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PAPER

Evaluating the Impact of Mobile-Integrated Generative AI on University Students' Critical Thinking and Problem-Solving Skills

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ABSTRACT

This study explored how mobile-integrated generative artificial intelligence (AI) affects university students' critical thinking, problem-solving, and higher-order cognitive skills. It focused on the influence of generative AI and mobile learning on mobile-assisted language learning (MALL), considering human–AI Interaction as a mediating factor. Researchers used a quantitative approach and gathered data from 320 university students through a structured questionnaire based on validated scales. Partial least squares structural equation modeling (PLS-SEM) was used to evaluate the measurement and structural models, looking at both direct and mediating effects. The results showed that generative AI and mobile learning both had a positive impact on human–AI Interaction, thereby significantly improving MALL. MALL also played a strong role in developing higher-order thinking skills (HOTS). The mediation analysis showed that human–AI Interaction partially explained the link between the independent variables and MALL, underscoring the importance of interactive, personalized AI-supported learning experiences. These results are important for higher education policy and curriculum design. They show the need to include AI-enabled mobile learning tools and encourage interactive engagement to improve cognitive outcomes. In summary, combining AI and mobile learning can help university students develop language skills and higher-order thinking skills.

KEYWORDS

generative AI, mobile learning, human–AI interaction, mobile-assisted language learning (MALL), higher-order thinking skills (HOTS), partial least squares structural equation modeling (PLS-SEM)

1 INTRODUCTION

The rapid advancement of digital technologies has transformed higher education, particularly in terms of students' access to, processing, and synthesis of knowledge [1]. Among these innovations, mobile learning facilitates flexible, personalized, and

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context-aware educational experiences [2]. Mobile devices support learning anytime, anywhere, allowing students to access resources, communicate with peers, and use digital tools to enhance their knowledge acquisition [3]. Recent studies show that mobile learning helps students interact more and develop higher-order thinking skills, such as critical thinking, problem-solving, and collaborative learning [4]. At the same time, using generative artificial intelligence (AI) in education brings both new opportunities and challenges to teaching and learning [5]. Generative AI can help students combine information, think more creatively, and solve complex tasks by producing human-like text, summaries, and suggestions. Research shows that AI-based learning tools can boost engagement, give personalized feedback, and support self-directed learning, which can improve the learning experience and help students build cognitive skills [6]. However, the success of AI in higher education depends on how well students and AI interact. Factors such as responsiveness, personalization, and student control affect how students turn AI support into meaningful learning [7]. Mobile-assisted language learning (MALL) is one area where mobile learning and generative AI work especially well together. MALL uses mobile devices and digital tools to help people learn languages, offering instant feedback, interactive features, and flexible learning options [8].

Studies have shown that MALL does not only enhance language proficiency but also has a positive effect on motivation, exposure, and learning efficacy perceptions among students [9]. Although these advantages exist, the processes in which mobile learning and AI can improve MALL results are under-researched, especially in terms of how the interaction between humans and AI mediates the language acquisition and acquisition of higher-order cognitive skills. One of the key goals of modern higher education is the development of higher-order thinking skills (HOTS). Among the key skills that the students can explore are critical thinking, problem solving, teamwork, and creative practice, which allow them to cope with complex real-world situations. The possible benefits of technology-enhanced learning environments in developing these skills have been noted in previous research, especially in the case of interactive, adaptive, and collaborative learning [10]. However, there are few empirical studies on the impact of mobile-integrated generative AI on HOTS, either directly or indirectly via enhancements in MALL. This is a very important gap in the literature because an understanding of these pathways is necessary to design interventions that achieve the best outcomes in terms of cognitive and language learning.

Although AI and mobile learning are increasingly being embraced in higher education, there are several research gaps. To begin with, the current literature does not pay enough attention to the combined impact of mobile learning and AI on cognitive and language learning outcomes, as many studies present either mobile learning or AI separately. Second, there is a dearth of literature that has directly investigated the mediating effect of human-AI interaction in the description of the impact of such technologies on learning outcomes. Third, most studies are based on qualitative insights or small-scale experimental studies, which does not allow generalization of the results to larger student samples [11].

Addressing these gaps is essential for advancing both theoretical understanding and practical application in higher education. Accordingly, this study investigates the impact of mobile-integrated generative AI on university students' learning outcomes, with particular emphasis on MALL and higher-order thinking skills and on the mediating role of human-AI interaction. The study integrates constructs from technology acceptance, mobile learning, and cognitive skill development frameworks to offer a comprehensive perspective on the role of AI-assisted mobile learning environments in promoting effective language acquisition and cognitive skill enhancement.

2 LITERATURE REVIEW

2.1 Generative AI and mobile learning in higher education

Generative AI and mobile learning are among the most significant technological advancements influencing higher education in recent years. Generative AI has expanded the scope of digital learning by enabling students to generate explanations, summaries, examples, and problem-solving hints in real time, thereby supporting more dynamic and interactive learning experiences [12]. Simultaneously, mobile learning has innovated the limits of higher education by enabling students to study academic materials anytime and anywhere using portable digital devices, thereby enhancing flexibility, convenience, and continuity of the learning processes [13]. These two technologies have become especially important in a university environment, where students are supposed to handle rather complicated academic assignments and participate in more self-directed learning. The mobile devices introduce how students will be able to always access learning resources, and generative AI improves the quality of these interactions by providing students with instant and personalized academic assistance [14].

Generative AI has significant consequences in terms of mobile learning quality and effectiveness of higher education. Implemented in mobile platforms, generative AI can assist students in their academic activities by answering their questions, personalizing information to their requirements, and engaging in greater interaction with the learning activities [15]. The integration is of relevance in the higher education setting since it is in line with the increased focus of student-centered, flexible, and technology-enhanced models of learning. Previous studies have demonstrated that mobile learning helps to increase the motivation of learners, their efficiency, and social interaction, whereas AI-based assistance enhances personalization and control over learners [16].

These technologies together can also produce a learning environment where students not only have an easier time accessing information but also have a more meaningful interaction with it. Consequently, generative AI and mobile learning can be interpreted as complementary learning tools that can complement each other to enhance the academic experiences and performance of students in higher education [17].

2.2 Human–AI interaction as a mediating mechanism

The human-AI interaction is a concept that has gained more significance in educational research because it entails the quality of interaction between intelligent systems and learners [18]. In the learning settings with AI, students are not the passive recipients of information; they are the users of systems that can react to their input, change to their needs, and shape their cognitive and behavioral learning. With AI systems functioning well and providing students with personalized assistance, students can become more interested, more independent, and more confident in their learning [19]. The contribution of human-AI interaction as a mediating factor is theoretically important due to its contribution to the understanding of how the affordances of the technology could be transformed into significant educational gains. That is, mobile learning and generative AI can offer the framework in which learning is possible, yet it is the quality of interaction between students and AI that will dictate whether these technologies can deliver any real educational value [20]. Prior studies have demonstrated that interactive online platforms may boost learner motivation, the perceived effectiveness of learning, and self-regulated learning behaviors [21].

2.3 MALL

Mobile-assisted language learning has received significant academic interest with the integration of mobile technologies into language learning. MALL can be defined as the application of mobile devices and apps to facilitate language learning by providing portable, interactive, and frequently personalized learning experiences [22]. In comparison with the traditional classroom-based strategies, MALL provides students with a better exposure to language input, a chance to practice language immediately, and access to learning materials in real-life contexts. [23] Demonstrated that MALL has the potential to positively impact the perception of students on the effectiveness of the learning process, expand their exposure to language learning activities, and enhance their disposition towards language education with the help of technology. Mobile learning combined with generative AI can potentially enhance the effectiveness of MALL even further. Mobile language learning with AI can offer instant feedback, create contextual examples, clarify mistakes, and produce interactive language tasks based on the needs of the learner [24]. These characteristics could build a stronger confidence and engagement of the students and make the learning of languages more adaptive and meaningful. Nevertheless, despite previous research investigating MALL as a byproduct of mobile learning and digital interaction, a smaller number of studies have considered the effect of human-AI interaction on the effectiveness of MALL in AI-based learning contexts [25]. The significance of this gap is that the process of language learning is an interactive one, and the quality of the interaction between students and AI can condition the emergence of the AI-based support into the enhanced learning experiences.

2.4 HOTS in technology-enhanced learning

The ability to think on a higher level is generally considered the all-important product of modern higher education since it allows students to critically analyze information, find solutions to complex problems, work in a team, and come up with new ideas [26]. Consequently, universities should be able to produce learning environments that do not merely impart knowledge but also help develop students' ability to reason, judge, and take creative action [27]. One of the avenues that have been advanced to facilitate this goal has been technology-enhanced learning, particularly when the digital tools promote interaction, reflection, and active engagement. Mobile learning and generative AI can be used to help HOTS, exposing learners to a wide array of information, scaffolding inquiry-based learning, and providing one-to-one help in solving cognitive problems [28]. To illustrate, mobile platforms can be used to promote collaboration and problem-based learning, whereas generative AI can be used to help students to summarize complex materials, to compare perspectives, and to consider alternative solutions [29]. Figure 1 shows the research model of the present study, which indicates all variables and their respective path relationships with other variables of this study.

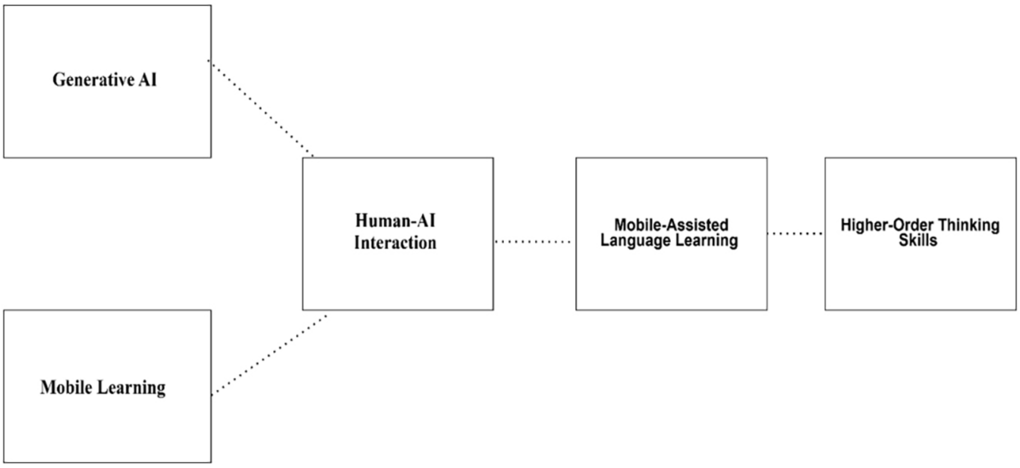

Fig. 1. Research model

3 METHODOLOGY

3.1 Research design

A positivist, quantitative research design was employed, utilizing a cross-sectional survey to statistically examine the relationships between mobile-integrated generative AI and students' higher-order thinking skills. Empirical data collected at a single point in time were used to validate a structural model assessing the impact of human AI interaction and mobile learning on critical thinking and problem-solving abilities.

3.2 Sampling and sample size

A non-probability purposive sampling technique was used to select 320 university students with experience in mobile learning and AI-assisted tools. This targeted sampling ensured that participants possessed the requisite expertise to offer valid insights regarding the influence of generative AI on cognitive outcomes and language learning. The sample size of n = 320 was statistically sufficient to support robust partial least squares structural equation modeling (PLS-SEM) analysis, including structural model testing, bootstrapping, and complex mediation analysis.

3.3 Instruments

The survey instrument consisted of several sections measuring the constructs included in the proposed model. All measurement items were adapted from previously published and validated scales, thereby enhancing the content validity and theoretical grounding of the study. The constructs included generative AI, mobile learning, human–AI interaction, MALL, and HOTS.

The instrument was designed to capture students' perceptions of these constructs in the context of mobile-integrated generative AI use in higher education.

The construct of generative AI was adapted from [30] and was measured using 8 items. The second independent variable, mobile learning, was adapted from

[31] and was measured as a multidimensional construct. It included Flexibility (8 items), Suitability (4 items), Enjoyment (4 items), Efficiency (4 items), Economic value (3 items), and social value (5 items). These dimensions reflected the diverse affordances of mobile learning, including accessibility, convenience, contextual appropriateness, motivational value, performance support, affordability, and social connectedness.

The mediating construct, human–AI interaction, was adapted from [32] and comprised four dimensions: Responsiveness (5 items), Learner Control (3 items), Learning Engagement (6 items), and Personalization (3 items). This construct measured the quality of interaction between students and AI-enabled learning systems. The dependent variable MALL was adapted from [33] and was measured using five dimensions: Effectiveness of MALL (3 items), Teachers' Influence (3 items), Degree of Exposure to MALL (3 items), Surplus Value of MALL (3 items), and Orientation toward MALL (3 items). The second dependent variable, HOTS, was adapted from [34] and included four dimensions: Critical Thinking Skills (12 items), Problem-Solving Skills (8 items), Teamwork Skills (10 items), and Practice Innovative Skills (8 items). This construct was used to measure advanced cognitive and collaborative capabilities that are increasingly recognized as essential outcomes in higher education. All items in the questionnaire were measured using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. This response format was used because it allowed respondents to indicate the degree of their agreement with each statement in a simple and consistent manner. It also aligned with common practice in educational and behavioral research involving latent constructs measured through self-report instruments.

3.4 Data analysis techniques

Data analysis was conducted using PLS-SEM via SmartPLS to accommodate the model's complexity, multidimensional variables, and predictive goals. The process involved a two-stage evaluation: first, assessing measurement model reliability and validity (Cronbach's alpha, CR, AVE, and HTMT), and second, testing the structural model through path coefficients, R^2, and f^2 values. Bootstrapping was further employed to validate the significance of direct and indirect effects, specifically examining the mediating role of human-AI interaction on MALL and higher order thinking skills.

4 RESULT AND DISCUSSION

4.1 Descriptive statistics

Table 1 presents descriptive results showing that the mean scores for all major constructs were above the midpoint of the five-point Likert scale. This means respondents generally had positive views of mobile-integrated generative AI, mobile learning, human–AI interaction, MALL, and HOTS. Of these, HOTS had the highest mean (M = 3.90, SD = 0.55), suggesting students saw these learning environments as especially helpful for developing higher-order thinking skills. Mobile Learning also had a high mean (M = 3.86, SD = 0.58), followed by Generative AI (M = 3.84, SD = 0.66), MALL (M = 3.83, SD = 0.57), and Human–AI Interaction (M = 3.82, SD = 0.61). The standard deviation values were moderate, indicating that responses varied but were not widely dispersed. Skewness and kurtosis values were also within normal limits, which means the data were close to a normal distribution and suitable for further multivariate analysis.

Table 1. Descriptive statistics of constructs

Construct	Mean	Standard Deviation	Skewness	Kurtosis
Generative AI	3.84	0.66	–0.48	–0.21
Mobile Learning	3.86	0.58	–0.44	–0.18
Human–AI Interaction	3.82	0.61	–0.39	–0.27
MALL	3.83	0.57	–0.36	–0.14
HOTS	3.9	0.55	–0.52	

4.2 Measurement model assessment

The measurement model was assessed to establish the reliability and validity of the latent constructs employed in this study. Following recommended procedures in PLS-SEM, the evaluation included indicator reliability, internal consistency reliability, and convergent validity. Indicator reliability was examined using outer loadings, while internal consistency reliability was assessed through Cronbach's alpha and composite reliability (CR). Convergent validity was evaluated using the average variance extracted (AVE).

Table 2. Measurement model assessment

Construct	No. of Items Retained	Loading Range	Cronbach's Alpha	CR	AVE
Generative AI	8	0.741–0.861	0.912	0.928	0.617
Mobile Learning	28	0.703–0.848	0.956	0.961	0.523
Human–AI Interaction	17	0.726–0.872	0.941	0.948	0.525
MALL	15	0.718–0.856	0.924	0.934	0.587
HOTS	38	0.701–0.844	0.972	0.974	0.501

Table 2 demonstrates that the measurement properties of all constructs were satisfactory. Outer loadings ranged from 0.701 to 0.872, indicating that the indicators exhibited acceptable to strong relationships with their respective latent constructs. Cronbach's alpha values ranged from 0.912 to 0.972, and CR values ranged from 0.928 to 0.974, confirming high internal consistency for all measures. Additionally, the AVE ranged from 0.501 to 0.617, all exceeding the 0.50 threshold, thereby establishing convergent validity. These results indicate that the construct measures were reliable and that the items adequately represented the intended theoretical concepts. Consequently, the measurement model was deemed robust and suitable for subsequent evaluation of discriminant validity and the structural model.

Figure 2 presents the measurement model of the present study using PLS-SEM, illustrating all path relationships between study variables, their dimensions, and indicators.

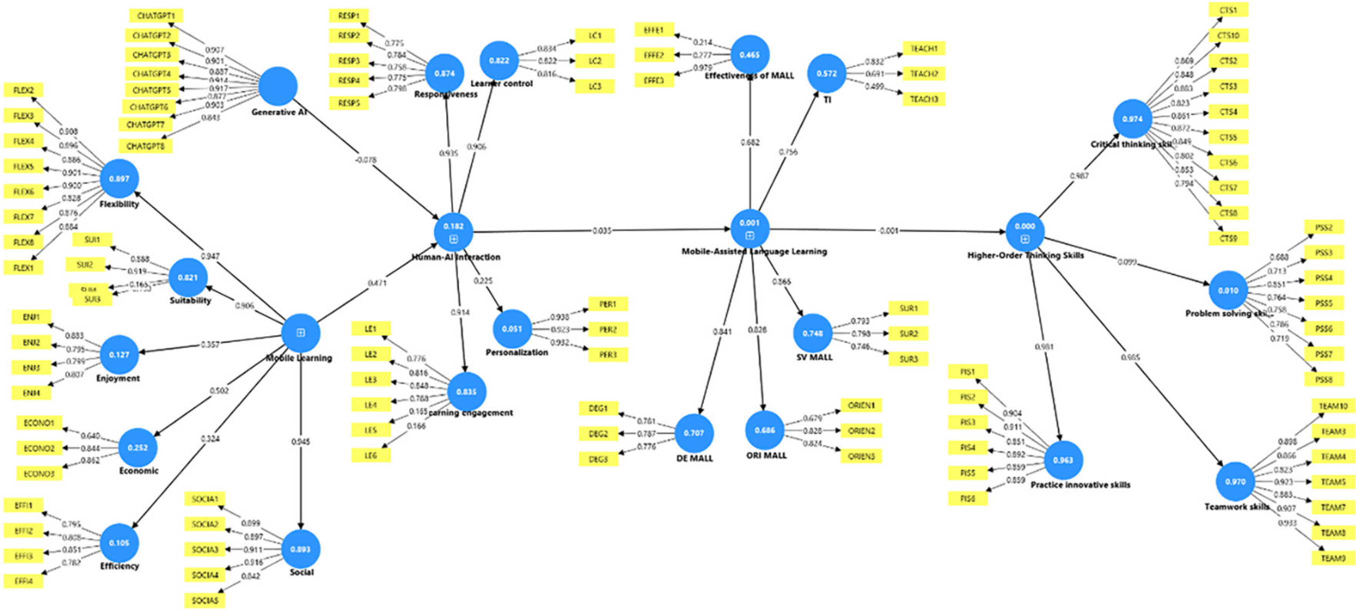

Fig. 2. Established measurement model

Table 3. HTMT results

Construct	1	2	3	4	5
1. Generative AI	–				
2. Mobile Learning	0.742	–			
3. Human–AI Interaction	0.801	0.836	–		
4. MALL	0.693	0.781	0.824	–	
5. HOTS	0.716	0.768	0.852	0.809	–

Table 3 shows that all constructs in the study met the requirements for discriminant validity. The values ranged from 0.693 to 0.852, all below the recommended threshold of 0.90. The highest HTMT value was between Human-AI Interaction and HOTS (0.852), suggesting a strong conceptual link but still within the acceptable range. The correlations between Human-AI Interaction and MALL (0.824) and between Mobile Learning and Human-AI Interaction (0.836) were moderate and did not pose any issues. Overall, the results indicate that the constructs were distinct, as none of the HTMT values exceeded the critical threshold.

4.3 Structural model assessment

Structural model assessment is a very important step in PLS-SEM, as it is the way to estimate the proposed hypothesized relationships between the latent constructs so that the researcher can reveal whether the theoretical model can be empirically confirmed or not. This step looks at the size, direction, and statistical significance of path coefficients and the explained variance (R 2) of endogenous constructs. It also gives an understanding of the mediating mechanisms and predictive potential of the model, hence giving a holistic picture of the effects of independent variables in direct and indirect ways.

Table 4. Structural model results

Hypothesis	Path	β (Path Coefficient)	t-Value	p-Value	Result
H1	Generative AI → Human–AI Interaction	0.431	6.52	<0.001	Supported
H2	Mobile Learning → Human–AI Interaction	0.487	7.15	<0.001	Supported
H3	Human–AI Interaction → MALL	0.538	8.02	<0.001	Supported
H4	MALL → HOTS	0.612	9.27	<0.001	Supported
H5	Generative AI → Human–AI Interaction → MALL	0.232	5.11	<0.001	Supported
H6	Mobile Learning → Human–AI Interaction → MALL	0.262	5.76	<0.001	Supported

Table 4 indicated that all direct and mediating hypotheses were supported. Generative AI ($\beta = 0.431$, $p < 0.001$) and Mobile Learning ($\beta = 0.487$, $p < 0.001$) were found to have significant positive effects on Human–AI Interaction, confirming H1 and H2. Furthermore, Human–AI Interaction significantly influenced MALL ($\beta = 0.538$, $p < 0.001$), supporting H3, and MALL in turn positively affected HOTS ($\beta = 0.612$, $p < 0.001$), confirming H4. Regarding mediation, Human–AI Interaction partially mediated the effect of both Generative AI (H5, $\beta = 0.232$, $p < 0.001$) and Mobile Learning (H6, $\beta = 0.262$, $p < 0.001$) on MALL, indicating that part of the influence of the independent variables on MALL was transmitted through enhanced human–AI interactions. Overall, the structural model results provided strong empirical support for the proposed theoretical framework, demonstrating both direct and indirect pathways through which mobile-integrated generative AI and mobile learning contribute to language learning and higher-order cognitive skills.

5 DISCUSSION

The results of this study show strong evidence that using generative AI with mobile learning can improve how students interact with AI. This, in turn, leads to better outcomes in MALL.

Generative AI and mobile learning directly affect how students interact with technology. Students see AI-based tools and mobile learning as flexible and engaging, which helps their learning. This aligns with earlier research highlighting the value of adaptive technology and learner-centered mobile design for supporting interaction, engagement, and user agency in online learning.

Moreover, the results underscore the significance of Human–AI Interaction as a mediating mechanism. The substantial mediation effects indicate that the positive influence of AI and mobile learning on MALL is contingent upon the quality of interaction between students and AI systems. These findings support the theoretical perspective that the mere provision of technology is insufficient; the pedagogical value of AI emerges through responsive, personalized, and engaging interactions that guide learners, facilitate self-regulated learning, and enhance most students' learning. Furthermore, the perceived sense of control experienced by students in AI-mediated learning environments is a key determinant of learning effectiveness. Finally, the positive link between MALL and HOTS indicates that AI-powered mobile learning can help develop abilities such as critical thinking, problem-solving, innovation, and teamwork. This finding is important for higher education, as it suggests that combining AI with mobile learning can improve language learning and help build key 21st-century skills. The research provides evidence that using technology thoughtfully can support the development of cognitive skills.

6 CONCLUSION AND RECOMMENDATIONS

This study showed that using generative AI with mobile learning can strongly influence students' learning outcomes by improving how students and AI interact. This improved interaction supports language learning and higher-order thinking skills. The study's results confirmed both direct and indirect effects, highlighting that the quality of interaction is key to turning technology features into real educational benefits. Overall, the study expands our understanding of how AI and mobile tools can support not only learning facts but also the development of advanced thinking and teamwork skills. The findings show that it is important to design technology-based learning experiences that are interactive, flexible, and focused on teaching goals. This gives useful guidance to educators, instructional designers, and policymakers who want to support well-rounded learning for today's students.

To better understand AI-mediated learning, future research could use objective performance measures, learning analytics, or qualitative analysis. It would also be helpful to explore how different AI tools, mobile learning designs, and subject areas affect the role of technology in supporting higher-order thinking skills.

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