross-sectional study. *BMC medical education*, 19(1), 211. https://doi.org/10.1186/s12909-019-1640-9

Zhang, Z., Li, Z., Liu, H., Cao, T., & Liu, S. (2020). Data-driven online learning engagement detection via facial expression and mouse behavior recognition technology. *Journal of Educational Computing Research*, 58(1), 63-86.