Investigating the Influence of Learning Perception and Autonomy on Mobile Learning Outcomes in Higher Education

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Abstract Although numerous studies have explored mobile learning, relatively little attention has been given to the impact of learning perception and learning autonomy on mobile learning performance. The primary aim of this study is to examine the relationships between perceived flexibility advantage, perceived interest advantage, learning autonomy, and mobile learning performance. Additionally, the study seeks to explore the mediating effect of learning continuance on mobile learning performance. A total of 456 college students with prior mobile learning experience participated in this study. Data were analyzed using partial least squares structural equation modeling analysis and SPSS-AMOS PROCESS. The findings indicate that perceived flexibility advantage, perceived interest, and learning autonomy positively influence mobile learning performance. Furthermore, the results reveal that learning continuance mediates the relationships between perceived flexibility advantage and mobile learning performance, perceived interest and mobile learning performance, as well as learning autonomy and mobile learning performance. Notably, the study also finds that the total effect of perceived interest on mobile learning performance is the most significant, while the direct effect of learning continuance on mobile learning performance is the largest.

Keywords: • Mobile learning • perceived flexibility • structural equation model • learning continuity • mediating effect

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1 Introduction

With the rapid advancement of communication technology, driven by factors such as socio-economic development, educational paradigms, and evolving learning models, mobile learning has quietly emerged and exerted a profound influence. It has been applied across various stages of education. For university students, who have easy access to wireless devices such as smartphones and tablets, mobile learning has become an indispensable method of learning. Due to its significant advantages—being unrestricted by time, space, and location—mobile learning offers greater flexibility, a wealth of resources, and more convenient problem-solving, making it highly popular among university students and leading to rapid growth. This trend has been especially pronounced during the COVID-19 pandemic, when platforms such as Massive Open Online Courses (MOOC) and Xuexitong have significantly contributed to the popularization and maturation of mobile learning. According to statistics from the Ministry of Education, China has launched over 76,800 online courses, with 454 million registered users and 415 million student credits awarded through these courses. The digital development of education in China has provided the foundation for university students to fully leverage mobile learning methods to enhance learning outcomes and develop human capital.

As the pace of life accelerates, individuals' study time has become increasingly fragmented. Traditional learning methods are often constrained by time and space limitations, while mobile learning breaks these barriers, offering greater freedom and flexibility. Mobile learning allows students to make use of scattered moments, thereby improving learning efficiency. With its convenience and flexibility, mobile learning has become a vital tool for achieving lifelong learning. Under the mobile learning model, learners exhibit diverse behavioral patterns, and factors such as autonomy and self- discipline significantly influence learning outcomes. Through mobile learning platforms, high-quality educational resources can be more easily disseminated to remote areas and non-"Double First Class" universities, promoting the sharing of excellent course materials and top-tier faculty. As mobile learning continues to spread among university students, addressing the challenges that hinder its sustainability and impact on learning performance has become increasingly urgent. Effectively harnessing the benefits of mobile learning, advancing educational digitization, fostering university teaching innovation, and enhancing the effectiveness of mobile learning are critical to the sustainable development of mobile learning models.

2 Literature review

With the advancement of information technology, mobile learning has become a central focus in the fields of distance education and digital learning. Particularly since the Covid-19 pandemic, numerous educational digital platforms, such as smart classrooms and learning management systems, have emerged in universities. Online teaching, along with hybrid teaching models that combine online and offline components, has become increasingly prevalent. As a result, the learning outcomes and the factors influencing them in the context of college students' online courses have garnered significant attention.

Several studies have explored the factors influencing college students' mobile learning engagement. Miao et al. (2022) investigated the effects of teacher-student interaction and found that teachers' involvement in students' learning is crucial in the context of hybrid courses. They emphasized the importance of teachers adhering to a "student-centered" approach in their teaching design to better guide students' participation and investment in course activities. Long et al. (2021) and Salhab and Daher (2023) demonstrated that the teacher-student relationship positively predicts mobile learning engagement among university students. Additionally, research has shown that both learning environment factors and students' personal characteristics significantly affect the sustainability of online learning, which in turn impacts learning outcomes. Moreover, the innovation of teaching methods has played a key role in enhancing online learning effectiveness (Cheng et al., 2023; Liu et al., 2023).

Several studies have explored the evaluation of mobile learning performance. Chen et al. (2023) demonstrated that factors such as students' online homework completion rates and video viewing completion rates significantly influence mobile learning outcomes. Chin et al. (2024) developed a mobile learning system to assess whether it could improve museum learning outcomes. The results indicated that the experimental group exhibited significantly better learning performance than the control group. Yang (2023) examined how the characteristics of mobile learning applications affect outcomes using the Stimulus-Organism-Response (S-O-R) framework, finding that concentration is a key characteristic influencing the flow experience and learning outcomes of mobile learning. In recent years, there has been considerable interest in academic monitoring and warning systems based on big data from mobile learning, enabling timely intervention measures (Alzahrani et al., 2022; Sun et al., 2022; Abdelazim et al., 2023).

Factors influencing mobile learning have garnered increased attention in recent years. Oluwajana et al. (2023) employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the impact of the Trello online network platform on college students' learning. They found that students' social influence and learning motivation positively affect collaborative learning and emphasized the crucial role of teachers in fostering collaborative learning. Xu and Li (2021) explored the factors influencing online learning involvement during the COVID-19 pandemic, using questionnaire data from Chinese college students. They found that teacher, student, and environmental factors were positively correlated with online learning participation, with live classes having a more significant impact on student engagement compared to recorded classes. Huang (2022) used the PLS method to investigate the factors influencing the acceptance of mobile learning. The study found a positive relationship between subjective norms, attitude, self-regulated learning, and mobile learning acceptance intention. Additionally, positive expected emotions were found to mediate the relationship between attitude and intention. Consequently, learners' expected emotions and subjective norms should be given particular attention during the mobile learning process. Some researchers have applied the Technology Acceptance Model (TAM) to explore factors influencing mobile learning willingness and the effects of this willingness on learning performance. They found that perceived ease of use (PEU) and perceived usefulness (PU) are critical factors affecting mobile learning acceptance, which is positively correlated with learning performance (Abeer, 2021; Amir, 2023; Hsu and Lin, 2024).

3 Theoretical analysis and research hypotheses

3.1 Perceived flexibility

The perceived flexibility advantage of mobile learning arises from the flexibility and convenience it offers. It is widely believed that learners'perception of flexibility in mobile learning projects is a key factor that significantly influences their acceptance of mobile learning and its outcomes (Alghazi et al., 2023). Since perceived flexibility is closely related to learners ’ perceived usefulness in the TAM (Davis, 1989), the extent to which learners perceive flexibility in mobile learning projects has a substantial impact on their beliefs about the potential for improved learning performance. Leveraging technological advantages, such as wireless technology, mobile learning projects provide learners with the opportunity to learn anytime and anywhere. This flexibility enables them to make efficient use of fragmented time, allowing convenient access to awide range of learning resources in various contexts—particularly beneficial for individuals with busy schedules in modern life. In other words, the flexibility of mobile learning offers an additional, convenient learning option, potentially increasing learners'investment in learning time and improving learning efficiency, which, in turn, significantly impacts learning outcomes. Arbaugh (2000) explored the characteristics of virtual classrooms in internet-based MBA courses and their impact on student satisfaction. He found that the flexibility and interactivity of mobile learning methods are key factors affecting students ’ satisfaction. Similarly, Mariam et al. (2023) demonstrated that the flexibility of online course design enhances the interactive learning experience between students and teachers, as well as between students and course content. This flexibility also helps create a relaxed and enjoyable learning environment, which stimulates students' continued engagement and results in better learning outcomes. In general, the more flexible students perceive mobile learning to be, the more time they are likely to invest in it, leading to longer learning continuance (Chow and Shi, 2014; Sung et al., 2015; Patil and Undale, 2023).

Therefore, this study proposes the following hypotheses:

H1: Perceived flexibility has a positive impact on mobile learning performance.
H2: Perceived flexibility has a positive impact on the continuance of mobile learning.

3.2 Perceived interest

The perceived interest in mobile learning is related to how learners experience mobile learning projects or courses, particularly in terms of physical and mental pleasure, entertainment, and satisfaction. A positive and enjoyable mobile learning experience can enhance students' enthusiasm for learning and encourage greater focus on their studies, helping to fulfill their learning interests and, in turn, improve academic performance. Numerous empirical studies have found that the perceived interest in the mobile learning process plays a crucial role in determining whether learners will adopt this learning style and the amount of time and attention they devote to mobile learning (Hardway et al., 2018; Hanif, 2020; Shanshan and Wenfei, 2022).

In general, the more enjoyment learners derive from mobile learning, the more time they are likely to invest in this learning style. As a result, when learners are deeply engaged with this learning method and dedicate more time to it, they are more likely to achieve strong academic performance. For instance, Gruber et al. (2014) found that curiosity enhances students' ability to retain what they have learned, thereby positively impacting academic outcomes. Learning apps that incorporate game elements or game- based features can increase learners'interest in mobile learning and positively influence their willingness to continue with this learning style. Based on these findings, the following hypotheses are proposed in this study:

H3: Perceived interest has a positive impact on mobile learning performance.
H4: Perceived interest has a positive impact on the sustainability of mobile learning.

3.3 Learning autonomy

Learning autonomy, also referred to in the literature as self-management of learning, self-regulated learning, self-directed learning, learning self-discipline, and self-efficacy, is closely related to learning focus, learning attitude, and learning performance (Prior et al., 2016; Liu et al., 2021; Won et al., 2024). In comparison to offline learning environments, learners' self-regulation abilities tend to be weaker in online learning modes, leading to challenges such as low attendance, low engagement, low course satisfaction, and low completion rates. However, students with strong self- discipline or initiative in learning are better able to formulate effective learning plans and self-monitor their progress, thereby maximizing the advantages of online learning to acquire more knowledge and skills. This process builds confidence, enhances self- efficacy, and fosters a flow experience, ultimately resulting in improved learning outcomes (Huang et

al., 2022). Huang & Yu (2019) and Kim et al. (2019) found empirical evidence showing a significant positive linear correlation between learning self-discipline and learning performance. Based on these findings, this study proposes the following hypotheses:
H5: Autonomous learning ability has a positive impact on mobile learning performance.
H6: Autonomous learning ability has a positive impact on the sustainability of mobile learning.

3.4 Learning continuance

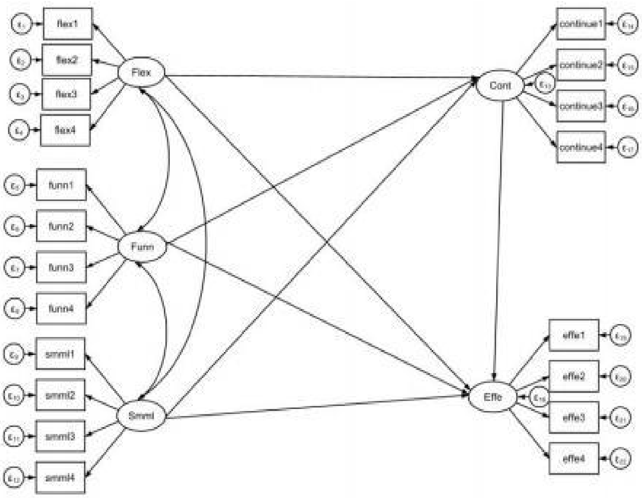
There is no doubt that the amount of time invested in learning is a fundamental factor for students to achieve favorable learning outcomes. In the mobile learning environment, the ongoing investment in learning has also garnered increasing attention in research (Mohammadyari and Singh, 2015; He and Li, 2023). Students' continued commitment to their courses results from a combination of perceived flexibility, perceived interest, and the teaching methods employed by instructors. In this context, continued learning engagement is typically measured through mobile learning satisfaction (Wei and Chou, 2020; Conrad et al., 2022; Taghizadeh et al., 2022), which mainly focuses on the factors affecting mobile learning satisfaction. However, the relationship between continuous learning engagement and learning performance is often overlooked. In fact, learning continuance is not only a result of students' satisfaction with mobile learning but also a critical and direct factor influencing their mobile learning performance. Accordingly, the following hypothesis is proposed in this study:
H7: Learning continuance has a positive impact on mobile learning performance.

4 Research design and empirical results analysis

4.1 Model

Based on the UTUAT model, this paper examines the impact of four factors on mobile learning performance: perceived flexibility, perceived interest, learning autonomy, and learning continuance. Additionally, it tests a structural equation model of mobile learning performance, with learning sustainability as the mediating variable (Figure 1). SPSS software is used to analyze demographic variables from the questionnaire data on college students'mobile learning performance and to investigate the relationships between perceived flexibility (Flex), perceived interest (Funn), learning autonomy (Smml), learning persistence (Cont), and mobile learning performance (Effe).

Figure 1: Research framework of the study



4.2 Descriptive statistical analysis of data

The questionnaire data for this study were collected through the Questionnaire Star platform. The sample includes participants from 46 universities across mainland China. Table 2 presents the descriptive statistical characteristics of the sample surveyed through the mobile learning questionnaire. Of the 456 samples, 174 male college students (38.16%) and 282 female college students (61.84%) participated in the survey. Among the participants, 147 students (32.24%) were college juniors, followed by 141 sophomores (30.92%). Regarding the participants' age, the largest group was 21 years old, followed by those who were 20 years old. The average age of participants, excluding missing values, was 20.66 years. In terms of institutional distribution, 188 students (41.23%) were from "Double First-Class" universities, while 268 students (58.77%) were from non-"Double First-Class" universities. To ensure a scientifically robust evaluation of the key variables, the questionnaire items were derived from various psychological research studies and mobile learning literature (see Table 1). Each item used a Likert 5-point scale, with values ranging from "1" to "5," representing "very inconformity", "inconformity", "general", "conformity" and "very conformity" respectively.

Table 1: Constructs, Items, and References

Construct	Item Code	Items	References
Perceived flexibility (Flex)	flex1	I can arrange my study schedule more easily with the use of mobile learning technology or devices.	Amberg et al. (2004)、Chen et al. (2017)

	flex2	I can use mobile learning technology/devices to be more flexible in creating my learning schedule.	
	flex3	I can use mobile learning technology/devices to make better use of my time for learning.	
	flex4	I can learn at anytime and anyplace with mobile learning technology/devices.	
Perceived interest (Funn)	funn1	I feel relaxed and happy when I am learning mobile/online.	Agarwal and Karahanna (2000)、Lin et al. (2005)、Alraimi et al. (2015)
	funn2	Mobile learning or online learning can increase my interest in learning.	
	funn3	I think mobile learning or online learning is interesting.	
	funn4	Overall, the learning experience of mobile learning is a fun one.	
Learning autonomy (Smml)	smml1	As for study, I am a person with strong self-discipline.	Sweeney and Soutar (2001)、Diep et al. (2017)
	smml2	I was able to arrange my study time efficiently and complete the course tasks easily and on time.	
	smml3	On the mobile learning platform, I can control the time that is not related to study.	
	smml4	In learning, I will consciously set learning goals and have strong learning autonomy.	
	cont1	I will continue to use mobile learning	

		technology/devices for learning in the future.	
Learning continuance (Cont)	cont2	I currently use mobile learning technology/devices a lotfor learning.	Bhattacherjee (2001)、Mohammadyari and Singh (2015)
	cont3	I often use mobile learning platforms and mobile learning technologies to learn and master various knowledge and skills.	
	cont4	I would recommend my classmates and relatives to use mobile learning technology/devices for learning.	
Learning Performance (Effe)	effe1	Mobile learning platform (including website)/ software can help me to complete the study and work tasks faster.	Venkatesh and Davis (2000)、Huang (2008)
	effe2	The use ofmobile learning technologies/devices/platforms has helped me improve my abilities.	
	effe3	Mobile learning enables me to learn more what I want to learn and improve my knowledge level.	
	effe4	Mobile learning has enhanced my abilities and boosted my confidence to face future challenges.	

Table 2: Demographic data for respondents

Demographics	Items	Number	Percentage of respondents
Gender	Male	174	38.16
	Female	282	61.84
Age	17	2	0.44
	19	84	18.42
	20	112	24.56
	21	143	31.36
	22	68	14.91
	23	23	5.04
	24	8	1.75
	Missing data	16	3.51
Academic level	Freshman	87	19.08
	Sophomore	141	30.92
	Junior	147	32.24
	Senior	63	13.82
	Missing data	18	3.94
University level	"Double first-class"	188	41.23
	others	268	58.77

4.3 Reliability and validity analysis

Table 3 presents the results of the confirmatory factor analysis, assessing the reliability and validity of the variables. It is evident that the Cronbach's α coefficients for the five variables exceed 0.85, well above the standard threshold of 0.7. The composite reliability (CR) for all five variables also exceeds 0.85, significantly surpassing the recommended value of 0.7. Furthermore, the average variance extracted (AVE) for each factor is greater than 0.6, clearly exceeding the standard value of 0.5. Based on the confirmatory factor analysis results, including the Cronbach's α coefficient, the questionnaire measurements for the five variables related to mobile learning demonstrate strong internal consistency (Fornell and Larcker, 1981).

Additionally, based on the average variance extracted (AVE), the square root of the AVE can be used to assess the discriminant validity of the questionnaire data. The results of the discriminant validity test, as shown in Table 4, reveal that the square root of the AVE for each of the five variables, such as perceived flexibility, is greater than the correlation coefficients between the variables. This indicates that the discriminant validity of the questionnaire data is highly satisfactory. Therefore, considering the findings in both Table 3 and Table 4, the measurement model comprising 20 items across the five variables, including perceived flexibility, is deemed acceptable.

Table 3: The result of CFA

Construct	Items Code	CR	AVE	Cronbach's α
Perceived flexibility	flex1 flex2 flex3 flex4 funn1	0.8652	0.6166	0.863
Perceived interest	funn2 funn3 funn4 smml1	0.8789	0.6449	0.879
Learning autonomy	smml2 smml3 smml4 cont1	0.9118	0.7212	0.911
Learning continuance	cont2 cont3 cont4 effe1	0.8771	0.6410	0.876
Learning performance	effe2 effe3 effe4	0.8720	0.6302	0.870

Table 4: Validity and reliability evaluation

	Perceived flexibility	**Perceived interest**	**Learning autonomy**	**Learning continuance**	**Learning performance**
Perceived flexibility	0.7852				
Perceived interest	0.4990	0.8031			
Learning autonomy	0.2640	0.5030	0.8492		
Learning continuance	0.4520	0.6000	0.3930	0.8006	
Learning performance	0.5480	0.6920	0.5960	0.6840	0.7939

Note: The values on the diagonal are the arithmetic square root of the average extracted variance (AVE), and the rest are the correlation coefficients between the variables.

4.4: Structural equation model estimation results

The SPSS-AMOS structural equation modeling module was employed to conduct an overall fit evaluation and hypothesis testing on the mobile learning performance model. Table 5 presents the estimated results of the goodness-of-fit test for the structural equation model. It is evident that the CMIN/DF (chi-square to degrees of freedom ratio) value is 2.028, which falls within the ideal range of 1-3. The RMSEA value is 0.048, below the threshold of 0.05, indicating a good fit. The RMR value is 0.021, also below 0.05, further confirming a good fit. Additionally, the CFI, GFI, RFI, and TLI values all exceed 0.9, meeting the criteria for an excellent fit. Therefore, it is clear that the structural equation model of the influencing factors on mobile learning performance, based on the questionnaire design data, demonstrates strong model fit.

Table 5: Goodness fit indices for SEM

Type of measure	Acceptable level offit	Values
CMIN/DF	between 1 and 3 perfect, between 3 and 5 good	2.028
RMSEA	<0.05 perfect, <0.08 good	0.048
RMR	<0.05 perfect, <0.08 good	0.021
CFI	>0.9 perfect, >0.8 good	0.971
GFI	>0.9 perfect, >0.8 good	0.932
RFI	>0.9 perfect, >0.8 good	0.934
TLI	>0.9 perfect, >0.8 good	0.966

Table 6 presents the results of the path relationship hypothesis test for the structural equation model (SEM) of the influencing factors on mobile learning performance. It is evident that the four variables—perceived flexibility ($\beta = 0.197$, $P = 0.000$), perceived interest ($\beta = 0.249$, $P = 0.000$), learning autonomy ($\beta = 0.288$, $P = 0.000$) and learning persistence ($\beta = 0.333$, $P = 0.000$)exert significant positive effects on mobile learning performance at the 1% significance level. Therefore, hypotheses H1, H3, H5, and H7 are supported. Regarding the impact on mobile learning sustainability, the standardized coefficients for the paths from perceived flexibility and perceived interest are 0.201 and 0.440, respectively, both of which show a significant positive impact at the 1% significance level. As such, hypotheses H2 and H4 are also supported. The standardized coefficient for the path from learning autonomy to mobile learning sustainability is 0.118 ($P = 0.022$), indicating a significant positive impact at the 5% significance level, thus confirming the validity of hypothesis H6. The path analysis results highlight that the four factors— perceived flexibility, perceived interest, learning autonomy, and learning sustainability — positively influence college students' mobile learning performance.

Table 6 Path Relationship Hypotheses Test Results

Path Relationship		Estimate	S.E.	C.R.	P
Learning continuance ←	Perceived flexibility	0.201	0.055	3.732	***
Learning Continuance	**Perceived** interest	**0.440**	**0.057**	**6.932**	***
Learning continuance	Learning autonomy	0.118	0.043	2.285	0.022
Learning performance	Perceived flexibility	0.197	0.040	4.366	***
Learning performance	Perceived interest	0.249	0.043	4.491	***
Learning performance	Learning autonomy	0.288	0.031	6.590	***
Learning performance	Learning continuance	0.333	0.044	6.469	***

Note: *** indicates a P value less than 0.01.

4.5: Estimation results of intermediary effects

Based on the mediation effect model (1) - (3), this study employs the three-step mediation effect test method to examine the mediating role of mobile learning persistence in mobile learning performance. Table 7 presents the estimated results of the mediation effect test. The dependent variables in columns (1) and (3) are mobile learning performance, while the dependent variable in column (2) is mobile learning persistence. From the baseline regression results in column (1), it is evident that the variables of perceived flexibility, perceived interest, and learning autonomy do not include zero at the 1% significance level, indicating that these factors significantly positively affect mobile learning performance. In column (2), the results show that the variables of flexibility, interest, and learning autonomy in mobile learning also do not include zero at the 1% significance level, suggesting a significant positive effect on learners' continuous engagement with mobile learning. Finally, in column (3), it is observed that the four variables, including perceived flexibility, do not contain zero at the 1% significance level, further supporting that these factors have a significant positive effect on mobile learning performance. Thus, mobile learning persistence plays a significant mediating role between perceived flexibility, perceived interest, learning autonomy, and mobile learning performance.

$$Effei = \alpha 0 + \alpha 1\ Flexi + \alpha 2\ Funni + \alpha 3smmli + ui \quad (1)$$
$$conti = Y0 + Y1\ Flexi + Y2\ Funni + Y3smmli + vi \quad (2)$$
$$Effei = \beta 0 + \beta 1\ Flexi + \beta 2\ Funni + \beta 3smmli + \beta 4\ conti + \varepsilon i(3)$$

Table 7: Results of mediation effect estimation

	(1) Learning performance	(2) Learning continuance	(3) Learning performance
Perceived flexibility	0.321*** (0.049)	0.201*** (0.053)	0.197*** (0.044)
Perceived interest	0.472*** (0.051)	0.440*** (0.057)	0.249*** (0.054)
Learning autonomy	0.404*** (0.047)	0.118** (0.051)	0.288*** (0.041)
Learning continuance	/	/	0.333*** (0.048)
R-squared	0.488	0.402	0.680

Note: ***, **, * indicate significant at the significance level of 1%, 5%, 10% respectively, standard error in brackets.

4.6; The decomposition result of effect

Table 8 presents the decomposition results of the effects of four variables, including perceived flexibility, on mobile learning performance. It is evident that the factor with the greatest impact on the overall mobile learning performance is perceived interest (0.396), followed by mobile learning persistence (0.333), learning autonomy (0.327), and perceived flexibility (0.264), all of which are significant at the 1% statistical level. These findings further highlight that the four variables, including perceived flexibility, have a significant positive effect on mobile learning performance. Among them, perceived interest, mobile learning persistence, and learning autonomy play a more substantial role. In terms of direct effects, the direct effect of mobile learning persistence on mobile learning performance is the largest (0.333),followed by learning autonomy (0.288), perceived interest (0.249), and perceived flexibility (0.197), all significant at the 1% statistical level. This indicates that for college students, the sustainability of mobile learning — i.e., the direct effect of their time investment in mobile learning—has the greatest influence on learning performance, followed by their self-discipline and self-management ability in mobile learning. Regarding indirect effects, the largest indirect effect on mobile learning performance is observed for perceived interest (0.149), followed by perceived flexibility (0.067), while learning autonomy has the smallest indirect effect (0.039). The indirect effects of perceived interest and perceived flexibility are significant at the 1%

statistical level, and the indirect effect of learning autonomy is significant at the 5% statistical level.

Table 8: Direct and indirect effects

Construct	Effect	SE	Lower	Upper	P
Direct effect					
Perceived flexibility	0.197	0.049	0.116	0.277	0.000
Perceived interest	0.249	0.067	0.140	0.358	0.000
Learning autonomy	0.288	0.047	0.214	0.367	0.000
Learning continuance	0.333	0.066	0.229	0.443	0.000
Indirect effect					
Perceived flexibility	0.067	0.028	0.031	0.123	0.002
Perceived interest	0.147	0.041	0.089	0.226	0.000
Learning autonomy	0.039	0.022	0.007	0.080	0.045
Total effect					
Perceived flexibility	0.264	0.051	0.179	0.348	0.000
Perceived interest	0.396	0.061	0.293	0.492	0.000
Learning autonomy	0.327	0.051	0.245	0.413	0.000
Learning continuance	0.333	0.066	0.229	0.443	0.000

It is evident that learners' perceptions of flexibility, interest, and self-discipline in mobile learning not only directly influence mobile learning performance but also indirectly affect it through their level of attention and investment in mobile learning. From the effect decomposition results, it is clear that the total effect of perceived interest on mobile learning outcomes is the largest, and the indirect effect mediated by mobile learning persistence is also substantial. This suggests that when universities implement mobile learning platforms and hybrid teaching modes, they should focus on integrating professionalism with engaging content to maintain students' interest. Additionally, they should prioritize the innovation and reform of mobile teaching methods to capture students' attention and stimulate their enthusiasm for learning. Notably, the direct effect of mobile learning persistence on learning outcomes is the largest, and the total effect ranks second, emphasizing that sustained investment in learning is essential for achieving favorable results. The adage "hard work pays off" remains highly relevant, as consistent effort is crucial to success.

5: Conclusion

Based on the influencing factors of college students' mobile learning performance in the context of digital education, this paper constructs a structural equation model that includes perceived flexibility, perceived interest, learning autonomy, learning sustainability, and learning performance. It also examines the mediating role of learning sustainability, providing empirical evidence to clarify the factors influencing mobile learning performance. The main conclusions of this study are as follows: First, from the perspective of path relationships, the four factors—perceived flexibility, perceived interest, learning autonomy, and learning sustainability—each have a positive impact on mobile learning performance at the 1% statistical significance level. Among these, the most direct impact is observed from learning sustainability (0.333), followed by learning autonomy (0.288), perceived interest (0.249), and perceived flexibility (0.197). This suggests that whether in traditional offline learning or in online learning environments enabled by modern digital technology, continuous learning investment is essential for achieving better learning outcomes. In other words, the principles of "diligence makes up for weakness" and "hard work is rewarded" still hold significant value in the context of mobile learning. Second, in terms of total and indirect effects, perceived interest has the largest impact on mobile learning performance, with a total effect of 0.396 and an indirect effect of 0.147. This highlights the significant role that the physical and mental engagement of mobile learning content plays in influencing students' learning outcomes. Therefore, when implementing online or hybrid teaching, educators should prioritize the novelty, playfulness, and engagement of the content. Mobile learning platforms (such as Rain Classroom) should focus on developing features that are both easy to use and enjoyable. Third, learning persistence serves as a notable mediator between perceived flexibility, perceived interest, learning autonomy, and mobile learning performance. According to the mediation effect test results from the econometric model, learning persistence mediates the relationship between perceived flexibility, perceived interest, learning autonomy, and mobile learning performance with statistical significance at the 1% level. The effect decomposition results from the structural equation model show that perceived flexibility and perceived interest positively affect learning persistence at the 1% significance level, while learning autonomy positively affects learning persistence at the 5% level. Among these, perceived interest has the largest indirect effect on mobile learning performance through learning persistence (0.147). Both the mediation effect tests and the structural equation model confirm the significant mediating role of learning persistence in the relationship between various factors and mobile learning performance.

Based on the research findings, this paper proposes the following suggestions: First, optimize the incentive mechanisms for mobile learning to encourage students to invest more time in this mode of learning. College educators should consider the proportion of mobile learning in the overall curriculum assessment and research project training. By dividing long-term learning goals into short-term, achievable milestones, educators can reward students for reaching these milestones. Additionally, updating online learning content and innovating teaching methods will help maintain student motivation and interest, thus increasing satisfaction with mobile learning. This approach will allow students to fully leverage the advantages of mobile learning, enhance learning efficiency, and ensure sustained time investment, ultimately improving learning outcomes. Second, fully utilize the benefits of digital information technology to enhance the structure of courses and increase the interest and interactivity of mobile learning. University instructors and developers of mobile learning platforms (including government agencies or private companies) can significantly impact students'perceptions of interest in the mobile learning process. College teachers should focus on improving their digital literacy and intelligent teaching capabilities, integrating modern digital technologies throughout the learning process. This includes using tools for pre-class self-study, in-class interaction, and post-class feedback, promoting curriculum system reforms, teaching method innovations, and evolving evaluation methods. These efforts should aim to upgrade the curriculum's level of innovation and challenge, leveraging modern educational technologies to their fullest potential. On the other hand, mobile learning platform developers (government units or companies) should design platforms that closely align with students' interests and learning needs. They should adopt diverse content formats, such as animation, games, and virtual reality (VR) or augmented reality (AR), to enhance the platform's functionality. A particular emphasis should be placed on optimizing social learning features, such as learning communities, online discussion areas, and peer reviews, to foster collaboration among learners. These improvements will enhance students' social engagement and sense of belonging, enriching the learning experience and fully stimulating their desire to learn. Third, for college students to achieve optimal learning performance, it is essential that they develop the right learning motivation and improve self-discipline and focus on mobile learning. By maintaining the correct learning mindset and attitude, students will be more likely to persist in mobile learning courses and resist distractions from unrelated online content or activities. Cultivating the ability to concentrate on learning tasks without distractions allows students to maximize the advantages of mobile learning, gaining more knowledge and skills, and achieving better academic outcomes.

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