Artificial intelligence literacy among Chinese Master of Education students: Current situation, influencing factors and generative pathways

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As future high-quality educators, Master of Education students' levels of artificial intelligence literacy (AIL) directly influence the quality of future talent cultivation. The study, grounded in the technological pedagogical content knowledge framework and the unified theory of acceptance and use of technology, employed covariance-based structural equation modelling and fuzzy-set qualitative comparative analysis to empirically examine the AIL of 1,575 Master of Education students in China. The findings reveal that the overall level of AIL is moderate. Students scored lower in knowledge, competence and thinking dimensions than in attitudes and ethics. Significant differences in AIL were observed across gender, institutional type, affiliation and regional location. Effort expectancy, performance expectancy, behavioural intention, facilitating conditions, social influence and technological pedagogical content knowledge all showed significant positive effects on AIL. Moreover, AIL is shaped by the complex interplay of multiple influencing factors. The high AIL level includes three generative paths: external support-driven, cognitive-social synergy and self-directed development. Conversely, the low AIL level includes two generative paths: weak cognitive ability and motivation-social deficit.

Implications for practice or policy:
- Universities should require AIL in all Master of Education programmes through discipline-integrated modules.
- Governments must reduce regional disparities by funding digital infrastructure and collaborative platforms for under-resourced institutions.
- Universities should tackle gender gaps via targeted support, peer mentoring and inclusive AI teaching practices.
- Universities should partner with technology companies to develop adaptable, secure AI tools suited to varied disciplines and teaching contexts.

Keywords: artificial intelligence literacy (AIL), Master of Education, current situation, influencing factors, generative pathways

Introduction

Amid the intertwined evolution of new scientific, technological and industrial revolutions, education is undergoing profound transformation (Bonfield et al., 2020). The rapid, iterative advancement and disruptive integration of modern information technologies – such as artificial intelligence (AI), big data and the metaverse – are reshaping educational ecosystems, reconfiguring teaching environments and optimising governance models (Celik et al., 2024; Weng et al., 2024). These innovations drive high-quality, equitable educational development (Ji et al., 2023). As designers and implementers of intelligent technology, teachers play a pivotal role. Their AI literacy (AIL) influences both the direction and quality of educational transformation. Governments and education authorities worldwide are actively building AI-empowered teaching teams and advancing AI-driven reforms (Guo & Xu, 2025). As future educators, Master of Education (MEd) students bear dual responsibilities as learners and future teachers. Their AIL is crucial for developing competence in intelligent teaching and shaping the next generation of talent (Abykenova et al., 2016; Yuan, 2015), ultimately affecting the quality of future talent cultivation.

AI applications in education – such as intelligent tutoring systems, personalised learning platforms and educational data analytics – place multidimensional demands on MEd students' AIL, including technological understanding, practical competence and ethical awareness. Yet, many countries lack systematic frameworks for cultivating AIL in MEd programmes (Chee et al., 2024; Pratiwi et al., 2025; Tillmanns et al., 2025). Research has largely focused on in-service teachers or K–12 students, leaving MEd students under-studied (Casal-Otero et al., 2023; Chiu et al., 2024; Sperling et al., 2024). Questions regarding the current status, influencing factors and pathways of AIL remain insufficiently addressed.

To bridge this gap, this study integrated the technological pedagogical content knowledge (TPACK) framework (Mishra & Koehler, 2006) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), employing both covariance-based structural equation modelling (CB-SEM) (Hair et al., 2017) and fuzzy-set qualitative comparative analysis (fsQCA) (Fiss, 2011). Using data from 1,575 MEd students in China, the study aims to understand their AIL, identify key influencing factors and explore effective generative pathways, providing theoretical and practical guidance. Accordingly, the study addressed the following research questions (RQs):

- RQ1: What is the current level of AIL among MEd students, and are there differences across demographic groups?
- RQ2: What are the key factors influencing the AIL of MEd students?
- RQ3: What generative pathways explain variations in AIL among MEd students?

Literature review

AIL

The rapid advancement of AI technologies has profoundly reshaped operations across diverse sectors, including education (Mishra et al., 2025). In higher education, AI has transformed knowledge creation, teaching practices and assessment systems, driving systemic reform in educational goals, content, pedagogy and evaluation (Michel-Villarreal et al., 2023; Zawacki-Richter et al., 2019). These changes aim to cultivate innovative talents capable of thriving in the intelligent era. Against this backdrop, AIL has emerged as a core construct for understanding and responding to AI-driven educational transformation (Ning et al., 2025). Early studies often viewed AIL as a unidimensional construct emphasising knowledge (Celik et al., 2022). Later research reconceptualised it as multidimensional – typically including AI knowledge, skills and attitudes (Kim et al., 2021; Wong et al., 2020) – and further expanded frameworks to include ethical or thinking dimensions (Newman-Griffis, 2025; Ren & Luo, 2024). Building on these perspectives, this study defines MEd students' AIL as an integrated competence encompassing AI knowledge (AIK), AI competence (AIC), AI attitude (AIA), AI thinking (AIT) and AI ethics (AIE), developed through continuous learning and reflective practice to meet the professional demands of the intelligent era.

AIL enables MEd students to develop innovative thinking, engage in deep learning and adapt to intelligent environments, fostering collaboration with AI and creative self-development (Chiu et al., 2024; Lim et al., 2023). Studies have confirmed that educators' AIL levels are positively associated with teaching quality (Pei et al., 2025). Educators with higher AIL can leverage AI more effectively to enhance students' learning outcomes and satisfaction (Chiu et al., 2023; Zhao & Huang, 2025). Conversely, inadequate AIL may lead to alienation or technological overdependence, resulting in digital marginalisation (Wijaya et al., 2024). Although the importance of AIL in higher education and teacher preparation has been widely recognised, empirical research has largely focused on K–12 contexts (Casal-Otero et al., 2023; Sperling et al., 2024). Little is known about MEd students' AIL, particularly regarding its influencing factors from both symmetric and asymmetric analytical perspectives. As AI continues to reshape the educational ecosystem, systematically investigating the AIL levels and generative pathways of MEd students is crucial for improving teacher education systems and advancing the intelligent transformation of higher education.

UTAUT

UTAUT is a widely adopted framework in information technology research (Im et al., 2011). Proposed by Venkatesh et al. (2003), it integrates eight classical models to explain factors influencing individuals' technology acceptance and adoption behaviours. UTAUT identifies four core constructs – performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC) – as predictors of behavioural intention (BI) and actual use. Specifically, PE reflects the perceived usefulness of a technology; EE denotes its perceived ease of use; SI captures perceived social pressure to use it; and FC represents the perceived availability of technical and organisational support. Although the original model suggested that PE, EE, and SI directly predict BI, later studies in educational settings have shown that FC can also exert a significant positive effect on BI (Wangdi et al., 2023; Yeop et al., 2019). Accordingly, this study proposed the following hypotheses:

- H1: PE significantly and positively influences BI.
- H2: EE significantly and positively influences BI.
- H3: SI significantly and positively influences BI.
- H4: FC significantly and positively influences BI.

From a developmental perspective, MEd students' AIL relies on continuous learning and sustained engagement with intelligent technologies. Its formation is shaped by factors such as individuals' prior knowledge, willingness to adopt new technologies, peer influence and institutional support (Pei et al., 2025; Wang et al., 2024). Research has indicated that teachers' acceptance of technology is a prerequisite for developing their information literacy (Li, 2021). Similarly, Cengiz and Peker (2025) found that insufficient PE, EE, SI and FC hinder students' AI capabilities, while higher technology acceptance correlates with stronger AIL. Tram (2024) also confirmed the explanatory power of the UTAUT model in understanding language teachers' AI adoption behaviours. Therefore, this study posited that UTAUT provides a suitable theoretical basis for explaining the influencing factors of AIL among MEd students. Accordingly, this study proposed the following hypotheses:

- H5: PE significantly and positively influences AIL.
- H6: EE significantly and positively influences AIL.
- H7: SI significantly and positively influences AIL.
- H8: FC significantly and positively influences AIL.
- H9: BI significantly and positively influences AIL

TPACK

The TPACK framework, proposed by Mishra and Koehler (2006), is widely recognised as a key competency framework that supports teachers' effective integration of technology in education (Koh et al., 2013). Recent studies have extended TPACK research to explore its influence on various digital literacies, such as information, data and media literacy, consistently confirming its positive predictive effects (Chen, 2023; Ning et al., 2024; Tang et al., 2024). For MEd students, the cultivation of AIL is inherently linked to their mastery of technology-related pedagogical and content knowledge. Therefore, this study hypothesised that:

- H10: TPACK significantly and positively influences AIL.

Several studies have further integrated TPACK with the UTAUT model to enhance explanatory power across educational contexts. Tang et al. (2024) used a TPACK–UTAUT framework to examine digital teaching among elementary mathematics teachers and found that TPACK positively affected PE, EE, SI, FC and BI. Similarly, Al-Adwan et al. (2024) revealed that FC significantly influenced teachers' TPACK, which in turn positively impacted PE and EE. Bai et al. (2024) also demonstrated that TPACK enhances teachers' technology self-efficacy, attitudes and BI. Based on these findings, the following hypotheses were proposed:

- H11: TPACK significantly and positively influences PE.
- H12: TPACK significantly and positively influences EE.
- H13: TPACK significantly and positively influences BI.
- H14: FC significantly and positively influences TPACK.

Method

Data collection

The data were collected through Wenjuanxing, a professional online survey platform widely used for academic research and data collection in China. The platform supports questionnaire design, distribution, real-time response monitoring and automated statistical analysis. The survey covered a range of universities, including Central China Normal University, Hubei University, Huanggang Normal University, Kashgar University and Huzhou University, ensuring good representativeness across different regions and institutional types. Participation in the study was entirely voluntary. All participants were informed about the purpose of the research and provided their informed consent prior to completing the questionnaire. Responses were anonymous and confidential, and all data were used solely for academic purposes in accordance with research ethics. A total of 1,887 questionnaires were collected. After excluding 312 invalid responses such as those completed in an extremely short time or with identical answers throughout, 1,575 valid responses were retained, yielding an effective response rate of 83.47%. Among the valid respondents, 40.25% were male and 59.75% were female. Students from centrally administered universities by the Ministry of Education or other national ministries accounted for 28.64%, while those from provincial universities accounted for 71.36%. In China's higher education system, centrally administered universities usually have stronger resources and national prestige, whereas provincial universities, managed by local governments, constitute the majority and focus on regional talent cultivation (Dong et al., 2022; Yang & Wang, 2020). A total of 65.91% of students studied at normal universities, which focus on teacher education, educational sciences and foundational disciplines, whereas 34.09% were from comprehensive universities that offer a broader range of academic programmes beyond education. Geographically, 31.24% of students were enrolled in universities located in eastern China, 51.43 % in central China and 17.33% in western China. These regional divisions reflect China's geographic and socio-economic structure, which influence the distribution of educational resources.

Instruments

The Artificial Intelligence Literacy Scale for MEd students, adapted from Ning et al. (2025) and Younis (2025), divided AIL into five dimensions – AIA, AIK, AIC, AIT and AIE – with six items for each dimension. The scale employed a 5-point Likert scoring method, where higher scores indicated higher levels of AIL. Exploratory factor analysis (EFA) yielded a cumulative variance explained of 71.94%, with the identified factor structure aligning with the theoretical framework of the scale. The factor loadings ranged from 0.528 to 0.786. Confirmatory factor analysis (CFA) demonstrated good model fit with $\chi^2/df = 1.982$, root-mean-square error of approximation (RMSEA) = 0.025, goodness-of-fit index (GFI = 0.979, normed fit index (NFI = 0.979), Tucker-Lewis index (TLI = 0.989) and comparative fit index (CFI = 0.990) (Ning et al., 2025; Suzukamo et al., 2011).

The UTAUT Scale, adapted from Tang et al. (2024) and Al-Adwan et al. (2024), included four items for each of the five constructs: PE, EE, SI, FC and BI. It also used a 5-point Likert scale, where higher scores reflected higher levels in each dimension. The EFA revealed a cumulative variance explained of 71.36%, with item loadings ranging from 0.748 to 0.838, all consistent with theoretical expectations. The CFA results indicated a good model fit: $\chi^2/df = 2.664$, RMSEA = 0.033, GFI = 0.975, NFI = 0.975, TLI = 0.981 and CFI = 0.984 (Ning et al., 2025; Suzukamo et al., 2011).

The TPACK Scale, adapted from Tang et al. (2024) and Bai et al. (2024), consisted of six items and was likewise rated on a 5-point Likert scale, with higher scores indicating a higher level of TPACK. EFA showed a cumulative variance explained of 64.44%, while CFA results were as follows: $\chi^2/df = 12.326$, RMSEA = 0.085, GFI = 0.977, NFI = 0.977, TLI = 0.964 and CFI = 0.978 (Ning et al., 2025; Suzukamo et al., 2011).

Data analysis

This study employed a combination of CB-SEM and fsQCA as research methods. Specifically, SmartPLS 4 was employed to construct the CB-SEM model, which was used to assess the conceptual framework of factors influencing the AIL of MEd students and to test the validity of the proposed research hypotheses (Hair et al., 2017). Building upon this, fsQCA 4.1 was applied to examine the necessity and sufficiency of individual factors, explore the combined effects of multiple variables on AIL and identify generative causal pathways. This approach compensates for the limitations of CB-SEM in analysing asymmetric causality and complex variable interactions (Kraus et al., 2018). By integrating both methods, the study offers a comprehensive analysis of the influencing factors of MEd students' AIL from the perspectives of statistical correlation and logical causation, thereby enhancing the explanatory power and scientific rigor of the research findings (Chanda et al., 2024).

Results

Measurement model evaluation

The measurement model was evaluated using SmartPLS 4 software, focusing on assessments of reliability, convergent validity and discriminant validity (Cheung et al., 2024). As shown in Table 1, regarding reliability, the Cronbach's alpha coefficients for all latent constructs exceeded 0.8, indicating strong internal consistency. Similarly, the composite reliability values for all constructs were above 0.8, further confirming the scale's internal reliability. For convergent validity, the average variance extracted values of all constructs exceeded the standard benchmark of 0.5, suggesting that the observed items effectively reflect their respective latent constructs.

Table 1
Convergent validity

Constructs	Cronbach's alpha	Composite reliability	Average variance extracted
TPACK	0.889	0.888	0.570
BI	0.862	0.842	0.571
FC	0.867	0.867	0.620
EE	0.873	0.873	0.633
SI	0.877	0.877	0.640
PE	0.840	0.842	0.569
AIL	0.912	0.900	0.651

Discriminant validity was assessed using the heterotrait-monotrait ratio. As shown in Table 2, all HTMT values were below the conservative threshold of 0.85, indicating strong discriminant validity and sufficient differentiation among the constructs (Henseler et al., 2015).

Table 2
Discriminant validity

Constructs	TPACK	BI	FC	EE	AIL	SI	PE
TPACK							
BI	0.522						
FC	0.464	0.510					
EE	0.311	0.402	0.344				
AIL	0.449	0.524	0.497	0.612			
SI	0.435	0.526	0.584	0.329	0.464		
PE	0.425	0.560	0.520	0.462	0.535	0.511	

Descriptive statistics and correlation analysis

Descriptive statistics and correlation analysis were conducted on the research data, and the results are presented in Table 3. The average AIL score among the 1,575 MEd students was 3.196. The mean scores of the five dimensions ranged from 3.107 to 3.302, indicating that the overall level of AIL among these students is moderate, with significant potential for improvement. Among the five dimensions, the mean scores for AIA and AIE were higher than the overall average, but the mean scores for AIK, AIT and AIC were below the overall average. Correlation analysis showed that the coefficients between each dimension and overall, AIL ranged from 0.816 to 0.898, indicating strong positive correlations. These results suggest that the development of AIL in MEd students is the result of the integrated effect of multiple interrelated factors that together constitute a cohesive and mutually reinforcing system.

Table 3
Results of the descriptive statistics and correlation analysis

Dimension	Mean	SD	AIA	AIK	AIC	AIT	AIE	AIL
AIA	3.229	0.656	1					
AIK	3.191	0.677	0.702**	1				
AIC	3.151	0.712	0.674**	0.802**	1			
AIT	3.107	0.837	0.608**	0.730**	0.712**	1		
AIE	3.302	0.714	0.699**	0.641**	0.614**	0.573**	1	
AIL	3.196	0.619	0.847**	0.898**	0.883**	0.856**	0.816**	1

Note. "**" indicates significance at the 0.01 level.

Group difference analysis

Based on the overall mean scores, independent samples *t* tests were conducted on the three binary variables – gender, university affiliation and university type – while a one-way analysis of variance was used to examine the impact of the university location, a multi-category variable. The results are presented in Table 5. The findings indicate that gender, university affiliation, university type and university location all significantly affect the AIL levels of MEd students.

Table 4
Results of the group difference analysis

Variable	Category	Mean	SD	*F*(t)	*p* value
Gender	Male	3.276	0.681	4.089	$p < 0.001$
	Female	3.142	0.567		
University affiliation	Centrally administered	3.401	0.663	8.065	$p < 0.001$
	Provincial	3.113	0.580		
University type	Normal	3.217	0.592	1.968	0.049
	Comprehensive	3.153	0.664		
University location	Eastern	3.271	0.601	5.919	0.003
	Central	3.173	0.612		
	Western	3.128	0.657		

Structural model evaluation

An explanatory analysis of the hypothesised model was conducted using SmartPLS 4, and the results are presented in Figure 1. Each path in the model is annotated with its standardised path coefficient and corresponding two-tailed *p* value. The model fit indices were as follows: $\chi^2/df = 5.866$, RMSEA = 0.056, GFI = 0.904, NFI = 0.915, TLI = 0.921 and CFI = 0.929, indicating a good model fit (Ning et al., 2025; Suzukamo et al., 2011). The *t* values for the 14 hypothesised paths ranged from 3.055 to 18.142, all with $p < 0.05$, indicating statistical significance. This supports hypotheses H1–H14, suggesting that TPACK, BI, EE, PE, SI and FC all exert significant and positive direct effects on the AIL.

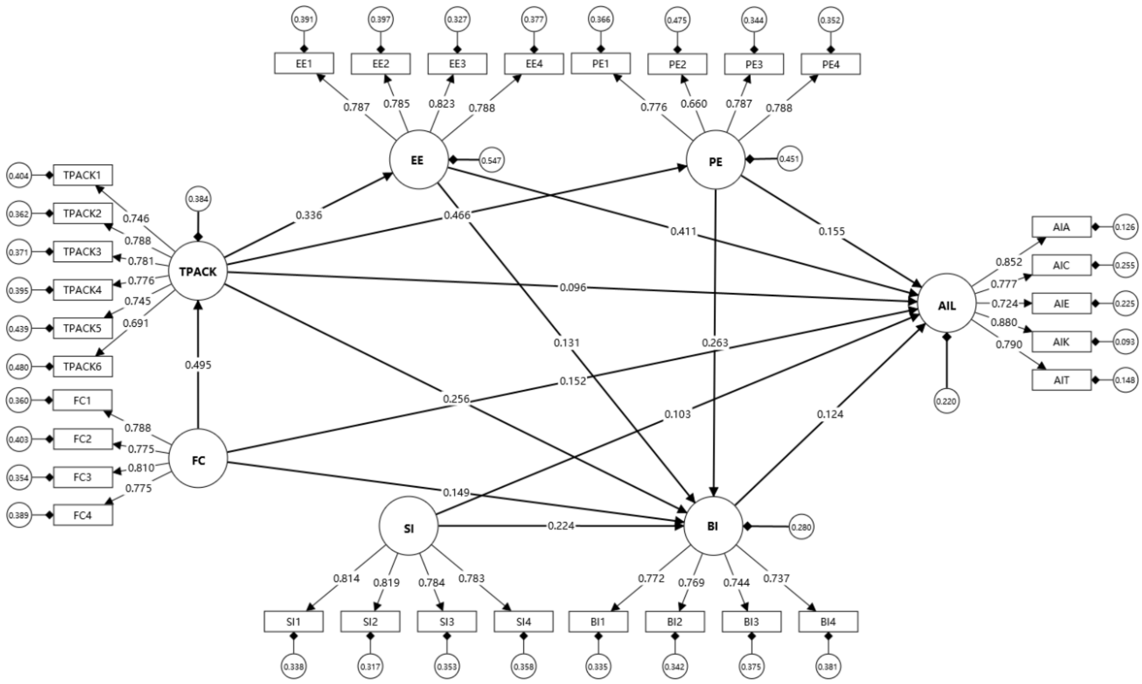

Figure 1. Results of the CB-SEM

Note. PE: performance expectancy, EE: effort expectancy, SI: social influence, FC: facilitating conditions, AIL: AI literacy, AIK: AI knowledge, AIC: AI competence, AIA: AI attitude, AIT: AI thinking, AIE: AI ethics, TPACK: technological pedagogical content knowledge

Based on the research topic, the bootstrapping method was used to calculate the total effects and indirect effects of various influencing factors on AIL, summarised in Table 5.

Table 5

Results of the path effect testing

Effect type	Path relationship	*β*	*t*	*p* value
Indirect effects	TPACK → EE → AIL	0.138	8.638	$p < 0.001$
	TPACK → PE → AIL	0.032	3.299	0.001
	TPACK → BI → AIL	0.015	3.195	0.001
	FC → TPACK → AIL	0.019	2.556	0.011
	FC → BI → AIL	0.047	3.047	0.002
	EE → BI → AIL	0.016	2.895	0.004
	SI → BI → AIL	0.028	3.177	0.002
	PE → BI → AIL	0.033	3.187	0.002
	TPACK → PE → BI → AIL	0.005	2.834	0.005
	TPACK → EE → BI → AIL	0.016	3.186	0.002
	FC → TPACK → BI → AIL	0.068	7.056	$p < 0.001$
	FC → TPACK → EE → AIL	0.036	4.360	$p < 0.001$
	FC → TPACK → PE → AIL	0.003	2.730	0.007
	FC → TPACK → EE → BI → AIL	0.008	3.062	0.002
	FC → TPACK → PE → BI → AIL	0.072	4.551	$p < 0.001$
Total effects	TPACK → AIL	0.314	10.875	$p < 0.001$
	BI → AIL	0.115	3.636	$p < 0.001$
	FC → AIL	0.284	10.534	$p < 0.001$
	EE → AIL	0.339	14.110	$p < 0.001$
	SI → AIL	0.108	4.398	$p < 0.001$
	PE → AIL	0.154	5.483	$p < 0.001$

In terms of total effects, the impact on AIL, ranked from highest to lowest, is as follows: EE, TPACK, FC, PE, BI and SI. For indirect effects, all path relationships were significant. Specifically, six indirect paths were mediated by TPACK, 4 by EE, four by PE and 10 by BI, with seven chain mediation paths identified. Notably, BI, PE and EE form the key transmission chain, acting as core hubs in shaping AIL. TPACK and FC, as critical antecedents, directly influence AIL and also work synergistically through multiple indirect paths with other factors.

Generative pathways analysis

This study conducted a necessity analysis of antecedent conditions using the direct calibration method (Koengkan et al., 2023). The 95th percentile, 50th percentile and 5th percentile of each condition were used as the anchor points for full membership, crossover and full non-membership, respectively (Kraus et al., 2018). Raw scores were transformed into fuzzy membership scores ranging from 0 to 1. After calibration, fsQCA 4.1 software was used to assess the necessity of each antecedent condition. As shown in Table 6, for both high and low levels of AIL, the consistency scores of all conditions were below 0.9, indicating that no single factor alone qualifies as a necessary condition. This suggests that AIL results from a combination of multiple interacting factors.

Table 6
Results of the necessity analysis

Condition	High AIL		Low AIL	
	Consistency	Coverage	Consistency	Coverage
PE	0.830	0.728	0.587	0.556
~ PE	0.494	0.526	0.713	0.819
EE	0.778	0.780	0.516	0.559
~ EE	0.559	0.517	0.797	0.795
SI	0.798	0.729	0.608	0.600
~ SI	0.562	0.571	0.725	0.795
FC	0.785	0.741	0.577	0.588
~ FC	0.563	0.552	0.746	0.789
BI	0.793	0.752	0.581	0.596
~ BI	0.574	0.559	0.758	0.798
TPACK	0.774	0.733	0.577	0.590
~TPACK	0.567	0.554	0.739	0.779

Note. "~" indicates negative set.

The sufficiency analysis aimed to identify configurations of antecedent conditions that are sufficient for producing high or low AIL. The consistency threshold was set at 0.8, PRI at 0.7 and frequency at 10 (Fiss, 2011; Kraus et al., 2018). Based on the truth table, both intermediate and parsimonious solutions were generated to identify core and peripheral conditions in the configurations. As summarised in Table 7, three configurations explained high AIL. Across all three, EE and BI were core conditions, PE was a marginal condition, while TPACK, SI and FC showed pairwise interchangeable roles. This indicates that MEd students' cognitive understanding and usage of AI technologies are central to AIL, while external factors like SI and FC play a more supportive role. Configuration 1 was labelled "external support-driven", configuration 2 "cognitive-social synergy" and configuration 3 "self-directed development". For low AIL, two configurations were identified. In both, EE and FC were missing core conditions, PE and BI were marginal missing and TPACK and SI alternated. This suggests that the absence of either AI-related cognition or environmental support may lead to low AIL. Configuration 4 was termed "weak cognitive ability" and configuration 5 "motivation-social deficit". Overall, the coverage for each configuration ranged from 0.464 to 0.539, indicating strong explanatory power. The robustness of these results was confirmed by re-running the analysis with a higher consistency threshold of 0.9, which yielded identical configurations.

Table 7
Results of the configuration path

Condition	High AIL			Low AIL	
	Path 1	Path 2	Path 3	Path 4	Path 5
PE	●	●	●	⊗	⊗
EE	⬤	⬤	⬤	⨂	⨂
SI	●	●			⊗
FC	●		●	⨂	⨂
BI	⬤	⬤	⬤	⊗	⊗
TPACK		●	●	⊗	
Consistency	0.924	0.923	0.925	0.942	0.942
Raw coverage	0.539	0.533	0.525	0.464	0.465
Unique coverage	0.036	0.029	0.021	0.030	0.031
Overall consistency		0.910		0.938	
Overall coverage		0.590		0.494	

Note: " ⬤ " indicates a core condition, " ● " indicates a marginal condition, "⨂" indicates a missing core condition, "⊗" indicates a marginal missing and blank indicates either present or missing.

Discussion

RQ1: Current status and group differences

The overall AIL level among MEd students is moderate (*Mean* = 3.196, *SD* = 0.619). Descriptive statistical analysis indicates that conceptual dimensions of AIL – such as AIA (*Mean* = 3.229, *SD* = 0.656) and AIE (*Mean* = 3.302, *SD* = 0.714) – tend to be slightly stronger, while practical dimensions – including AIK (*Mean* = 3.191, *SD* = 0.677), AIT (*Mean* = 3.107, *SD* = 0.837) and AIC (*Mean* = 3.151, *SD* = 0.712) – are comparatively weaker, placing the overall proficiency at an average level. This suggests that the current state of AIL among MEd students is suboptimal and requires further development or strengthening. In the context of educational transformation in the intelligent era, they generally possess a basic conceptual understanding of AI and recognise its value, yet a clear knowledge–action gap remains (Hadar Shoval, 2025; Yuwono et al., 2024). This gap hinders the effective translation of AI-related concepts into tangible teaching behaviours and technical practices (Dantas et al., 2022).

Further group difference analysis reveals that gender (t = 4.089, p < 0.001), university affiliation (t = 8.065, p < 0.001), university type (t = 1.968, p = 0.049) and university location (F = 5.919, p = 0.003) all significantly influence AIL levels. Survey studies have found that there is a gender gap in the use of AI technology: males (*Mean* = 3.276, *SD* = 0.681) are more likely to use AI than females (*Mean* = 3.142, *SD* = 0.567) and with a higher frequency of use (Aldasoro et al., 2024). Skalka (2025) also found that male college students demonstrate a higher level of readiness and satisfaction with AI, as well as a stronger interest in and willingness to engage with intelligent technologies. Regarding university affiliation and location, students from centrally administered universities (*Mean* = 3.401, *SD* = 0.663) or those located in eastern China (*Mean* = 3.271, *SD* = 0.601) show notably higher levels of AIL. This may be attributed to these universities' advantages in terms of resource allocation, faculty expertise, research support and practical training opportunities (Chen et al., 2023; Wolszczak-Derlacz, 2017), all of which contribute to the development of AIL. Additionally, students from normal universities (*Mean* = 3.217, *SD* = 0.592) tend to outperform those from comprehensive universities (*Mean* = 3.153, *SD* = 0.664). Normal universities are explicitly oriented towards cultivating future educators, which gives them distinctive advantages in offering targeted and practice-oriented guidance (Hayhoe & Li, 2010; Mei, 2010). Their curricula emphasise pedagogical theories and practical educational technology integration. This often includes training MEd students to design differentiated lesson plans using AI, critically evaluate AI-powered adaptive learning platforms or utilise learning analytics to inform pedagogical decisions (Li & Xue, 2021; Wu et al., 2025). Moreover, these institutions often possess specialised faculties in education and pedagogy, fostering stronger mentorship and professional support.

RQ2: Influencing factors of AIL

EE (β = 0.339, t = 14.110, p < 0.001), TPACK (β = 0.314, t = 10.857, p < 0.001), FC (β = 0.284, t = 10.534, p < 0.001), PE (β = 0.154, t = 5.483, p < 0.001), BI (β = 0.115, t = 3.636, p < 0.001), and SI (β = 0.108, t = 4.398 and p < 0.001) all positively impact the AIL of MEd students. EE has a significant positive effect, supporting Batubara (2025) and Izhar et al. (2025), and aligns with studies highlighting the importance of technology ease of use in educational adoption (Alkawsi et al., 2025). Generative AI tools such as DeepSeek offer user-friendly interfaces, intuitive operations and low learning thresholds, facilitating efficient teaching, targeted learning and streamlined research (Hu et al., 2025; Michel-Villarreal et al., 2023; Zawacki-Richter et al., 2019). These experiences foster emotional acceptance and motivate sustained engagement, promoting AIL (Choi et al., 2022). TPACK directly affects AIL and indirectly influences it through PE, EE and BI, consistent with Al-Abdullatif (2024), Tram (2024) and Oved and Alt (2025). As an integrated practical knowledge system, TPACK equips MEd students to evaluate the usefulness and usability of AI, reinforcing adoption and enhancing AIL (Ning et al., 2024; Tang et al., 2024). MEd students with high levels of TPACK are better equipped to assess the usefulness and usability of intelligent technologies, which reinforces their willingness to adopt such tools and, in turn, supports the enhancement of their AIL. FC is crucial in fostering AIL, as confirmed by Zhang et al. (2023) and Hu et al. (2025). Adequate technological resources, institutional support, training and dedicated learning time facilitate students' progression from "being able to use" to "proficiently using" AI (Pei et al., 2025; Yu et al., 2025). PE significantly contributes to AIL, supporting Pasupuleti and Thiyyagura (2024) and Yakubu et al. (2025). MEd students value research efficiency and output quality, emphasising practical tool utility (Hu et al., 2025). High performance expectations foster identification with AI and motivate proactive exploration of its functions and value (Choi et al., 2022; Tram, 2024). BI, a key predictor of usage behaviour (Venkatesh et al., 2003), indicates that stronger willingness to integrate AI accelerates AIL development (Yeop et al., 2019). SI affects AIL both directly and indirectly via intention to use, consistent with Al-Adwan et al. (2024) and Chen et al. (2024). Through interactions with teachers, peers and students, MEd students replicate, adapt, disseminate and enrich AI-related experiences, further promoting AIL (Tang et al., 2024; Yu et al., 2025).

RQ3: Generative pathways to AIL

EE, PE, FC, SI, BI and TPACK together produce three pathways leading to high levels of AIL (consistency = 0.910, coverage = 0.590) and two pathways leading to low levels of AIL (consistency = 0.938, coverage = 0.494). No single factor is necessary, highlighting that the development of AIL depends on the synergistic effects of multiple variables, consistent with research (Ng et al., 2021; Ning et al., 2025; Pei et al., 2025). This finding aligns with the results of CB-SEM. Sufficiency analysis shows that the influence of these factors follows a *multiple conjunctural* logic. In high AIL configurations, PE, EE and BI consistently act as core conditions, whereas TPACK, SI and FC function as interchangeable marginal conditions. Three main pathways were identified: external support–driven, emphasising robust resources and community support; cognitive-social synergy, where internal competence and motivation compensate for weaker enabling conditions; and self-directed development, driven by intrinsic motivation and professional capability. Low AIL pathways typically lack EE and FC as core conditions, with PE and BI missing or marginal, and TPACK and SI showing substitutive roles. This indicates that the absence of single factors cannot be offset by others, leading to underdeveloped AIL. The "weak cognitive ability" path reflects insufficient technical competence and foundational knowledge, while the "motivation-social deficit" path highlights the combined effect of low motivation and weak external support. Notably, the pathways for high and low AIL are asymmetric: absence of factors leading to high AIL does not automatically result in low AIL. This underscores the non-linear, configurational nature of AIL development, complementing CB-SEM findings by revealing complex, multi-level causal mechanisms.

Conclusion

Relying on the UTAUT and TPACK frameworks for integrating technology into pedagogy, this study empirically analysed the AIL of 1,575 MEd students. A combination of CB-SEM and fsQCA was employed. The findings reveal that the overall AIL level of MEd students is moderate, with significant differences based on gender, school affiliation, school type and school region. MEd students demonstrate stronger conceptual knowledge of AI but exhibit weaknesses in practical knowledge, critical thinking and competence. Furthermore, there is a lack of a systematic and in-depth approach to the development of high-level AIL. Key factors influencing AIL in MEd students include EE, PE, FC, SI, BI and TPACK. The combined effects of these factors create multiple pathways, with external support and cognitive motivation playing crucial roles. High AIL in MEd students can be generated through multiple pathways, such as the external support-driven path, the cognitive-social synergy path and the self-directed development path. Conversely, low AIL is associated with weak cognitive abilities and motivation-social deficit.

Based on the findings, this study proposes enhancing the cultivation of AIL among MEd students through curriculum reconstruction, regional collaboration and systemic support. At present, most universities have yet to offer dedicated courses on AI applications in education across other disciplines (Hutson et al., 2022; Southworth et al., 2023). Intelligent education courses are often elective, fragmented and disconnected from specific subject learning, limiting the development of AIL for each student (Wong et al., 2025; Yao et al., 2025). In the future, AI should be integrated into interdisciplinary core courses to promote cross-disciplinary learning and authentic application. Educational authorities should establish clear national standards and dedicated management units to guide the design, implementation, and evaluation of such courses. From a regional perspective, differences between regions and schools should be considered, particularly addressing resource shortages in central and western regions. Strengthening policy support, promoting inter-regional cooperation and utilising both online and offline approaches can help enhance MEd students' AIL. Gender differences should also be emphasised, with particular efforts to encourage female MEd students to overcome challenges in technology learning and achieve gender balance in the field. Finally, universities need to build a multidimensional support system linking individuals, technology and environment by fostering motivation, promoting university–enterprise collaboration, providing accessible intelligent tools, and encouraging participation in innovation activities to sustain AIL improvement.

This study has several limitations that suggest directions for future research. First, the sample was drawn from Chinese MEd students, which may limit the generalisability of the findings to other cultural or institutional contexts. Cross-cultural studies are needed to examine whether the identified pathways and influencing factors hold in different education systems. Second, data were collected primarily through self-report questionnaires, which may introduce common method bias. Future research should incorporate multi-source data, such as mentor evaluations, classroom observations or system logs. Finally, qualitative or mixed-method approaches, such as interviews and case studies, are recommended to explore the contextual mechanisms behind AIL development.

Author contributions

Jinrun Xu: Conceptualisation, Investigation, Writing – original draft, Writing – review and editing; **Ruizi Shen**: Data curation, Investigation; **Jiarui Li**: Investigation, Formal analysis, Writing – review and editing; **Dianshun Hu**: Supervision, Writing – review and editing; **Maodong Tian**: Writing – review and editing.

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