

ARTICLE

What motivates university students to learn AI? The role of competency and interest in educational demand

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Abstract

As artificial intelligence (AI) becomes increasingly embedded in university curricula, identifying factors associated with students' motivation to learn AI has become an important issue in higher education. This study surveyed 1,474 undergraduate students and used structural equation modeling with a validated five-construct framework to examine how AI knowledge and practical use of AI tools were related to students' perceived demand for AI learning. The results showed that foundational AI knowledge was positively associated with educational demand both directly ($\beta = 0.401$, $p < 0.001$) and indirectly, primarily mediated by learning interest ($\beta = 0.226$, $p < 0.001$). In contrast, practical AI tool competency was not directly associated with educational demand; however, it was indirectly related to learning interest, whereas general optimism about AI was not necessarily associated with a stronger demand for formal AI learning. Multi-group analyses also indicated experience-based differences: students without prior AI learning experience showed a stronger association between hands-on tool interaction and interest, whereas students with prior AI learning experience showed a stronger association between existing AI knowledge and educational motivation. Overall, the findings suggest that higher-education AI literacy programs may benefit from cultivating students' interest in and engagement with learning, rather than assuming that tool exposure or future-oriented attitudes alone will lead to stronger demand for AI learning.

Keywords: University students; Artificial intelligence literacy; Prior artificial intelligence experience; Learning interests; Learning motivation

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1. Introduction

The advent of ChatGPT has brought global attention to artificial intelligence (AI), transforming how university students perceive and interact with technology across many disciplines. This growing interest in AI underscores the urgent need for two complementary approaches: (i) developing ethical AI systems at the production stage and (ii) cultivating responsible, well-informed users at the consumption level. In this context, AI literacy has emerged as an essential competency for students preparing for

an AI-integrated future. AI literacy encompasses the ability to understand, critically evaluate, and effectively engage with AI systems (Pinski & Benlian, 2023; UNESCO, 2021). While the precise definition of AI literacy continues to generate discussion within academic circles, scholarly consensus is building around several core components: understanding AI technologies and their broader societal implications, evaluating their impact, and applying them meaningfully in everyday contexts (Kim & Kwon, 2023; Weber *et al.*, 2023).

The importance of AI literacy is reflected in policy initiatives worldwide. The United States launched the “AI4K12” initiative in 2019, establishing foundational guidelines for AI education in elementary and secondary schools. The National AI Initiative Act of 2021 reinforced this commitment by emphasizing AI talent development and promoting the integration of AI instruction within Science, Technology, Engineering, and Mathematics (STEM) education frameworks (Bosarge, 2025; Zhang *et al.*, 2023).

However, current approaches face notable limitations. Celik (2023) observes that many national strategies remain narrowly focused on training high-level AI specialists for industry applications, often overlooking the educational needs of the general population. While curriculum development for AI literacy has received considerable attention in academic and policy circles, AI literacy programs for university students majoring in non-STEM disciplines have received comparatively little attention. This gap represents a significant obstacle, as differentiated instruction and empirical evaluation of educational impact require robust measurement instruments. Consequently, understanding students’ AI literacy represents a fundamental prerequisite for successfully integrating AI education into broader educational frameworks.

To fill a gap in the existing literature, this research aims to explicitly examine AI literacy among university students and investigate how their AI-related competencies affect their perceived educational needs. The study focuses particularly on identifying the mediating roles of learning interest and future attitudes within higher education settings. The research questions were designed as follows:

- (i) RQ1: How do university students’ AI knowledge and tool usage competencies influence their perceived need for AI education?
- (ii) RQ2: What roles do learning interest and future attitudes play in mediating these relationships?

This study makes several contributions to the literature on AI literacy and AI education. First, it provides empirical evidence on the relationship between university students’

AI knowledge, practical tool use competency, and perceived demand for AI education, thereby extending prior research that has largely focused on conceptual definitions or general perceptions of AI literacy. Second, it identifies learning interest as a key motivational mechanism linking AI-related competencies to educational demand, offering a more nuanced understanding of how students’ engagement with AI may translate into a perceived need for formal instruction. Third, by comparing students with and without prior AI learning experience, the study highlights the importance of differentiated approaches to AI literacy education, suggesting that students’ prior exposure to AI may shape how knowledge, tool use, interest, and educational demand are interrelated.

Taken together, these contributions offer practical implications for designing AI literacy curricula that are responsive to students’ diverse levels of readiness and learning experience in higher education.

2. Literature review

In this section, we review the theoretical and empirical foundations that inform the present study. First, we examine major conceptualizations of AI literacy, with particular attention to how scholars have defined the competencies required to understand, evaluate, and use AI in educational and social contexts. Then, we review recent empirical studies on university students’ AI literacy, focusing on measurement approaches, prior AI learning experiences, and the role of AI-related knowledge and tool use competency. By synthesizing these strands of literature, this section establishes the rationale for examining how students’ AI competencies are associated with their perceived demand for AI education.

2.1. Conceptualizations of artificial intelligence literacy

The concept of AI literacy has attracted diverse scholarly interpretations since its emergence, reflecting the complexity and evolving nature of the field across diverse disciplines. For example, Ng *et al.* (2021) present a comprehensive framework that positions AI literacy as encompassing not only the technical ability to understand, use, evaluate, and create AI technologies, but also the critical competence to navigate the ethical dimensions of AI implementation. This multidimensional approach is consistent with the work of Long and Magerko (2020), who characterize AI literacy through three interconnected capabilities: (i) the capacity for critical analysis and employment of AI technologies, (ii) the ability to communicate and collaborate effectively within AI-mediated environments, and (iii) the competence to integrate AI applications meaningfully across domestic and professional spheres. Kong *et al.*

(2021) offer a similarly structured but distinct perspective, identifying three foundational elements: (i) a conceptual understanding of AI systems, (ii) an evaluative assessment of AI technologies, and (iii) the practical application of AI tools to address real-world challenges.

Within higher education settings, previous researchers have developed nuanced interpretations of AI literacy. Park (2016) advances a culturally informed definition that emphasizes adaptive capacity in the face of AI-driven societal transformation, highlighting the importance of critical reflection and future-oriented planning as core competencies. Lee (2021) expands this conceptual territory by introducing relational literacy as a fundamental dimension, encompassing both the ability to establish meaningful connections across temporal and spatial boundaries through advanced technologies such as social media platforms and the capacity to engage productively with various technological agents, including avatars, virtual humans, and AI programs. Kim *et al.* (2022) contribute a process-oriented perspective, defining AI literacy as the integration of conceptual comprehension, practical utilization in everyday contexts, critical evaluation of societal applications, and understanding of AI development and implementation processes. This framework emphasizes the importance of procedural knowledge alongside declarative understanding.

Recent investigations have examined the practical implications and influencing factors of AI literacy across various domains. Shin *et al.* (2022) employed survey methodology to investigate the relationship between AI literacy and user trust, specifically examining how literacy levels affect evaluations of personalized recommendation algorithms. Their findings reveal significant correlations between AI literacy and both perceived reliability and evaluative judgment regarding algorithmic personalization, suggesting that literacy levels substantially influence user experience and technology acceptance.

Hwang *et al.* (2023) developed a digital literacy scale tailored to the era of AI through a systematic, multi-phase process. Drawing on an extensive review of prior digital literacy frameworks and emerging AI literacy scholarship, they proposed 23 preliminary items across four conceptual dimensions: (i) critical comprehension ability, (ii) AI social impact recognition, (iii) AI technology utilization, and (iv) ethical behavior. Exploratory factor analysis on a sample of 318 undergraduates reduced the instrument to 19 items, with all four extracted factors demonstrating acceptable internal consistency (Cronbach's α ranging from 0.78 to 0.85) and a cumulative explanatory power of 62.23%. Subsequent confirmatory factor analysis (CFA) confirmed adequate model fit (chi-square/degrees of freedom ratio

$[\chi^2/df] = 2.56$; goodness-of-fit index = 0.89; comparative fit index [CFI] = 0.91; root mean square error of approximation [RMSEA] = 0.07), and discriminant validity was established through comparisons of average variance extracted (AVE). Beyond its psychometric properties, the scale proved effective in predicting students' perceptions of technology. Hierarchical regression analyses revealed that AI technology utilization ability was the strongest statistical predictor of both perceived usefulness ($\beta = 0.224, p < 0.001$) and perceived ease of use ($\beta = 0.300, p < 0.001$) of AI recommendation services. At the same time, AI social impact recognition contributed to perceived usefulness, and all four sub-factors significantly predicted ease of use. These findings positioned the instrument as a robust, empirically grounded tool for assessing context-specific digital competencies among university populations navigating AI-integrated environments. This capacity made it appropriate for adoption in the present study, which sought to examine comparable dimensions of AI literacy across a larger, cross-institutional sample.

2.2. Research on university students' artificial intelligence literacy

The scholarly landscape of AI literacy has undergone a notable shift from primarily conceptual framework development to empirically grounded measurement and validation studies. This evolution reflects the maturity of the AI literacy field, as researchers move beyond definitional exercises to address practical challenges in assessment. For instance, Wang *et al.* (2023) recognized the pressing need for systematic evaluation of user competencies in AI interaction, particularly given the increasingly pervasive nature of AI technologies in daily life. Their methodological contribution involved developing a comprehensive measurement scale that underwent rigorous validation procedures. The researchers initially developed a 65-item instrument spanning four fundamental domains: perception, use, evaluation, and ethics. Through systematic content validation procedures and extensive survey administration, they refined this framework to 31 items before applying factor analysis, yielding a final validated instrument comprising 12 items.

Carolus *et al.* (2023) approached AI literacy measurement from a distinctly psychological perspective, developing a questionnaire that deliberately incorporates affective and motivational competencies alongside the cognitive and functional skills traditionally emphasized in AI literacy research. Their instrument integrates measures of emotional regulation and learning disposition with conventional assessments of AI knowledge, practical applications, ethical awareness, and developmental capabilities. A particularly noteworthy inclusion is

their measurement of AI self-efficacy, conceptualized as individuals' confidence in their ability to solve problems and engage in continuous learning through AI.

Li and Lee (2024) examined the perspectives of students from non-computer-science majors on the integration of AI into their academic trajectories. Their investigation involved administering an online survey to 177 students from diverse departmental backgrounds during the summer of 2023. The findings revealed that students generally recognized AI's relevance to their academic and professional futures and acknowledged the importance of AI education across disciplinary boundaries. Notably, the discovery that students with prior exposure to AI education demonstrated a greater appreciation for AI convergence opportunities was particularly significant. Conversely, students lacking such foundational experiences encountered substantial difficulties engaging with AI-focused liberal arts courses, highlighting the importance of prerequisite knowledge and preparation. These insights provided valuable guidance for developing inclusive AI convergence curricula responsive to the varied needs of university students beyond the computing disciplines.

Similarly, Lee and Davis (2025) investigated the associations between prior coding experience and age at first AI exposure with levels of understanding, with particular attention to non-STEM majors. This exploratory study found that university students with coding backgrounds demonstrated significantly higher AI literacy than their counterparts without such experience. Interestingly, the age at which students first encountered AI had little effect on their overall perceptions. These findings challenge prevailing assumptions about the necessity of coding skills for AI literacy development and suggest that further investigation is warranted to comprehensively identify the factors shaping AI literacy among students outside computing-related disciplines.

Finally, Li and Lee (2024) conducted a comprehensive examination of university students' perceptions of AI literacy and their educational experiences. Drawing on survey data from 300 participants, they analyzed students' literacy levels, prior instructional exposure, and key factors that influence their understanding of AI. The results indicated high levels of learning interest across the sample, with particularly noteworthy findings regarding the association of prior software (SW) education experience with AI literacy outcomes. Students with SW engineering educational backgrounds demonstrated higher levels of AI knowledge, greater confidence in applying AI technologies, and a more sophisticated understanding of fundamental AI concepts. In contrast, participants with

limited AI educational exposure expressed a clear need for additional learning opportunities and reported a decline in coding proficiency. The study further revealed that students who had engaged with SW education during their K–12 years demonstrated higher performance than those who had received only brief university-level training in mathematics.

These findings underscore the importance of addressing educational inequities and suggest that sustained, early exposure to AI and coding education may enhance students' literacy development and readiness for technological engagement. These emerging empirical investigations collectively signal a disciplinary transition from abstract theoretical development toward evidence-based measurement approaches.

3. Research method

This section describes the methodological procedures used to examine the relationships among university students' AI knowledge, AI tool usage competency, learning interest, attitudes toward the future with AI, and perceived need for AI education. It presents the study participants, survey instrument, and data analysis procedures in detail. Because the study aimed to test both direct and mediated relationships among latent constructs, the research design employed a quantitative survey approach and structural equation modeling (SEM). The section also explains how the measurement model was validated and how multi-group analyses were conducted to compare students with and without prior AI learning experience.

3.1. Study participants

This research examined undergraduate students enrolled at four universities in China. Data were collected through an online survey administered during the summer of 2025. Participation was open to undergraduate students at the participating universities who voluntarily accessed the online questionnaire and provided informed consent before completing the survey. In other words, participation was not limited to students enrolled in a specific course or program; any eligible undergraduate student who agreed to participate in the online survey could complete the questionnaire. A total of 1,500 students initially responded to the survey. After incomplete responses and responses showing highly similar response patterns were excluded, 1,474 valid questionnaires remained for the final analysis. Participation was entirely voluntary, and all respondents' personal information was kept strictly confidential and used solely for academic research purposes.

The final sample of 1,474 undergraduate students represented a diverse range of academic backgrounds

across the participating universities. The gender distribution showed a pronounced female majority, with 68.0% ($n = 1,003$) of participants being female and 32.0% ($n = 471$) male. The academic years showed that freshmen constituted the largest group, at 44.4% ($n = 655$), followed by sophomores at 34.6% ($n = 510$), juniors at 19.1% ($n = 281$), and seniors at 1.9% ($n = 28$).

Participants represented a broad spectrum of academic disciplines, reflecting the interdisciplinary nature of contemporary AI education interests. Engineering majors comprised the largest group at 29.0% ($n = 427$), followed by humanities majors at 23.7% ($n = 350$) and education majors at 20.8% ($n = 307$).

An examination of prior AI learning experiences revealed that 63.6% ($n = 937$) of survey participants had previously received AI-related education. The most common exposure occurred through university-level coursework (35.9%; $n = 529$), with additional participants having received AI instruction through high school SW education programs (13.2%; $n = 195$). Coding and programming experience varied considerably across the sample. Slightly more than one-third of participants (38.1%; $n = 561$) reported experience with text-based programming languages, including Python and Java. However, 50.0% of survey participants ($n = 737$) reported no prior instruction in AI programming, highlighting the diverse AI learning backgrounds represented in the study. Table 1 summarizes the demographic data of survey participants.

“Unplugged education” (Table 1) refers to prior programming-related or computational thinking education conducted without the direct use of computers, programming SW, or digital coding environments. Such activities may include learning basic algorithmic thinking, logical sequencing, problem-solving procedures, or computational concepts through paper-based tasks, cards, games, or classroom-based activities. Although this type of education does not involve coding with SW, it was categorized as programming-related education because it introduces foundational computational thinking concepts. By contrast, “None” indicates that the student had no prior experience with programming-related education, including unplugged education, graphical programming, or text-based programming.

3.2. Survey instrument

This research employed an online survey instrument based on measurement items developed by Hwang *et al.* (2023), who conducted an extensive literature review to identify and validate representative indicators for assessing AI literacy. All items were administered on a five-point Likert scale,

ranging from 1 (strongly disagree) to 5 (strongly agree). Permission to adapt and use the items was obtained from the original authors. For the Chinese version of the items, we followed a translation-back-translation procedure: the original items were translated into Chinese by two independent bilingual researchers, with the translations reconciled into a single forward translation, and then back-translated into English by an independent bilingual translator. Discrepancies were resolved by consensus among the research team to ensure semantic equivalence.

To address potential measurement limitations associated with self-reported questionnaire responses, several procedures were used to assess the instrument's validity and reliability. First, the survey items were adapted from a previously validated AI literacy scale developed by Hwang *et al.* (2023), which provided an initial basis for establishing content validity. Second, the translated items were reviewed by bilingual researchers through a translation-back-translation process to ensure semantic equivalence and conceptual consistency across languages. Third, CFA was conducted to examine the construct validity of the five latent variables used in this study. In addition, standardized factor loadings, composite reliability (CR), AVE, and Cronbach's α coefficients were examined to evaluate convergent validity and internal consistency. Although the questionnaire measured students' perceived knowledge, competencies, interests, and attitudes rather than objective performance, this approach was appropriate for the study's purpose, which was to examine students' perceived demand for AI education and the motivational mechanisms underlying that demand.

The questionnaire incorporated five primary constructs designed to capture distinct dimensions of university students' perceptions and competencies related to AI: (i) interest in learning AI, (ii) perceived need for AI education, (iii) knowledge of AI, (iv) AI tool usage competency, and (v) attitudes toward the future with AI. The interest in learning AI construct assessed participants' curiosity and motivation for exploring AI-related topics, providing insight into their intrinsic engagement with the subject matter. The perceived need for AI education construct reflected participants' evaluations of the importance of incorporating AI instruction within formal educational curricula, capturing their recognition of AI education's institutional value. The AI knowledge construct assessed participants' self-reported understanding of fundamental AI concepts and technologies, providing insight into their perceived competency levels across core technical domains. AI tool usage competency assessed students' confidence and practical ability with AI-powered applications, such as chatbots and machine translation SW. This construct

Table 1. Demographics of survey participants

Category	Frequency (<i>n</i> = 1,474)	Percentage (%)
Gender		
Male	471	32.0
Female	1,003	68.0
Grade		
Freshman	655	44.4
Sophomore	510	34.6
Junior	281	19.1
Senior	28	1.9
Major		
Humanities	350	23.7
Social sciences	30	2.0
Natural sciences	37	2.5
Education	307	20.8
Engineering	427	29.0
Business and economics	219	14.9
Physical education	97	6.6
Arts	7	0.5
Previous AI experience		
Yes	937	63.6
No	537	36.4
Type of AI learning		
Software education at the primary, middle, or high school level	195	13.2
University courses (professional or general education)	529	35.9
Other programs (e.g., online/offline, informal education)	213	14.5
None	537	36.4
Type of programming education		
Unplugged education	88	6.0
Graphical programming (e.g., Scratch, Entry)	88	6.0
Text-based programming (e.g., C, Python, Java)	561	38.1
None	737	50.0
Willingness for future AI education		
Yes	1,301	88.3
No	173	11.7

Abbreviation: AI: Artificial intelligence.

emphasized operational skills, providing a complementary perspective to the knowledge construct. Finally, the attitudes toward the future with AI construct examined students' perspectives on how AI technologies might influence societal development, educational practices, and employment landscapes.

To evaluate the psychometric properties of the measurement model, CFA was conducted to assess the overall model fit and the construct validity of the five latent variables. As presented in Table 2, the model fit indices were $\chi^2/df = 25.749$, RMSEA = 0.10, CFI = 0.832, incremental fit index (IFI) = 0.832, and normed fit index = 0.827. Although the incremental fit indices were below the commonly recommended threshold of 0.90, they were considered alongside the instrument's theoretical basis, the use of previously validated measurement items, standardized factor loadings, CR, AVE, and Cronbach's α coefficients. Therefore, rather than interpreting the model fit as fully satisfactory, the results were treated as indicating a marginally acceptable measurement structure for examining the proposed relationships. This point is acknowledged as a methodological limitation of the study.

Table 2. Results of measurement model fit evaluation

Model	χ^2/df	RMSEA	CFI	IFI	NFI
Measurement model	25.749	0.10	0.832	0.832	0.827

Abbreviations: χ^2 : Chi-square; CFI: Comparative fit index; df: Degrees of freedom; IFI: Incremental fit index; NFI: Normed fit index; RMSEA: Root mean square error of approximation.

Table 3 presents the validity and reliability analyses for each construct in the measurement model. Factor loadings demonstrated generally acceptable psychometric properties, with the majority exceeding 0.80. At the same time, a few items within the "AI tool usage competency" and "attitudes toward the future with AI" constructs showed factor loadings above 0.38. CR values ranged from 0.820 to 0.956, substantially surpassing the recommended threshold of 0.70 and thereby indicating adequate internal consistency across all measured constructs. AVE values spanned from 0.449 to 0.879 across the five constructs.

Although some constructs exhibited AVE values below the conventional cutoff of 0.50 (notably "attitudes toward the future with AI"), the corresponding CR values remained acceptable according to Fornell and Larcker's (1981) established criteria for construct validity. This pattern suggests that, while individual items within specific constructs may capture somewhat diverse aspects

of the underlying latent variable, the overall measurement of the construct remains adequately reliable. Cronbach's α coefficients for all constructs fell within the acceptable-to-high reliability range, ranging from 0.809 to 0.940. These values substantially exceed conventional reliability thresholds, indicating that the measurement instrument demonstrates adequate internal consistency and reliability for assessing students' AI literacy dimensions and related attitudes. The consistently high reliability coefficients across all constructs provide confidence in the instrument's ability to yield stable, dependable measurements of the target constructs within the study sample.

Table 3. Results of validity and reliability

Category	Question	Estimate	CR	AVE	Cronbach's α
Interest in learning AI	1	0.939	0.956	0.879	0.940
	2	0.915			
	3	0.894			
The need for AI education	1	0.912	0.944	0.850	0.928
	2	0.913			
	3	0.877			
Knowledge of AI	1	0.881	0.922	0.799	0.899
	2	0.851			
	3	0.861			
AI tool usage competency	1	0.453	0.868	0.539	0.853
	2	0.450			
	3	0.819			
	4	0.870			
	5	0.876			
	6	0.810			
Attitudes toward the future with AI	1	0.382	0.820	0.449	0.809
	2	0.415			
	3	0.638			
	4	0.738			
	5	0.822			
	6	0.744			

Abbreviations: AI: Artificial intelligence; AVE: Average variance extracted; CR: Composite reliability.

3.3. Data analysis

The data analysis proceeded through several systematic stages to comprehensively examine the research questions. Initially, the measurement instrument's validity and reliability were rigorously assessed. CFA was employed to

evaluate construct validity across the five latent variables, examining model fit indices, standardized factor loadings, AVE, CR, and Cronbach's α coefficients. All constructs demonstrated acceptable levels of convergent validity and internal consistency, thereby establishing a solid foundation for subsequent analyses.

Following psychometric validation, descriptive statistics were computed to examine the overall distribution and central tendencies of participants' responses across all measured constructs. This preliminary analysis provided essential insights into students' perceptions, self-reported knowledge levels, and attitudes toward AI and perceived needs for AI education, establishing a baseline understanding of the sample characteristics. The primary analytical approach involved SEM to examine relationships among variables within the proposed model. The model specification positioned the need for AI education as the dependent variable, with knowledge of AI and AI tool usage competency as independent variables. Two mediating variables—attitudes toward the future with AI and interest in learning AI—were incorporated to explore their indirect effects on the outcome variable.

The SEM analysis used maximum likelihood estimation procedures, with overall model fit assessed using multiple indices, including χ^2/df , RMSEA, CFI, and IFI. The final analytical stage involved multi-group analysis to investigate whether structural relationships varied between participants with and without prior AI learning experience. Measurement invariance testing was conducted initially to assess construct comparability across groups, ensuring that observed differences could be interpreted as reflecting group variations rather than measurement artifacts. Subsequently, path coefficients were compared systematically to identify potential differences in relationship strength or direction among constructs. This comparative analysis provided a deeper understanding of how prior AI exposure is associated with differences in students' educational needs, knowledge development, and practical competency acquisition within the AI domain.

4. Survey results

This section presents the results of the empirical analyses conducted to address the study's objectives. It begins by reporting descriptive statistics to identify the current status of university students' AI literacy across the five measured constructs. It then presents the results of the SEM analysis, focusing on the direct and indirect pathways through which AI knowledge and AI tool usage competency relate to students' perceived need for AI education. Finally, the section reports the results of the multi-group analyses, highlighting how these relationships differ across students' prior AI learning experience.

4.1. Artificial intelligence literacy among university students

Descriptive statistics were computed to examine university students' current AI literacy levels across five key domains: interest in learning AI, need for AI education, knowledge of AI, AI tool usage competency, and attitudes toward the future with AI.

As presented in Table 4, students demonstrated considerable enthusiasm for AI learning opportunities, with interest in learning AI receiving relatively high ratings across all measured items. The highest mean score was observed for the statement "I want to receive education related to AI" (mean [M] = 3.84, standard deviation [SD] = 0.829), indicating a high level of demand for formal AI instruction. Students similarly expressed substantial interest in acquiring core AI skills (M = 3.78, SD = 0.867) and demonstrated general curiosity about AI topics (M = 3.79, SD = 0.848). These findings suggest that students show high receptiveness to AI-related educational opportunities and recognize their future relevance.

Regarding institutional responsibility for AI instruction, students expressed positive perceptions of AI education across university settings. Participants expressed support for the inclusion of AI content throughout higher education, with strong agreement for statements such as "AI should be taught in all university departments" (M = 3.63, SD = 0.879) and "education related to AI should be part of the regular university curriculum" (M = 3.63, SD = 0.870). Students similarly supported AI technical training, rating "universities should teach AI-related coding skills to all students" at comparable levels (M = 3.61, SD = 0.865). These responses suggest that students perceive an institutional responsibility for equipping students with comprehensive AI competencies, regardless of their disciplinary focus.

Self-assessed knowledge of AI revealed moderate ratings, reflecting a potential disconnect between interest and perceived knowledge levels. While students expressed confidence in their ability to comprehend AI-related writings (M = 3.53, SD = 0.846), their perceived overall knowledge levels were considerably lower, as evidenced by their responses to the question "I am knowledgeable about AI" (M = 3.27, SD = 0.894). Students also provided moderate self-assessments of their capacity to articulate informed opinions about AI (M = 3.44, SD = 0.841). These patterns suggest a notable gap between enthusiasm for AI learning and self-perceived AI knowledge, highlighting the potential importance of systematic AI education initiatives. The demonstrated competency in using AI tools varied across tools with different complexity and technical requirements.

Table 4. Descriptive statistics of current artificial intelligence literacy levels

Category	Question	Mean	SD
Interest in learning AI	I am interested in AI	3.79	0.848
	I want to learn the core knowledge and skills of AI	3.78	0.867
	I want to receive education related to AI	3.84	0.829
The need for AI education	AI should be taught in all university departments	3.63	0.879
	Education related to AI should be part of the regular university curriculum	3.63	0.870
	Universities should teach AI-related coding skills to all students	3.61	0.865
Knowledge of AI	I can understand the content of writings or articles about AI	3.53	0.846
	I am knowledgeable about AI	3.27	0.894
	I can express my opinion about AI	3.44	0.841
AI tool use competency	I can use machine translation services to write in English	3.75	0.860
	I can interact with chatbots	3.75	0.859
	I can use a translation device to communicate in a foreign language	3.76	0.844
	I can use an AI speaker	3.83	0.851
	I can do block coding using tools such as Scratch or Entry	3.00	1.108
	I can do basic coding using Python	3.06	1.117
Attitudes toward the future with AI	AI will create more jobs in the future than it does now	3.58	0.898
	AI will make people happier	3.71	0.822
	There will be human jobs that AI cannot replace	3.95	0.865
	AI will destroy human jobs	2.25	0.871
	I am concerned that AI might surpass human intelligence	2.77	0.992
	AI will pose a threat to human survival	2.79	1.018

Abbreviations: AI: Artificial intelligence; SD: Standard deviation.

Students reported relatively high confidence levels when using AI applications, including machine translation services ($M = 3.75$, $SD = 0.860$), chatbots ($M = 3.75$, $SD = 0.859$), translation devices ($M = 3.76$, $SD = 0.844$), and AI speakers ($M = 3.83$, $SD = 0.851$). However, programming-related competencies received substantially lower ratings. Block coding using platforms such as Scratch or Entry was rated at a mean of 3.00 ($SD = 1.108$), while Python programming competency was similarly modest at a mean of 3.06 ($SD = 1.117$), indicating lower self-perceived proficiency with development tools and programming environments.

Students' attitudes toward the future with AI reflected a predominantly optimistic yet cautious perspective. Participants expressed confidence that AI would not completely replace human employment ($M = 3.95$, $SD = 0.865$) and believed in AI's potential to enhance human well-being ($M = 3.71$, $SD = 0.822$). They also demonstrated moderate optimism regarding AI's capacity to generate more employment opportunities than it eliminates ($M = 3.58$, $SD = 0.898$). Conversely, more pessimistic projections received relatively low endorsement. Concerns about AI destroying human jobs ($M = 2.25$, $SD = 0.871$), AI surpassing human intelligence ($M = 2.77$, $SD = 0.992$),

and AI threatening human survival ($M = 2.79$, $SD = 1.018$) all received limited agreement. These findings suggest that while students acknowledge the potential risks associated with AI development, they generally maintain a positive outlook on AI's future societal integration.

Table 4 shows descriptive statistics of current AI literacy levels.

4.2. Mediation effect

Structural equation modeling was employed to investigate whether attitudes toward the future with AI and interest in learning AI mediated the relationships between the independent variables (knowledge of AI and AI tool usage competency) and the outcome variable (need for AI education), as illustrated in Figure 1. The significance of direct, indirect, and total effects was evaluated through bootstrapping procedures with 95% confidence intervals. The results of the direct, indirect, total, and mediation effects are presented in Table 5.

The analysis revealed a significant total effect of AI knowledge on the need for AI education ($\beta = 0.647$, standard error [SE] = 0.048, $p < 0.001$). The direct effect remained statistically significant ($\beta = 0.401$, SE = 0.051, $p < 0.001$), indicating that students who perceive themselves

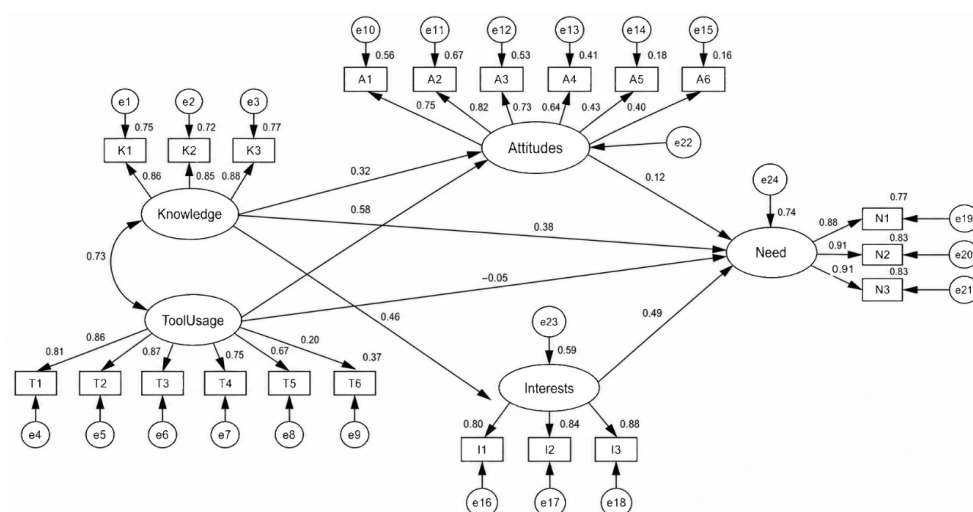


Figure 1. Structural equation modeling

as more knowledgeable about AI tend to report a greater perceived need for incorporating AI instruction into university curricula. Examination of indirect effects revealed differential mediation patterns across the two proposed pathways. The mediating pathway through attitudes toward the future with AI demonstrated only marginal significance ($\beta = 0.038$, $SE = 0.020$, $p = 0.051$), failing to reach conventional statistical significance at the 0.05 level.

Conversely, the pathway mediated by interest in learning AI was statistically significant ($\beta = 0.226$, $SE = 0.030$, $p < 0.001$), suggesting that students' AI knowledge is positively associated with their learning interest, which, in turn, is associated with their perceived need for formal AI education. The total indirect effect proved statistically significant ($\beta = 0.265$, $SE = 0.039$, $p < 0.001$), confirming partial mediation primarily through learning interest rather than future-oriented attitudes. For AI tool usage competency, the total effect on need for AI education was statistically significant ($\beta = 0.196$, $SE = 0.047$, $p < 0.001$).

However, the direct effect was negative and non-significant ($\beta = -0.084$, $SE = 0.091$, $p = 0.312$), indicating that students' practical experience with AI tools is not directly associated with a higher perceived educational necessity. Analysis of indirect pathways revealed that mediation through attitudes toward the future with AI remained non-significant ($\beta = 0.070$, $SE = 0.039$, $p = 0.051$), falling just short of the significance threshold.

In contrast, the pathway mediated by interest in learning AI was statistically significant ($\beta = 0.180$, $SE =$

0.033 , $p < 0.001$). The total indirect effect was statistically significant ($\beta = 0.251$, $SE = 0.060$, $p < 0.001$), indicating complete mediation, with the indirect association primarily operating through learning interest, while the attitude-based pathway remained statistically non-significant. These findings suggest that the relationships between AI competencies and educational needs are primarily explained by motivational pathways centered on learning interest. At the same time, future-oriented attitudes show a weaker mediating association in these relationships.

4.3. Comparison results of multiple groups

To explore potential group differences associated with students' prior experience with AI learning, a multi-group analysis was conducted. Participants were categorized into two groups: those with AI-related learning experience and those without. The comparison examined both overall model fit across groups and path-level differences to identify potential variations in structural relationships.

As shown in Table 6, a series of nested model comparisons was conducted to examine measurement and structural invariance across the two groups. The unconstrained model, which imposed no equality constraints, demonstrated comparatively better fit indices ($CFI = 0.821$, $RMSEA = 0.094$). When measurement weights (factor loadings) were constrained to be equal across groups, the model yielded similar fit statistics ($CFI = 0.820$, $RMSEA = 0.092$).

However, the χ^2 difference test revealed a significant difference ($\Delta\chi^2 [16] = 48.731$, $p < 0.001$), suggesting that

Table 5. Results of direct, indirect, total, and mediation effects

Path	Effect	β	SE	p	95% CI LB	95% CI UB
Knowledge → need	Total effect	0.647	0.048	0.004**	0.552	0.745
	Direct effect	0.401	0.051	0.004**	0.298	0.478
	Knowledge → attitudes → need	0.038	0.020	0.051	−0.001	0.081
	Knowledge → interests → need	0.226	0.030	0.004**	0.171	0.282
	Indirect effect	0.265	0.039	0.004**	0.188	0.339
Tool use → need	Total effect	0.196	0.047	0.004**	0.098	0.282
	Direct effect	−0.084	0.091	0.312	−0.171	0.065
	Tool use → attitudes → need	0.070	0.039	0.051	−0.002	0.152
	Tool use → interests → need	0.180	0.033	0.004**	0.123	0.248
	Indirect effect	0.251	0.060	0.004**	0.144	0.373

Notes: β = Standardized coefficient; 95% CI = 95% confidence interval (bias-corrected bootstrap with 5,000 resamples). ** $p < 0.01$ indicates statistical significance.

Abbreviations: CI: Confidence interval; LB: Lower bound; SE: Standard error; UB: Upper bound.

Table 6. Comparison of multiple groups with and without artificial intelligence learning experience

Model	χ^2	df	χ^2/df	NFI	IFI	CFI	RMSEA
Unconstrained	2,706.721	180	15.037	0.826	0.835	0.835	0.124
Measurement weights	2,332.944	180	12.961	0.788	0.801	0.801	0.139
Structural weights	5,039.760	360	13.999	0.810	0.821	0.821	0.094
Structural covariances	5,088.491	376	13.533	0.808	0.820	0.820	0.092
Structural residuals	5,092.576	384	13.262	0.808	0.820	0.820	0.091

Abbreviations: χ^2 : Chi-square; CFI: Comparative fit index; df: Degrees of freedom; IFI: Incremental fit index; NFI: Normed fit index; RMSEA: Root mean square error of approximation.

full measurement invariance was not achieved between the groups. Further constraining structural paths to equality across groups resulted in additional significant model deterioration ($\Delta\chi^2 [24] = 52.816, p = 0.001$), indicating that some structural relationships may differ between students with and without prior AI learning experience. These findings suggest that previous exposure to AI education is associated with differences in the relationships among AI literacy constructs and educational needs. The significant χ^2 differences across both measurement and structural models indicate that students' prior AI learning experiences are associated with differences in the relationships among AI-related concepts and educational opportunities. This finding suggests that educational interventions and assessments could consider students'

experiential backgrounds when designing AI literacy programs or interpreting literacy assessments.

Table 7 presents a detailed comparison of standardized path coefficients across the two groups, revealing both consistent patterns and differences in the effects of prior AI learning experience. In both groups, knowledge of AI significantly predicted attitudes toward AI and interest in learning AI, although the relationships were slightly stronger in the group with prior AI learning experience. For instance, the effect of knowledge of AI on interest in learning AI was greater among students with experience ($\beta = 0.497$) than among those without ($\beta = 0.451$). However, the critical ratio (−0.438) was not statistically significant.

A particularly noteworthy finding emerged regarding the relationship between tool usage and educational need.

Table 7. Comparison of path coefficient results with and without artificial intelligence learning experience

Path	With AI learning experience	Without an AI learning experience	Critical ratio
Knowledge → attitudes	0.324**	0.292**	−0.220
Knowledge → interests	0.497**	0.451**	−0.438
Knowledge → need	0.357**	0.395**	0.501
Tool usage → attitudes	0.581**	0.594**	1.973*
Tool usage → interests	0.340**	0.391**	2.351*
Tool usage → need	−0.080	−0.023	0.549
Attitudes → need	0.179**	0.060	−1.612
Interests → need	0.476**	0.508**	0.534

Note: * $p < 0.05$ and ** $p < 0.001$ indicate statistical significance.
Abbreviation: AI: Artificial intelligence.

The path from AI tool usage competency to the need for AI education was negative in both groups and statistically non-significant ($\beta = -0.080$ and $\beta = -0.023$, respectively), suggesting that tool use competence alone was not directly associated with educational demand, regardless of students' prior experience levels. This pattern suggests that familiarity with practical AI tools may not be sufficient to increase perceived educational necessity, possibly due to students' perceptions that their existing tool use abilities are adequate or limited awareness of the additional knowledge required for AI learning.

However, significant differences emerged in several mediating pathways between the groups. The relationship between attitudes toward the future with AI and the need for AI education was stronger among students with AI learning experience ($\beta = 0.179$) than among those without such experience ($\beta = 0.060$). Although this difference approached statistical significance, the critical ratio (−1.612) did not exceed the threshold for significance. More notably, the indirect path from AI tool usage competency through interest in learning AI differed statistically between the two groups, with the non-experienced group showing higher coefficients ($\beta = 0.391$) than the experienced group ($\beta = 0.340$), yielding a significant critical ratio (2.351). This finding suggests that students without prior AI experience showed a stronger association between AI tool usage competency and interest in learning AI when forming educational expectations.

In contrast, experienced students may have more established learning frameworks that are less influenced by tool interaction. The relationship between knowledge of AI and the need for AI education remained consistently significant across both groups ($\beta = 0.357$ for experienced students; $\beta = 0.395$ for non-experienced students),

indicating that perceived knowledge was consistently associated with educational need, regardless of experiential background. This consistency suggests that self-assessed knowledge represents an important factor associated with educational motivation that transcends specific learning histories.

5. Discussion

This study investigated two key research questions regarding university students' AI literacy and educational demands. The first research question addressed how students' AI knowledge and AI tool usage competencies influence their perceived need for AI education, while the second question addressed the mediating roles of learning interest and future attitudes in these relationships. Our results reveal complex pathways that challenge conventional assumptions about AI literacy development, providing new insights into the underlying motivations for AI education.

5.1. Artificial intelligence competencies on educational demand (RQ1)

Our analysis demonstrates that AI knowledge and AI tool usage competencies influence educational demand through distinct mechanisms. Students' foundational AI knowledge has both substantial direct effects on educational demand ($\beta = 0.401$, $p < 0.001$) and significant indirect pathways, confirming that conceptual understanding reliably predicts educational motivation. This finding aligns with previous research by Lee *et al.* (2024), who reported that students with stronger AI knowledge backgrounds demonstrated greater confidence and educational engagement. However, the relationship between AI tool usage competency and educational demand presents a more complex result. Unlike

knowledge, practical AI tool competency demonstrates no direct relationship with educational needs ($\beta = -0.084$, $p = 0.312$), suggesting that hands-on experience alone does not automatically translate into a perceived educational necessity. This counterintuitive finding contradicts the common assumption that exposure to AI tools naturally generates an appreciation for formal AI education.

The negative coefficient suggests that familiarity with AI tools may not significantly increase the perceived need for AI education. This pattern resonates with the framework proposed by Kong *et al.* (2021), which distinguishes between practical utilization and conceptual understanding of AI education. Our results indicate that while university students can develop operational AI skills through tool use, experiential learning alone is insufficient to generate educational demand unless it is coupled with deeper intellectual engagement. The complete absence of direct effects of AI tool use on educational needs indicates that practical competency must be channeled through other psychological mechanisms to influence students' motivation to learn AI. The differential effects of knowledge versus AI tool usage competencies have important implications for how educators in higher education conceptualize AI literacy development. While cognitive understanding provides a stable foundation for educational motivation, practical AI skills require additional motivational frameworks to translate into students' demand for AI learning. This finding suggests that AI literacy programs cannot rely solely on exposure to AI tools; instead, they must deliberately integrate conceptual learning with hands-on experiences to maximize their educational impact.

5.2. The primacy of learning interest (RQ2)

The second research question addressed the mediating roles of learning interest and future attitudes in connecting AI competencies to educational demand. Our results show a clear hierarchy in mediating effectiveness, with learning interest serving as the primary pathway while future-oriented attitudes play a substantially weaker role. Learning interest emerges as the dominant mediator for both AI knowledge ($\beta = 0.226$, $p < 0.001$) and AI tool usage competency ($\beta = 0.181$, $p < 0.001$). This pattern suggests that students' immediate curiosity and engagement with AI education are the most significant drivers of educational motivation. The strength of the learning interest-mediated pathways suggests that intrinsic motivation and intellectual curiosity are more influential than utilitarian considerations, such as future benefits or career prospects.

Additionally, attitudes toward AI's future potential exhibit weak and inconsistent mediating effects. For AI

knowledge, the pathway through future attitudes shows only marginal significance ($\beta = 0.038$, $p = 0.051$), while for AI tool usage competency, this pathway remains non-significant ($\beta = 0.070$, $p = 0.054$). These findings challenge prevailing assumptions about the motivational power of future-oriented thinking in educational contexts. While university students may hold positive attitudes toward AI's societal potential, these views do not translate into a concrete motivation to learn about AI. This differential mediating pattern has important theoretical implications.

For instance, Carolus *et al.* (2023) emphasized the importance of psychological competencies in AI literacy assessment, and our findings extend this perspective by identifying specific affective mechanisms that bridge these competencies with AI educational demand. The prominence of learning interest over future attitudes suggests that AI literacy development could be fundamentally driven by present-centered engagement with AI rather than by future-oriented planning. The weakness of attitude-based mediation is particularly noteworthy given the emphasis that many educational AI programs place on highlighting AI's future importance. Our results suggest that while awareness of AI's societal implications remains valuable, such awareness is less directly linked to educational motivation than immediate engagement and curiosity. This finding indicates that educators in higher education could achieve greater impact by focusing on fostering present-centered AI interest rather than relying primarily on future-oriented rationales for AI education.

5.3. Experience-dependent artificial intelligence learning pathways

Our multi-group analysis reveals that university students' prior experience with AI fundamentally alters the relationships among AI competencies, interest, and educational demand. Students with and without prior exposure to AI follow distinctly different pathways to educational motivation, each with unique characteristics and pedagogical implications. Students without prior AI experience show significantly greater sensitivity to AI tool use in developing learning interest ($\beta = 0.391$ vs. $\beta = 0.340$; $CR = 2.351$, $p < 0.05$). This pattern suggests that hands-on tool interactions serve as critical motivational catalysts for novice AI learners, providing tangible engagement opportunities that translate into deeper educational interest. For these students, practical experience appears to compensate for the lack of established knowledge frameworks by offering concrete entry points into AI learning.

Conversely, students with prior AI experience exhibit more stable knowledge-to-interest pathways ($\beta = 0.497$

vs. 0.451), suggesting that formal AI learning experiences foster more robust cognitive and affective development. These students appear less dependent on immediate experiential triggers and can draw more effectively on their existing conceptual foundations to generate AI educational motivation. This finding helps reconcile contradictory results in recent research. For instance, Li and Lee (2024) found that students with prior AI exposure were more likely to recognize educational value. At the same time, Lee and Davis (2025) demonstrated that coding experience enhanced AI literacy among non-STEM majors.

Our multi-group analysis provides a critical explanation: experienced AI learners rely more heavily on established knowledge frameworks, while inexperienced AI learners depend more on AI tool-mediated interest development. The differential pathways have important implications for differentiated pedagogy in AI education. Novice AI learners could benefit from AI tool-rich, experiential introductions that leverage their sensitivity to hands-on engagement. Experienced AI learners could respond better to conceptually driven AI instruction that builds upon their existing knowledge foundations. These results suggest that higher education institutions should implement diagnostic AI assessments to identify students' levels of AI learning experience and tailor pedagogical approaches accordingly.

6. Conclusion

This study examined university students' perceived need for AI education by analyzing the relationships among AI knowledge, AI tool use competency, learning interest, and attitudes toward the future with AI. The findings indicate that students' self-perceived AI knowledge was positively associated with their demand for AI education both directly and indirectly. In contrast, AI tool use competency was related to educational demand mainly through learning interest. These results suggest that conceptual understanding and motivational engagement play a more central role in shaping students' perceived need for AI education than practical tool familiarity alone. In particular, learning interest emerged as a key mediating factor, indicating that students are more likely to recognize the value of formal AI education when their engagement with AI is accompanied by curiosity and a desire for further learning.

The study contributes to the growing body of research on AI literacy in higher education by showing that both cognitive and affective factors shape students' educational demand for AI. It also highlights the importance of considering students' prior AI learning experience when designing AI literacy programs, as students with and without prior AI experience may develop educational motivation

through different pathways. These findings suggest that higher education institutions should move beyond simple exposure to AI tools and develop differentiated curricula that combine foundational AI knowledge, meaningful tool-based activities, and structured opportunities to cultivate students' interest in AI learning. Such an approach may support more inclusive and effective AI literacy education for students across diverse academic backgrounds.

Despite its contributions, this study has several limitations. First, the reliance on self-reported data may limit the extent to which the findings reflect university students' actual AI knowledge or AI tool competency. Although self-assessment measures are valuable for capturing students' perceived competencies, interests, and attitudes, they may not fully correspond to objectively measured knowledge, practical skills, or depth of understanding. Therefore, the findings should be interpreted as reflecting students' self-reported perceptions rather than direct evidence of their actual AI literacy or performance. Future research should address this limitation by incorporating performance-based AI assessments, interviews, observational data, or other qualitative methods to triangulate the findings and provide a more comprehensive evaluation of students' AI literacy.

Another limitation concerns the sample's demographic composition and representativeness. Although the study included a large number of undergraduate students from multiple universities, the sample was not designed to represent the entire population of university students in proportion to their numbers. Female students and first- and second-year students were relatively overrepresented, which appears to reflect the institutional and instructional contexts in which the data were collected. In particular, several participating institutions had a strong orientation toward teacher education and related academic programs, where female students were more highly represented among the accessible student population. In addition, the survey was distributed mainly through general education courses, which freshmen and sophomores commonly take as part of their foundational university curriculum. Therefore, the findings should be interpreted with caution when generalizing them to all Korean undergraduate students. Future research should employ more balanced, stratified sampling across gender, academic year, major, and institutional type to enhance the representativeness and generalizability of the findings.

In addition, the measurement model showed suboptimal but acceptable fit, as several model fit indices, including CFI, IFI, and normed fit index, were below the commonly recommended cutoff values. Although the reliability and validity indicators provided partial support

for the measurement structure, future studies should further refine the questionnaire items and retest the model using additional samples to improve model fit and strengthen construct validity.

Future research should investigate the longitudinal effects of AI education, examining how university students' knowledge, interest, and attitudes evolve throughout their educational experiences and how these changes influence learning outcomes. Such longitudinal studies could provide valuable insights into the stability of the identified mediation pathways and the long-term influence of different AI educational approaches. Lastly, this study primarily focused on individual-level factors, while giving limited attention to contextual influences that may shape university students' AI literacy development. Investigating the role of instructor support, peer collaboration, and institutional policies in shaping students' AI literacy could offer a more comprehensive understanding of educational ecosystems in the context of AI integration. These contextual factors may significantly moderate the relationships identified in this study and could provide meaningful guidance for institutional-level interventions and policy development.

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Conflict of interest

There is no conflict of interest among authors.

Author contributions

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Ethics approval and consent to participate

This study was approved by the Institutional Review Board of Changwon National University, Republic of Korea (Approval No.: 7001066-202512-HR-088).

Consent for publication

All participants provided written informed consent before participating in the study.

Availability of data

Data are available from the corresponding author upon reasonable request.

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