

PAPER

A Study of Generative Artificial Intelligence on Mobile Learning Adoption Based on SEM Models

Shiyuan Zhou¹, Yichao Si¹,
Jing Li²(✉), Otilia Manta^{3,4},
Gabriel Xiao-Guang Yue^{4,5}

¹School of Business, Henan University, Kaifeng, China

²School of General Education, Wuhan Business University, Wuhan, China

³Centre for Financial and Monetary Research "Victor Slăvescu", Romanian Academy, Bucharest, Romania

⁴Romanian American University, Bucharest, Romania

⁵Department of Computer Science and Engineering, European University Cyprus, Nicosia, Cyprus

390677982@qq.com

ABSTRACT

With the rapid development of information technology, the application of generative artificial intelligence (GAI) in the field of education is becoming more and more extensive, especially on contemporary college students' mobile learning, which has a profound impact. However, the attitudes of contemporary college students towards using GAI for mobile learning are characterized by complexity and diversity, so it is necessary to explore the factors affecting college students' willingness to use GAI. In view of this, this paper conducted a questionnaire survey with 1028 college students in China and adopted the structural equation modeling (SEM) model to identify and analyze the factors affecting college students' behavior of using GAI for mobile learning. The results show that performance expectation, effort expectation, social influence, convenience conditions, and perceived fun of GAI significantly affect college students' willingness to use GAI, while perceived risk and perceived learning resources have no significant direct influence effect on willingness to use. Based on the empirical results, future strategies for the advancement of GAI education are proposed to further optimize the application of GAI in m-learning.

KEYWORDS

generative artificial intelligence (GAI), mobile learning, usage willingness, influencing factors

1 INTRODUCTION

With the continuous development of 5G technology and mobile devices, mobile learning has become an important mode of learning for contemporary university students. Compared to traditional classroom learning and desktop-based e-learning, mobile learning offers unique advantages such as portability, efficiency, and personalization. It not only breaks the limitations of time and space, allowing learners to access educational resources anytime and anywhere but also supports interactive and social learning experiences [1]. Furthermore, mobile learning can enhance the convenience and attractiveness of learning by providing rich content and flexible learning methods through multimedia and Internet technologies.

Zhou, S., Si, Y., Li, J., Manta, O., Yue, G.X.-G. (2024). A Study of Generative Artificial Intelligence on Mobile Learning Adoption Based on SEM Models. *International Journal of Interactive Mobile Technologies (iJIM)*, 18(22), pp. 68–76. <https://doi.org/10.3991/ijim.v18i22.52343>

Article submitted 2024-07-21. Revision uploaded 2024-09-23. Final acceptance 2024-09-23.

© 2024 by the authors of this article. Published under CC-BY.

Despite the vast potential of mobile learning, its practical application faces several challenges. First, technological issues constitute a significant barrier to adoption, as the diversity of mobile devices, stability of network connections, and adaptability of learning resources can affect the smooth progress of mobile learning. Secondly, the habits and skills of learners also influence the effectiveness of mobile learning. Some learners are not familiar with the operation of mobile devices or lack self-management and autonomous learning abilities, leading to poor learning outcomes [2]. Additionally, the perceptions and attitudes of educators and educational institutions are also influencing factors. Traditional teaching concepts and assessment systems are often not adaptable to the innovative modes of mobile learning, and the lack of training and support for teachers hampers its development. Lastly, privacy and security issues are not to be overlooked, as mobile learning involves substantial personal data and privacy information, which, without effective protection measures, could lead to information leakage and misuse of data.

In this context, generative artificial intelligence (GAI) has emerged as a technology based on deep learning capable of generating new data and content. In recent years, GAI has made significant developmental strides in the educational sector, showing broad application prospects. It plays an important role in personalized teaching by analyzing learners' behavior data and learning records, enabling it to automatically generate personalized learning content and pathways to meet diverse needs, thereby enhancing learning efficiency. Additionally, GAI excels in the creation and management of educational resources; for example, educators can use it to quickly produce high-quality teaching materials, test questions, and learning resources, significantly reducing teachers' workloads and improving teaching efficiency.

Most importantly, in the realm of mobile learning, the positive impacts of GAI are particularly evident [3]. GAI can dynamically adjust learning content and difficulty based on learners' real-time feedback and progress, providing a personalized learning experience that enhances their interest and engagement. It also assists teachers in educational management and evaluation by intelligently analyzing learning data and promptly identifying and addressing issues in the learning process, thus improving teaching outcomes. Moreover, by employing natural language processing technology, GAI supports multilingual and cross-cultural learning exchanges, facilitating the global sharing of educational resources and collaborative learning. Lastly, GAI can offer immediate learning support and guidance to learners through virtual assistants and chatbots, enhancing the convenience and effectiveness of learning [4].

Overall, although mobile learning faces challenges related to technology, user habits, educational concepts, and privacy security, the application of GAI provides strong support, significantly enhancing the effectiveness and impact of mobile learning. Existing literature on the factors affecting mobile learning mostly focuses on the quality of learning resources and the level of learning satisfaction, but studies based on GAI are relatively scarce. This study focuses on GAI to explore the factors influencing university students' continued use of mobile learning, aiming to provide insights and suggestions for promoting the application of GAI technology and enhancing the technical level and user experience of mobile learning.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The academic study of mobile learning has begun with its conceptual definition. Overall, the definitions of mobile learning vary across different literature sources, but a commonality emerges that mobile learning involves learning activities conducted

through portable devices such as smartphones, tablets, and laptops at any time and place [5]. This learning mode leverages wireless communication technology and mobile computing technology, allowing learners to flexibly access educational resources, participate in learning activities, and interact with teachers and other learners [6]. Mobile learning is not only an extension of e-learning but also a part of digital learning. Crompton and others have noted that its development, alongside the advancements in information technology and the proliferation of mobile devices, has broken the constraints of time and space, greatly enriching the forms and content of learning [7].

Subsequently, researchers shifted their focus to the characteristics of mobile learning. Its portability, flexibility, personalization, and immediacy provide unique advantages in modern education. Firstly, learners can carry mobile devices and study in any environment, such as on public transport, in outdoor settings, or at home. Secondly, mobile learning is not restricted by time and location, allowing learners to choose their learning times freely [8]. Thirdly, through mobile devices, learners can access personalized learning content and resources tailored to their needs and interests [9]. Lastly, mobile learning enables real-time access to the latest learning resources and information, facilitating immediate feedback and interaction.

Further, based on the characteristics of mobile learning, scholars began to focus their research on mobile learning behaviors and influencing factors. Miangah and Nezarat pointed out that mobile learning facilitates learning anytime and anywhere, allowing learners to make full use of fragmented time in daily life for learning [10]. However, mobile learning also faces some limitations, such as small device screens, difficulties in text input, inadequate technical support, and issues with resource availability. Additionally, the multifunctionality of devices can distract learners, impacting learning effectiveness. The successful implementation of mobile learning depends on multiple factors, including the availability of technology, the professional development needs of educators, and the design and development of learning resources. Studies by Li and others have shown that, compared to traditional teaching methods, GAI can improve the diversity and adaptability of learning resources through data generation and enhancement technologies [11]. Research by Celik found that AI-based teaching is superior to traditional methods [12]. Xodabande and others found that e-books not only help with vocabulary knowledge but also provide a good sensory experience and enhance the enjoyment of learning [13].

Despite the excellent performance of GAI in many areas, students' subjective attitudes and willingness to learn are crucial for the effectiveness of foreign language learning. Students' attitudes influence their acceptance of GAI technology-assisted learning. Lai and others emphasized that the primary subjects of mobile learning are the students themselves [14]. Learning with mobile technology should be based on the student's willingness and autonomy; even if the effects of GAI are excellent, they cannot be fully realized if students do not accept it. Therefore, GAI plays a significant role in enhancing learners' autonomous learning capabilities.

Based on a comprehensive review of existing literature, we propose the following hypotheses for this study:

- Hypothesis 1: Performance expectations of GAI positively influence the intention to use mobile learning.
- Hypothesis 2: The social influence of GAI positively influences the intention to use mobile learning.
- Hypothesis 3: The facilitating conditions of GAI positively influence the intention to use mobile learning.

- Hypothesis 4: The perceived playfulness of GAI positively influences the intention to use mobile learning.
- Hypothesis 5: The perceived risk of GAI positively influences the intention to use mobile learning.
- Hypothesis 6: The perceived cost of GAI negatively influences the intention to use mobile learning.

3 RESEARCH METHODOLOGY

The data for this study were collected from university students in China. To ensure data quality, several measures were taken during the survey process. First, to ensure the authenticity and reliability of the questionnaire responses, participants were informed of the academic significance of the survey before filling out the questionnaire. Additionally, to alleviate any concerns participants might have about the content they provided, the survey was conducted anonymously. Finally, after collecting the questionnaires, those that did not meet the research criteria or contained obviously patterned answers were excluded.

The questionnaires used in this study employed a five-point Likert scale, where “1” represents “strongly agree” and “5” represents “strongly disagree.” To ensure the reliability and validity of the scales, the measurement items were mainly adapted from mature scales used in high-quality journal publications and were adjusted according to the characteristics of GAI. Moreover, this study used a SEM analysis to examine the willingness of university students to use GAI software for learning. The main purpose of this study was to explore which characteristics of GAI influence students’ willingness to use it for mobile learning. The variables selected for analysis are detailed in Figure 1.

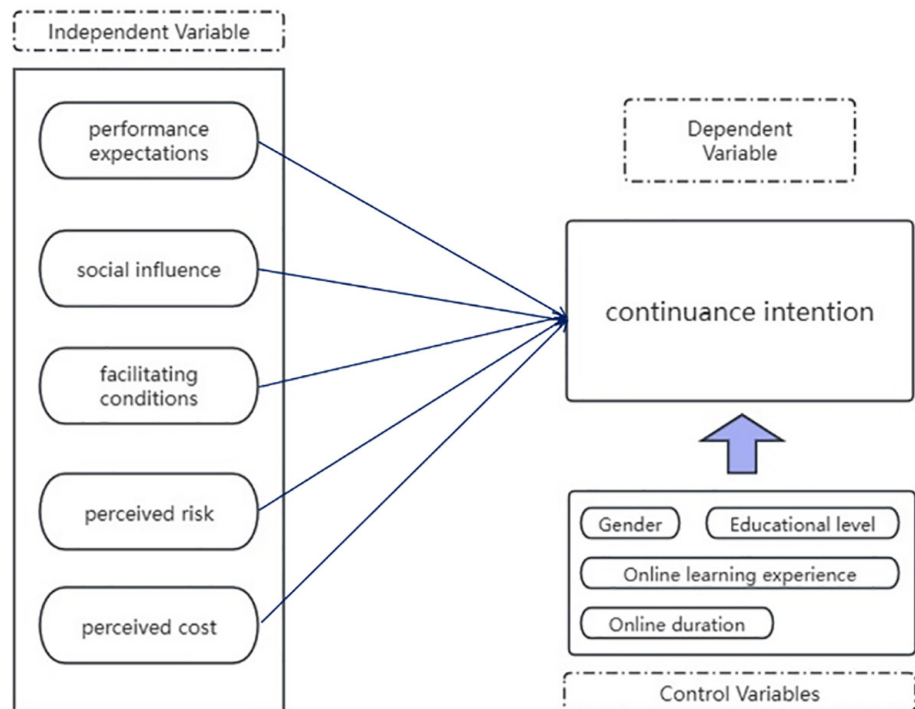


Fig. 1. Variable diagram

4 RESULTS

4.1 Test for common method bias

The study employed Harman's single-factor test to check for common method bias by conducting a factor analysis of all measurement variables. The results showed that the first unrotated factor explained 36.063% of the variance, which is below the critical value of 40%, indicating that common method bias does not significantly affect the data analysis.

4.2 Descriptive statistics of demographic characteristics

Table 1 provides the demographic characteristics of the survey participants, including gender, educational level, online learning experience, and weekly online duration.

Table 1. Demographic descriptive statistics

Variable	Category	Frequency	Percentage
Gender	Male	465	45.20%
	Female	563	54.80%
Educational level	Junior college or below	286	27.80%
	Undergraduate	450	43.80%
	Postgraduate	204	19.80%
	PHD	88	8.60%
Online learning experience	Within one year	244	23.70%
	Over a year	784	76.30%
Online duration	Within one hour	56	5.40%
	1–2 hours	195	19.00%
	2–4 hours	387	37.60%
	4–6 hours	234	22.80%
	More than 6 hours	156	15.20%

4.3 Reliability and validity test

The reliability and validity of the study variables were tested, and the results are presented in Table 2. All subscales in this study had Cronbach's alpha values greater than 0.7, indicating a good level of reliability. The composite reliability (CR) of each subscale was also greater than 0.7, and the average variance extracted (AVE) values were above 0.5, indicating adequate convergent validity. Moreover, the square root of all latent variable AVE values was greater than the correlation coefficients between the latent variables, demonstrating good discriminant validity.

Table 2. Reliability and validity test

Project	Question	Cronbach's	CR	AVE
Performance Expectations	GAI has significant application value for me	0.780	0.864	0.613
	Using GAI can improve my learning outcomes	0.773		
	Using GAI can enhance my learning efficiency	0.766		
	GAI enables me to learn more content	0.813		
Social Influence	A good development atmosphere for GAI can enhance my willingness to use it	0.792	0.859	0.604
	I prefer to choose GAI software recommended by teachers/peers	0.786		
	I prefer to choose GAI software used by teachers/peers	0.732		
	I prefer to choose GAI software that has positive reviews in the media	0.796	0.859	0.604
Facilitating Conditions	It is easy for me to use GAI for learning	0.787	0.868	0.621
	I can easily access GAI software through smartphones or computers	0.797		
	I can access GAI software anytime and anywhere there is an internet connection	0.792		
	GAI software offers multiple language options for me	0.776		
Perceived Playfulness	Using GAI for learning is enjoyable	0.801	0.869	0.624
	GAI sparks my curiosity	0.785		
	GAI stimulates my exploration in learning	0.784		
	GAI inspires my imagination	0.79		
Perceived Risk	GAI software might reveal my learning or purchasing habits	0.764	0.833	0.625
	GAI software might expose my privacy	0.818		
	Problems with GAI might be difficult to solve	0.789		
Perceived Cost	The cost of using GAI software is high	0.790	0.842	0.640
	The time and effort costs of learning to use GAI software are low	0.805		
	Learning with GAI software saves more time and effort compared to other methods	0.804		
Continued Usage Intention	I frequently use GAI software for learning	0.765	0.831	0.621
	I will continue to use GAI software for learning in the future	0.794		
	I am willing to recommend GAI software to others	0.804		

4.4 Hypothesis testing

The study utilized the Amos 24.0 software for structural equation modeling to conduct an overall fit assessment and hypothesis testing of the study model.

The fit indices of the structural model are presented in Table 3, and all model parameters fall within acceptable standards, indicating good model fit. The standardized path coefficients and their significance calculated by the Amos tool are presented in Table 4. The model validation results show that all hypotheses, except Hypothesis 5 (perceived risk of GAI positively influences the intention to use mobile learning), were supported.

Table 3. Model fit indices

Fit Index	Recommended Value	Fit Value
χ^2/df	< 3.0	2.846
GFI	> 0.9	0.925
RMSEA	< 0.08	0.069
NFI	> 0.9	0.919
IFI	> 0.9	0.936
CFI	> 0.9	0.935

Note: Other parameters: sample size 1028; $\chi^2 = 1451.736$; $p < 0.001$.

Table 4. Path testing and standardized path coefficients

Research Hypothesis	Pearson Correlation	P	Spc	Hypothesis Direction	Inspection Results
H1 PE→CI	0.216	***	0.481	Positive	Positive
H2 SI→CI	0.169	***	0.401	Positive	Positive
H3 FC→CI	0.173	***	0.388	Positive	Positive
H4 PF→CI	0.116	***	0.261	Positive	Positive
H5 PR→CI	0.204	0.113	0.457	Positive	\
H6 PC→CI	-0.192	***	-0.425	Negative	Positive

Note: ***indicates a p-value less than 0.001, and spc2 indicates the explanatory ratio of latent variables to the variance of the question.

5 CONCLUSION AND RECOMMENDATIONS

Mobile learning has become the predominant mode of learning outside of the classroom for university students in the contemporary era, with GAI serving as a powerful supplement to traditional classroom learning. Through the construction of a structural equation model, analysis revealed that university students' performance expectations, social influence, facilitating conditions, and perceived playfulness of GAI positively and actively influence their willingness to continuously use GAI. However, perceived financial costs negatively impact this willingness, and notably, the perceived risk of GAI does not affect their intention to use mobile learning, contradicting the initial hypothesis. This discrepancy might be due to university students typically harboring curiosity and enthusiasm for new technologies, leading them to adopt an optimistic view towards the development of GAI, thus minimizing their concerns over perceived risks in Table 5.

Table 5. Research hypothesis analysis results

Research Hypothesis		Inspection Results
H1	Performance expectations of GAI	Accepted
H2	Social influence of GAI	Accepted
H3	Facilitating conditions of GAI	Accepted
H4	Perceived playfulness of GAI	Accepted
H5	Perceived risk of GAI	Rejected
H6	Perceived cost of GAI	Accepted

Based on the findings, this paper makes the following recommendations:

1. Enhance the precision and contextual adaptation of generated content: GAI developers should integrate simple, easy-to-understand, short-text, and multi-link learning resources based on the latest natural language processing models and domain-specific corpora for fine-tuning.
2. Establish appropriate social ethical standards: System designers should incorporate ethical standards and transparency mechanisms in the systems to ensure that generated content does not negatively impact society.
3. Ensure intuitive and user-friendly interfaces: To enhance the mobile learning experience for university students, the user interface design of GAI should focus on intuitiveness and ease of use, reducing complex procedural steps and lowering the cognitive load on students, thereby enhancing their learning efficiency.
4. Strengthen personalized recommendations based on historical data: GAI can analyze users' behavior and content generation history to offer more targeted content recommendations, thus enhancing students' ongoing interest in the system.
5. Reduce financial burdens and improve technology accessibility: Allowing students to experience basic functionalities for free while charging for advanced features or personalized services can attract potential users to the system and ensure profitability for GAI design companies.

6 REFERENCES

- [1] X. Wang *et al.*, "Learners' perceived AI presences in AI-supported language learning: A study of AI as a humanized agent from community of inquiry," *Computer Assisted Language Learning (CALL)*, vol. 37, no. 4, pp. 814–840, 2022. <https://doi.org/10.1080/09588221.2022.2056203>
- [2] C. Lai and D. Zheng, "Self-directed use of mobile devices for language learning beyond the classroom," *ReCALL*, vol. 30, no. 3, pp. 299–318, 2018. <https://doi.org/10.1017/S0958344017000258>
- [3] S. Wang, F. Wang, Z. Zhu, J. Wang, T. Tran, and Z. Du, "Artificial intelligence in education: A systematic literature review," *Expert Systems with Applications*, vol. 252, p. 124167, 2024. <https://doi.org/10.1016/j.eswa.2024.124167>
- [4] M. Ovanovic and M. Campbell, "Generative artificial intelligence: Trends and prospects," *Computer*, vol. 55, no. 10, pp. 107–112, 2022. <https://doi.org/10.1109/MC.2022.3192720>
- [5] D. Parsons, "A mobile learning overview by timeline and mind map," *International Journal of Mobile and Blended Learning (IJMBL)*, vol. 6, no. 4, pp. 21, 2014. <https://doi.org/10.4018/ijmb.2014100101>

- [6] M. Sharples, T. Taylor, and G. Vavoula, "A theory of learning for the mobile age," in *Medienbildung in neuen Kulturräumen*, B. Bachmair, Ed., Germany: vs verlag für sozialwissenschaften, 2010, pp. 87–99. https://doi.org/10.1007/978-3-531-92133-4_6
- [7] H. Crompton, D. Burke, K. H. Gregory, and C. Gräbe, "The use of mobile learning in science: A systematic review," *Computers & Education*, vol. 110, pp. 51–63, 2016. <https://doi.org/10.1016/j.compedu.2017.03.013>
- [8] G. J. Hwang and P. H. Wu, "Applications, impacts and trends of mobile technology-enhanced learning: A review of 2008–2012 publications in selected SSCI journals," *International Journal of Mobile Learning and Organisation (IJMLO)*, vol. 8, no. 2, pp. 83–95, 2014. <https://doi.org/10.1504/IJMLO.2014.062346>
- [9] T. M. Miangah and A. Nezarat, "Mobile-assisted language learning," *International Journal of Distributed and Parallel Systems (IJDPS)*, vol. 3, no. 1, pp. 309–319, 2012. <https://doi.org/10.5121/ijdps.2012.3126>
- [10] G. Rysbayeva et al., "Students' attitudes towards mobile learning," *International Journal of Engineering Pedagogy (iJEP)*, vol. 12, no. 2, pp. 129–140, 2022. <https://doi.org/10.3991/ijep.v12i2.29325>
- [11] Y. Li and C. A. Hafner, "Mobile-assisted vocabulary learning: Investigating receptive and productive vocabulary knowledge of Chinese EFL learners," *ReCALL*, vol. 34, no. 1, pp. 66–80, 2022. <https://doi.org/10.1017/S0958344021000161>
- [12] O. Celik and F. Yavuz, "The effect of using mobile applications on literal and contextual vocabulary instruction," *International Journal of Learning and Teaching*, vol. 10, no. 2, pp. 126–136, 2018. <https://doi.org/10.18844/ijlt.v10i2.3407>
- [13] I. Xodabande and M. R. Hashemi, "Learning English with electronic textbooks on mobile devices: Impacts on university students' vocabulary development," *Education and Information Technologies*, vol. 28, pp. 1587–1611, 2023. <https://doi.org/10.1007/s10639-022-11230-1>
- [14] Y. C. Hsu and T. H. Ching, "Generative artificial intelligence in education, part two: International perspectives," *TechTrends*, vol. 67, pp. 885–890, 2023. <https://doi.org/10.1007/s11528-023-00913-2>

7 AUTHORS

Shiyuan Zhou is with the School of Business, Henan University, Kaifeng, China.

Yichao Si is with the School of Business, Henan University, Kaifeng, China.

Jing Li is with the School of General Education, Wuhan Business University, Wuhan, China (E-mail: 390677982@qq.com).

Otilia Manta is with the Centre for Financial and Monetary Research "Victor Slăvescu," Romanian Academy, 050711 Bucharest, Romania; Romanian American University, 012101 Bucharest, Romania.

Gabriel Xiao-Guang Yue is with the Romanian American University, 012101 Bucharest, Romania; Department of Computer Science and Engineering, European University Cyprus, Nicosia, Cyprus.