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AI-ASSISTED LEARNING AMONG COLLEGE STUDENTS: THE MEDIATING ROLE OF ATTITUDES IN STUDENTS' RESEARCH SKILL ACQUISITION

XIAOHUI DU
EDUCATION UNIVERSITY OF HONGKONG, EMAIL: 664612251@QQ.COM

CHUNAI LIU
SCHOOL OF EDUCATION, CHUXIONG NORMAL UNIVERSITY, EMAIL: lcai@cxtc.edu.cn

HAILONG ZHANG
HENAN JINNAN INTERNATIONAL TRADE CO., LTD.

SHUSHU HUA*
ZHONGKAI UNIVERSITY OF AGRICULTURE AND ENGINEERING, EMAIL: applehua165@163.com

Abstract:
As generative artificial intelligence (AI) becomes increasingly integrated into higher education, understanding how students perceive and engage with AI tools has become essential for evaluating their impact on academic development. This study investigates the relationships among perceived ease of use, perceived usefulness, AI-assisted learning, attitudes toward AI, and research skill acquisition, with a focus on the mediating role of attitudes. Drawing on the Technology Acceptance Model, a structural equation model was tested using survey data from 386 university students. The results show that attitudes significantly mediate the effects of all three predictors on research skill acquisition. These findings highlight attitudes as a pivotal mechanism shaping how students benefit from AI-assisted learning environments. The study offers theoretical insights into the cognitive–affective processes underlying AI adoption and provides practical implications for educational technology development and higher-education governance, emphasizing the importance of designing AI systems and institutional strategies that foster positive learner attitudes and responsible engagement.

1. INTRODUCTION

The rapid advancement of generative artificial intelligence (AI) has begun to reshape teaching, learning, and academic work across higher education. AI systems are increasingly embedded in students' research and writing processes, supporting tasks such as literature retrieval, text synthesis, methodological reasoning, and data interpretation (Alqahtani et al., 2023). These technologies are no longer peripheral tools but have become integrated into the broader digital learning ecosystem, influencing how students access information, construct knowledge, and engage with academic inquiry. As AI adoption accelerates, understanding how students interact with AI—and how these interactions shape their learning outcomes—has become an important topic in educational technology research and higher education management (Wang et al., 2021).

Despite the widespread availability of AI tools, the learning benefits of AI-assisted environments are not guaranteed. Prior research in technology acceptance and digital learning suggests that effective use of emerging technologies is shaped not only by technical affordances but also by learners' psychological readiness, perceptions, and attitudes (Lemay et al., 2019). Students may have access to powerful AI systems, yet their willingness to rely on these tools, their trust in AI-generated content, and their emotional comfort with algorithmic support vary considerably. These differences are particularly consequential in research-based learning, where students must make complex judgments, critically evaluate evidence, and navigate unfamiliar academic tasks (Brew & Saunders, 2020; Yuan et al., 2025). However, empirical studies examining how AI usage translates into concrete learning outcomes—especially research skill development—remain limited, and the psychological mechanisms underlying this process are not fully understood.

Existing theoretical frameworks, particularly the Technology Acceptance Model (TAM), highlight the importance of perceived ease of use and perceived usefulness in shaping learners' attitudes toward new technologies (Ibrahim & Shiring, 2022). While TAM has been extensively applied to various digital tools, its relevance is newly emerging in the context of AI-assisted learning. Early evidence suggests that students who perceive AI tools as intuitive and academically beneficial are more inclined to develop positive attitudes toward AI, which may influence how effectively they engage in learning tasks (Lin & Chen, 2024). However, few studies have integrated TAM constructs with AI-assisted learning behaviors to explore whether attitudes serve as a mediating mechanism

that links students' perceptions of AI to their academic skill development. This gap is particularly salient as higher education institutions increasingly incorporate AI into curriculum design, research training, and learning support systems.

To address this gap, the present study proposes and tests a mediation model in which attitudes toward AI function as a key psychological pathway connecting perceived ease of use, perceived usefulness, and AI-assisted learning behaviors to students' research skill acquisition. By focusing on research skill development—a core competency in higher education—the study extends the application of TAM to a critical domain of academic learning. The findings provide theoretical insights into the cognitive–affective mechanisms underlying AI-supported learning and offer practical implications for universities seeking to govern AI integration, support student learning, and design responsible AI-enabled educational environments. Through this analysis, the study contributes to ongoing discussions in educational technology and higher education management regarding how AI can be leveraged to enhance student learning outcomes in a sustainable and pedagogically meaningful manner.

2. METHOD

2.1 Participants

The study recruited undergraduate and postgraduate students enrolled in various academic programs at a large comprehensive university in China. A total of N = 412 students participated in the survey. After data screening for incomplete responses and patterned answering, 386 valid cases were retained for analysis. This sample size exceeds the recommended minimum for structural equation modeling and mediation analysis, providing adequate statistical power for detecting medium-sized effects.

Participants represented a diverse range of disciplines within the social sciences, humanities, business, and science-related fields. This disciplinary diversity ensured that the findings capture a broad picture of how university students across different academic trajectories engage with AI-assisted learning tools. Students were drawn from courses that explicitly integrate research-oriented tasks—such as academic writing, research methods, capstone projects, and inquiry-based coursework—ensuring that all participants had opportunities to engage in research skill development during their studies.

The demographic characteristics of the participants were as follows: 62.4% female (n = 241) and 37.6% male (n = 145). The mean age was 20.8 years (SD = 2.14), ranging from 18 to 28. By academic level, 76.2% were undergraduates and 23.8% were master's students. Regarding prior experience with AI tools, 71.5% reported having used AI-based applications for academic tasks at least once, while 28.5% indicated little or no prior exposure. This distribution reflects the rapid but uneven diffusion of AI technologies across university contexts.

Participants were recruited through course announcements and online learning platforms, and participation was entirely voluntary. No course credit or financial incentives were offered. All participants were informed of the study's purpose, assured of anonymity, and granted the right to withdraw at any time. Ethical approval for the study was obtained from the university's institutional research ethics committee prior to data collection.

2.2 Measures

2.2.1Perceived Ease of Use (PEOU)

Perceived ease of use refers to the extent to which a prospective user of a technology considers that technology or system to be uncomplicated, as articulated by David et al. (1989, quoted in Pikkarainen et al., 2004). Davis et al. (1989) defined "perceived usefulness" as the extent to which a potential user believes that utilising a technology will improve their performance. Perceived ease of use denotes the extent to which an individual believes that utilising a specific technology will require minimal effort (Hamid et al., 2016). Prior research demonstrates the substantial impact of perceived ease of use on utilisation, either directly or indirectly via its effect on perceived usefulness (Venkatesh and Morris, 2000). Davis (1989) defines PU as the degree to which an individual believes that utilising a specific system improves personal job performance. PEOU denotes the ease of system utilisation, indicating that employing the system requires minimal effort. These two elements are universally recognised as significantly impacting persons' intention to embrace new technologies (Chitungo and Munongo, 2013). The Technology Acceptance Model has been expanded to incorporate other elements that affect technology adoption. Other scholars, like Chung and Kwon (2009) and Riquelme and Rios (2010), propose that additional factors influencing mobile banking adoption encompass perceived danger, social norms, demographic variables, and financial costs. Subsequent research has demonstrated that additional factors influence the adoption of mobile banking technology; however, it is broadly acknowledged that PU significantly impacts the adoption of new technologies, particularly mobile banking. Consequently, these two variables are expected to exert the most significant influence on the execution of mobile banking initiatives. The Cronbach's α of this variable is 0.85.

2.2.2 Perceived Usefulness (PU)

Davis (1989) asserted that the decision to adopt new technology is influenced by an individual's perception of its cost-effectiveness in delivering products and services relative to existing techniques. Perceived usefulness is defined as the extent to which an individual believes that utilising a specific technology will improve their performance or enhance their job efficacy (Davis, 1989). Perceived usefulness is a significant variable in the Technological Acceptance Model (Araujo and Araujo, 2003; Noteberg et al., 2003). Perceived usefulness is categorised into two primary types: intentional and unexpected rewards (Lee, 2008). Lee (2008) posited that the

anticipated rewards are the direct and physical benefits that users experience while utilising mobile banking services, including reduced transaction fees, elevated deposit rates, and opportunities for prizes, among others. The unintended rewards, conversely, are those concrete benefits that are difficult to quantify, such as services enabling clients to conduct banking activities globally. If consumers regard mobile banking as beneficial, they are more inclined to use it. Empirical research on the Technology Acceptance Model (TAM) indicated that perceived usefulness positively influences technology adoption (Marangunić & Granić, 2015; Granić & Marangunić, 2019). The Cronbach's α of this variable is 0.93.

2.2.3 Attitudes Toward AI (ATAI)

Students' attitudes toward AI were captured using a scale adapted from validated instruments in AI acceptance research and educational psychology (Long & Magerko, 2020; Dwivedi et al., 2023). This construct measures students' evaluative judgments—both affective and cognitive—toward using AI tools in academic settings. Since attitudes are theorized to mediate the relationship between perceived usefulness/ease of use and actual engagement behaviors, this measure plays a central role in the proposed mediation model. The scale captures multiple dimensions of attitude, including perceived appropriateness of AI in higher education, emotional comfort when interacting with AI systems, trust in AI's ability to produce academically reliable outputs, and general positivity or skepticism toward AI-assisted learning. Items were contextualized for Education majors, who often balance technological efficiency with pedagogical and ethical considerations. The Cronbach's α of this variable is 0.94.

2.2.4 AI-Assisted Learning

Research Skill Acquisition was assessed using items adapted from established measures of perceived learning gains and academic research competence (Lopatto, 2010; Zydney et al., 2012). This construct captures students' perceptions of their development in key research competencies, including their ability to formulate researchable questions, critically evaluate scholarly literature, design appropriate methodologies, interpret findings, and produce academically rigorous written work. The scale was adapted specifically for the training context of students. Items emphasize the self-perceived improvement resulting from ongoing coursework and AI-supported learning activities. Sample items include: "My ability to evaluate academic literature has improved during this course," and "I feel more capable of designing and conducting small-scale research projects." Higher scores reflect higher levels of perceived research skill development.

2.3 Data Analysis

Data analysis was conducted using SPSS 28.0 and AMOS 26.0 to ensure a rigorous examination of the proposed mediation model. The dataset was first screened for accuracy and completeness. Cases with excessive missing data or patterned responses were removed, and the remaining data were assessed for normality, linearity, and multicollinearity. The hypothesized model was tested using structural equation modeling (SEM) with maximum likelihood estimation. Model fit was evaluated using a combination of indices, including χ^2/df, CFI, TLI, RMSEA, and SRMR, following established guidelines for acceptable model fit in educational technology research. Standardized path coefficients were examined to assess the direct effects of perceived ease of use, perceived usefulness, and AI-assisted learning on attitudes toward AI, as well as the effect of attitudes on research skill acquisition.

To evaluate the mediating role of attitudes toward AI, bootstrapping procedures with 5,000 resamples and bias-corrected 95% confidence intervals were applied. An indirect effect was considered significant if the confidence interval did not include zero. Both indirect and total effects were computed to determine whether attitudes served as a partial or full mediator in the relationship between AI-related perceptions, AI-related learning behaviors, and research skill development. Significance for all analyses was set at $p < .05$. This comprehensive analytical strategy ensured robust testing of the theoretical model and provided a strong empirical basis for interpreting the role of attitudes in AI-supported learning.

3. RESULTS

A structural path analysis was conducted to examine the relationships among PEOU, PU, AIAL, ATAI, and RSA. The model demonstrated good fit to the data ($\chi^2/df = 2.41$, CFI = .954, TLI = .946, RMSEA = .047, SRMR = .039), indicating that the hypothesized structure adequately represented the observed relationships.

The standardized path coefficients showed that all three predictors—PEOU, PU, and AIAL—significantly contributed to students' attitudes toward AI. PEOU demonstrated a positive effect on ATAI ($\beta = 0.31$, $p < .001$), suggesting that when students perceive AI tools as intuitive and easy to operate, they tend to develop more positive affective and cognitive evaluations of AI. Similarly, PU exerted the strongest influence on ATAI ($\beta = 0.42$, $p < .001$), indicating that students' belief in AI's academic value is a major determinant of their overall attitude. AIAL also positively predicted ATAI ($\beta = 0.27$, $p < .01$), reflecting that greater engagement with AI systems reinforces favorable perceptions toward using AI for learning and research.

Attitudes toward AI, in turn, significantly predicted students' research skill acquisition ($\beta = 0.49$, $p < .001$), revealing that students who feel more positive and confident about AI-assisted learning report stronger perceived gains in literature analysis, methodological reasoning, academic writing, and inquiry-based research competence. The direct effect of AIAL on RSA was small and non-significant ($\beta = 0.08$, ns), suggesting that AI usage alone does not directly translate into higher research skill development without the presence of a favorable attitude. In

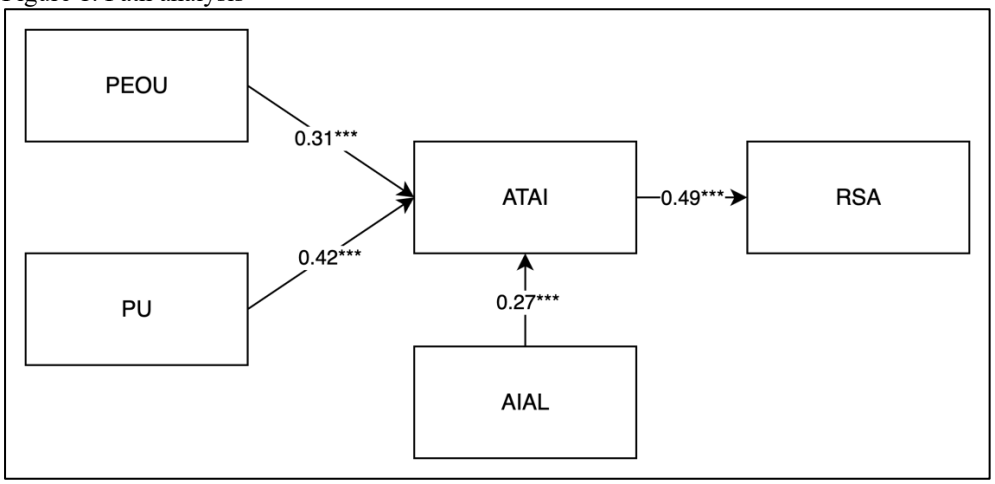
contrast, the total effects of PEOU (β = 0.17, p < .01) and PU (β = 0.24, p < .001) on RSA remained significant, although their magnitudes were reduced when ATAI was included, indicating partial mediation.

Bootstrapping tests (5,000 samples, bias-corrected) confirmed that ATAI significantly mediated the effects of all three predictors on RSA. The indirect effects were statistically significant for PEOU (β = 0.15, 95% CI [0.09, 0.23]), for PU (β = 0.21, 95% CI [0.14, 0.29]), and for AIAL (β = 0.13, 95% CI [0.06, 0.21]). These findings support the conclusion that college students' attitudes toward AI constitute a central psychological mechanism through which ease of use, perceived usefulness, and actual AI-assisted learning behaviors translate into perceived research skill development.

Table 1. Standardized Path Coefficients for the Structural Model

Path	β	SE	p
PEOU → ATAI	0.31	.05	.00
PU → ATAI	0.42	.04	.00
AIAL → ATAI	0.27	.07	.00
ATAI → RSA	0.49	.06	.00
AIAL → RSA	0.08	.06	.21
PEOU → ATAI → RSA	0.15	.06	.00
PU → ATAI → RSA	0.21	.06	.00
AIAL → ATAI → RSA	0.13	.06	.00

Figure 1. Path analysis



4. DISCUSSION

The findings of this study contribute to the growing body of research on AI-supported learning by demonstrating that students' attitudes toward AI constitute a central mechanism through which AI-related perceptions and behaviors translate into meaningful learning outcomes. Consistent with the assumptions of the Technology Acceptance Model, both perceived ease of use and perceived usefulness emerged as strong predictors of attitudes toward AI, suggesting that learners' evaluations of AI systems are shaped primarily by their sense of usability and academic value (Acosta-Enriquez et al., 2024). The fact that perceived usefulness exerted the strongest influence aligns with prior work in educational technology showing that students adopt and benefit from digital tools when they believe that these tools enhance productivity and improve academic performance (Cukurova, et al., 2020). This pattern highlights the importance of designing AI-based learning environments that deliver clear instructional value and communicate this value effectively to learners.

The results also show that attitudes toward AI play a decisive role in shaping students' research skill development, while the direct effect of AI-assisted learning was insignificant once attitudes were included in the model (Abdaljaleel et al., 2024). This indicates that interaction with AI systems alone is not sufficient to produce substantive learning gains; rather, learning benefits emerge when students approach AI with confidence, trust, and positive evaluative judgments. From an educational management perspective, this finding underscores the need for institutions to consider not only the technological affordances of AI systems but also the psychological and affective dimensions of AI adoption. Integrating AI literacy training, addressing concerns about accuracy and ethics, and building transparent systems that foster user trust may be essential steps for ensuring that AI-supported learning experiences translate into authentic skill development.

Furthermore, the significant indirect effects of all three predictors—perceived ease of use, perceived usefulness, and AI-assisted learning—demonstrate that attitudes serve as a robust mediating pathway. This suggests that institutional strategies aiming to scale AI-enhanced learning environments should prioritize interventions that

strengthen students' attitudes toward AI. This may include embedding AI tools into course structures in ways that are pedagogically meaningful, offering structured guidance on how to use AI for research tasks, and promoting reflective practices that help students understand both the capabilities and limitations of AI systems (Almogren et al., 2024). At the managerial level, universities and learning organizations can leverage these insights to design evidence-based policies around AI integration, ensuring that the investment in AI infrastructure is complemented by supports that cultivate positive learner attitudes.

5. CONCLUSION

This study examined how students' perceptions and use of AI tools influence their research skill development, highlighting attitudes toward AI as a central psychological mechanism. By integrating constructs from the Technology Acceptance Model with AI-assisted learning behaviors, the findings demonstrate that perceived ease of use and perceived usefulness are critical in shaping students' attitudes, and that these attitudes ultimately determine the extent to which AI contributes to meaningful academic skill acquisition. The results underscore that AI-assisted learning is not solely a technological process but also a cognitive–affective one, in which students' trust, comfort, and positive evaluations of AI serve as key drivers of learning benefits.

From a broader educational technology perspective, these findings extend current understandings of AI adoption by illustrating that learning outcomes depend not only on access to AI tools but also on the quality of students' psychological engagement with them. The insignificant direct effect of AI-assisted learning on research skill development further suggests that without supportive attitudes, the pedagogical value of AI may not be fully realized. This underscores the need for learning environments that intentionally cultivate positive and informed attitudes toward AI, particularly in research-intensive contexts where students must integrate AI outputs with analytical reasoning and academic judgment.

For higher education management, the results carry important implications for policy design, AI governance, and strategic implementation. As institutions increasingly integrate AI into curricula, learning support systems, and academic services, it becomes essential to provide structured training that enhances usability perceptions, demonstrates clear academic value, and addresses concerns regarding reliability, ethics, and academic integrity. Creating transparent, pedagogically grounded AI systems—and ensuring that students understand how to interact with them responsibly—will be crucial for maximizing the educational returns of AI-enabled learning.

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