The relationship between perceived artificial intelligence competencies and critical thinking skills: The role of digital literacy and cognitive engagement

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This study investigated the relationship between perceived artificial intelligence (AI) competency and critical thinking skills among Generation Z students, with a focus on the mediating roles of digital literacy and cognitive engagement. Grounded in social cognitive theory, the research posited that individuals who perceive themselves as competent in AI are more likely to engage deeply with digital tools and learning processes, thereby enhancing their critical thinking abilities. Data were collected from 464 university students in Türkiye using validated self-report measures. Structural equation modelling and bootstrapped mediation analyses revealed that both digital literacy and cognitive engagement significantly mediate the link between AI competency and critical thinking. Notably, a serial mediation pathway was also confirmed, highlighting how perceived AI competency fosters digital literacy, which in turn promotes cognitive engagement and ultimately strengthens critical thinking skills. These findings offer theoretical and practical insights into how AI-related self-efficacy supports higher-order cognitive processes in digitally mediated educational settings.

Implications for practice or policy:

- Curriculum designers should integrate AI literacy across disciplines to enhance students' critical thinking skills.
- Instructors can enhance engagement by using inquiry-based tasks that require students to actively use AI tools.
- University leaders can enhance outcomes by incorporating comprehensive digital literacy training into their programmes.
- Policymakers should address equity gaps by funding initiatives that promote AI literacy and digital inclusion.
- Faculty developers could prioritise training educators to model ethical and reflective AI practices.

Keywords: perceived AI competency, critical thinking skills, digital literacy, cognitive engagement, social cognitive theory

Introduction

The rapid integration of artificial intelligence (AI) into education has redefined the competencies required for effective learning and renewed interest in the cognitive and technological factors that shape academic outcomes. Among these, perceived AI competency (PAIC), defined as individuals' beliefs about their ability to understand and use AI technologies, has emerged as an important factor in digitally mediated learning environments (Chiu et al., 2024; Yuan et al., 2024). As AI tools increasingly support information search, feedback and problem-solving, the capacity to engage with them critically has become central to higher-order learning processes (Demir & Demir, 2025; Tenberga & Daniela, 2024). However, empirical evidence explaining how PAIC relates to critical thinking skills (CTS) remains limited.

Critical thinking is widely recognised as a core educational outcome because it supports reasoning, judgement and problem-solving (Chien et al., 2020; Kim et al., 2025). Recent studies suggest that learners' self-perceptions of technological competence are associated with their willingness to evaluate evidence, question assumptions, and synthesise diverse information sources (Greene, 2015; Liang et al., 2023). Yet the mechanisms linking PAIC to CTS remain underexplored. In particular, insufficient attention has been paid to the roles of digital literacy (DL) and cognitive engagement (CE) as explanatory pathways through which AI-related self-beliefs may relate to the development of critical thinking. At the same time, the educational value of AI should not be assumed to be uniformly positive. A growing body of scholarship warns that overreliance on AI systems may reduce cognitive effort, encourage passive acceptance of AI-generated outputs and weaken independent reasoning when complex tasks are delegated to automated tools (Carter et al., 2025; Mei et al., 2025; Memarian & Doleck, 2023). Accordingly, AI may support critical thinking only when learners evaluate, question and strategically integrate AI-generated information.

Drawing on social cognitive theory (SCT; Bandura, 2001), this study conceptualised PAIC as a domain-specific efficacy belief that shapes individuals' interactions with digital environments. Within this framework, DL is the ability to access, evaluate, create and communicate information effectively in technology-rich contexts (Dalgıç et al., 2024; Ng, 2012), whereas CE reflects purposeful mental effort, persistence and reflective learning strategies (Greene, 2015; Reeve & Tseng, 2011). These constructs may serve as complementary mechanisms linking PAIC to CTS.

The sample largely reflected individuals commonly described as Generation Z, a cohort frequently associated with intensive exposure to digital technologies and AI-enabled platforms, making it a relevant context for examining AI-related perceptions and learning processes (Yaşar, 2022). Validated instruments were used to measure PAIC, DL, CE and CTS, aligning with contemporary research on digital learning environments (Chee et al., 2024; Dalgıç et al., 2024; Kim et al., 2025). This study contributes to the literature by proposing a theoretically grounded, empirically validated model that clarifies the pathways from PAIC to critical thinking. While earlier studies have examined these constructs in isolation, the current research highlights their interconnectedness. It suggests that fostering AI-related self-efficacy alone may be insufficient without corresponding efforts to develop DL and promote active CE.

Literature review

PAIC and CTS

A central concept of SCT is self-efficacy, defined as individuals' beliefs in their capability to perform specific tasks successfully (Bandura, 2001). Such beliefs shape motivation, persistence and cognitive performance. In technology-enhanced learning contexts, PAIC can be understood as a domain-specific form of self-efficacy reflecting confidence in understanding, evaluating and using AI tools effectively (Chiu et al., 2024; Yuan et al., 2024). This includes recognising AI applications, interpreting outputs, assessing reliability and considering ethical implications of AI use (Demir & Demir, 2025; Sienkiewicz-Małyjurek & Zyzak, 2025; Tenberga & Daniela, 2024). From an SCT perspective, individuals with stronger PAIC may be more willing to engage with complex digital tasks that require judgement and reflection.

CTS involves analysing information, questioning assumptions, evaluating evidence and reaching reasoned conclusions (Kim et al., 2025; Rotgans & Schmidt, 2011). These competencies are increasingly important in AI-mediated environments where learners encounter large volumes of information, algorithmic recommendations and AI-generated content. Individuals who feel competent in using AI tools may be more likely to approach such environments with greater confidence and agency (Chee et al., 2024; Chien et al., 2020), which can support deeper evaluation of information sources and more deliberate decision-making (Greene, 2015).

SCT further suggests that efficacy beliefs are strengthened through mastery experiences, observation and social persuasion (Bandura, 2001). As learners successfully interact with AI systems, their sense of control may increase, encouraging exploratory behaviour, persistence and reflective inquiry. Research supports this logic. For example, Chiu et al. (2024) found that AI competence self-efficacy was associated with stronger strategic decision-making, while Tenberga and Daniela (2024) reported that AI literacy development enhanced participants' capacity to critically interpret algorithmic processes. These findings indicate that confidence in AI use may be linked with higher-order cognitive functioning.

However, the relationship should not be assumed to be automatically positive. Other studies have cautioned that uncritical dependence on AI tools may encourage cognitive offloading, superficial processing or passive acceptance of generated responses (Carter et al., 2025; Mei et al., 2025; Memarian & Doleck, 2023). In such cases, AI systems may substitute rather than stimulate reflective thinking. Therefore, PAIC is unlikely to be beneficial when it reflects mere operational confidence without evaluative awareness. Instead, the potential value of PAIC lies in enabling learners to interrogate AI outputs, compare alternative explanations, detect bias and integrate evidence from multiple sources. Individuals with stronger PAIC may be better positioned to recognise both the opportunities and limitations of AI technologies, thereby using them more strategically in learning contexts (Demir et al., 2024; Yuan et al., 2024). In this sense, PAIC may function as a psychological resource for critical thinking when used reflectively and responsibly with AI tools (Alon et al., 2024; Mei et al., 2025; Sienkiewicz-Małyjurek & Zyzak, 2025). Based on this reasoning, we proposed the following hypothesis (H):

H1. PAIC is positively associated with CTS (Figure 1).

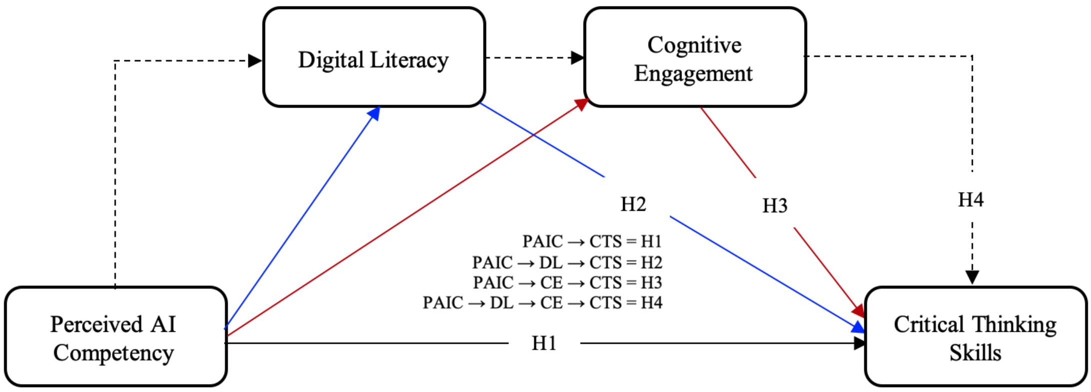

Figure 1. The conceptual model

The mediating role of DL

Within SCT, learning outcomes emerge through reciprocal interactions among personal beliefs, behaviours and environmental conditions (Bandura, 2001). This perspective suggests that the relationship between PAIC and DL may be theoretically dynamic rather than strictly one directional. Individuals with stronger DL may feel more confident when using emerging technologies, while those who perceive themselves as competent in AI may also be more willing to explore digital systems, practise new skills and adapt to technological change (Audrin & Audrin, 2022; Morgan et al., 2022). According to SCT, efficacy beliefs influence motivation, persistence and proactive behaviour in challenging environments (Dalgıç et al., 2024; Kim et al., 2025). In AI-mediated contexts, individuals who believe they can understand and use AI tools effectively may be more inclined to experiment with digital platforms, seek learning resources and engage in repeated practice. Through these experiences, broader digital competencies can develop (Bandura, 2001; Getenet et al., 2024; Liang et al., 2023).

DL is a multidimensional construct involving the ability to access, evaluate, create and communicate information through digital technologies (Hobbs, 2017; Ng, 2012). It extends beyond technical operation to include information judgement, ethical awareness, online safety and effective participation in digital environments (Demir & Demir, 2025). These competencies are particularly important in AI-rich settings, where users must assess the credibility of outputs, identify bias, interpret data-driven recommendations and make informed decisions. From a theoretical standpoint, DL may serve as a mechanism linking PAIC to CTS. Confidence in using AI tools may encourage individuals to interact more actively with digital environments, yet without sufficient DL, such engagement may remain superficial (Chai et al., 2013; Xu et al., 2025). By contrast, digitally literate individuals are better equipped to verify sources, compare perspectives, question algorithmic outcomes and transform information into reasoned judgements. These practices closely align with the core dimensions of critical thinking.

Empirical studies support these connections. Research has shown that digital competence is positively related to reflective reasoning, misinformation detection and analytical judgement in technology-supported learning contexts (Dalgıç et al., 2024; Siddiq et al., 2016; Xu et al., 2025). Other studies have emphasised that DL strengthens users' capacity to evaluate the quality of information and engage critically with algorithmic systems (Eshet, 2012; Redecker, 2017; Vuorikari et al., 2016). Accordingly, DL can be understood not only as a skill set but also as a cognitive bridge linking AI-related self-beliefs with higher-order thinking.

This framing also differs from studies such as that by Daulay et al. (2026), which modelled DL as an antecedent of self-efficacy in broader digital settings. The current study instead focused on AI-specific competency beliefs and examined whether such beliefs are associated with downstream digital capability development and critical thinking. These approaches should therefore be viewed as complementary rather than contradictory. Based on this reasoning, we proposed the following hypothesis:

H2. DL mediates the positive relationship between PAIC and CTS (Figure 1).

The mediating role of CE

SCT emphasises that beliefs about one's capabilities shape motivation, persistence and the quality of learning behaviours (Bandura, 2001). In AI-mediated learning environments, PAIC may therefore be associated with the degree to which individuals invest mental effort in learning tasks. Learners who believe they can understand and use AI tools effectively are more likely to approach complex tasks with confidence, persist when difficulties arise and employ reflective strategies during problem-solving (Dalgıç et al., 2024; Nouri et al., 2020; Yuan et al., 2024). CE refers to purposeful psychological investment in learning, including deep processing, self-regulation, sustained attention and the strategic use of learning resources (Greene, 2015; Reeve & Tseng, 2011). Rather than merely participating in tasks, cognitively engaged individuals seek meaning, connect new knowledge with prior understanding, monitor their progress and refine their reasoning (Jimenez-Liso et al., 2022; Zhu et al., 2009). These processes are central to critical thinking because they support analysis, evaluation and evidence-based judgement.

From an SCT perspective, efficacy beliefs can stimulate CE by increasing willingness to exert effort and maintain focus in demanding environments (Bandura, 2001). In AI-supported contexts, individuals with stronger PAIC may be more willing to experiment with tools, compare alternative outputs, revise prompts and reflect on the quality of generated responses (Laakso et al., 2021; Zhang et al., 2025). Such active involvement can create richer opportunities for reasoning and metacognitive monitoring than passive use of technology.

Empirical research supports these associations. Studies have shown that technology-related efficacy beliefs are positively linked with engagement and higher-order learning outcomes (Fabian et al., 2022; Laakso et al., 2021). Furthermore, research on AI-enhanced learning environments indicates that personalised systems and interactive digital platforms can foster deeper engagement, which is associated with stronger analytical and reflective performance (Li et al., 2023; Zhou & Hou, 2024). These findings suggest that CE may serve as an important pathway linking AI-related confidence to CTS. However, engagement should not be assumed simply because AI tools are available (Chai et al., 2013; Demir & Demir, 2025). If learners rely on automated outputs without reflection, technology use may remain superficial and contribute little to deeper thinking. The key mechanism is therefore not access to AI itself, but the extent to which learners actively interrogate, interpret and apply AI-generated information. Accordingly, we expected CE to function as a psychological process through which PAIC is positively associated with CTS:

H3. CE mediates the positive relationship between PAIC and CTS (Figure 1).

The serial mediating role of DL and CE

SCT proposes that learning outcomes develop through reciprocal interactions among personal beliefs, cognitive resources, and behavioural processes (Bandura, 2001). From this perspective, PAIC may not relate to CTS through a single pathway, but through a sequence of mechanisms involving DL and CE. Individuals who perceive themselves as competent in using AI tools may be more willing to explore digital environments, test new applications and seek additional resources (Liu et al., 2024; Pattemore & Gilabert, 2023). Such proactive behaviour can contribute to the development of DL, defined as the ability to access, evaluate, create and communicate information effectively in technology-rich settings (Hobbs, 2017; Ng, 2012). In AI-mediated contexts, DL is especially important because users must assess the credibility of outputs, recognise bias, compare sources and make informed judgements rather than accept automated responses uncritically (Hatlevik et al., 2018; Shatila et al., 2025).

DL may subsequently foster stronger CE. Individuals who possess the skills needed to navigate complex digital environments are more likely to participate actively in learning tasks, persist through difficulties and regulate their thinking strategically (Greene, 2015; Liang et al., 2023). When users can evaluate information quality and operate digital tools effectively, they are better positioned to devote cognitive resources to interpretation, synthesis and reflective problem-solving rather than to basic operational challenges (Getenet et al., 2024; Pattemore & Gilabert, 2023).

CE, in turn, is closely linked to critical thinking because it involves deep processing, self-monitoring and deliberate reasoning (Getenet et al., 2024; Pattemore & Gilabert, 2023). Learners who are cognitively engaged are more likely to question assumptions, consider alternative explanations and generate evidence-based conclusions (Pintrich, 2004; Shatila et al., 2025). Thus, DL may provide the functional skills required for effective participation, while CE represents the psychological investment through which those skills are translated into higher-order thinking outcomes (Liu et al., 2024; Pattemore & Gilabert, 2023).

This sequential logic is consistent with research showing that technological competencies, engagement processes and critical thinking are interrelated in digital learning settings. Studies have indicated that stronger digital capabilities are associated with greater persistence and reflective learning behaviours, which, in turn, are linked to improved reasoning and judgement (Liang et al., 2023; Liu et al., 2024). At the same time, the benefits of this pathway should not be assumed automatically. If digital skills are used only for efficiency or routine task completion, they may not generate meaningful CE. The proposed sequence, therefore, depends on reflective and purposeful use of technology.

Some studies (e.g., Liu et al., 2024; Pattemore & Gilabert, 2023) have argued that PAIC may be positively associated with CTS through a layered process: AI-related confidence encourages the development of digital capabilities, DL supports deeper CE, and CE is linked to stronger critical thinking performance. Therefore, we proposed the following serial mediation hypothesis:

H4. DL and CE sequentially mediate the positive relationship between PAIC and CTS (Figure 1).

Methodology

Data collection and sample

Data were collected from February 2025 to June 2025 using a structured questionnaire distributed via face-to-face and online channels. A total of 498 responses were received; after screening for missing values, patterned or inconsistent responses and ineligible participation, 464 valid questionnaires were retained for analysis. Participants were recruited from 14 universities across different regions of Türkiye to ensure geographical and institutional diversity. Most respondents belong to the cohort commonly described as Generation Z, although this label was used only for contextual purposes and not as an analytical variable. To reflect diverse academic perspectives, the sample comprised students from nine faculties, including education, tourism, business administration, and arts and sciences, at the associate, undergraduate, and graduate levels. Using both face-to-face and online data collection increased accessibility and participation despite institutional and logistical differences among universities. This mixed-mode strategy also strengthened the sample by reaching individuals who might have been missed by a single-method approach.

This study was approved by the Ethics Committee of Isparta University of Applied Sciences (approval no. 141/24, date: 1/22/2024). Participation was entirely voluntary, and informed consent was obtained from all participants before completing the questionnaire. Participants were informed about the purpose of the study, the survey's anonymity, their right to withdraw at any time without penalty and the confidential handling of their responses. All procedures were conducted in accordance with the ethical standards of the institutional research committee.

Measurement

Data were collected using a structured self-report questionnaire measuring four constructs: PAIC, DL, CE and CTS. All items were adapted from validated studies and contextualised for AI-mediated educational settings. Responses were recorded on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*), ensuring consistency and ease of interpretation.

PAIC was measured with eight items adapted from Chee et al. (2024), Chiu et al. (2024), Tenberga and Daniela (2024) and Yuan et al. (2024). The scale captured participants' perceived knowledge and use of AI technologies, including recognising AI tools, understanding their functions, evaluating AI-generated outputs and considering ethical issues.

DL was assessed using five items adapted from Dalgıç et al. (2024) and Deschênes (2024). These items reflected key digital competencies, including technical skills, information evaluation, security awareness and collaboration in digital environments.

CE was measured with six items adapted from Greene (2015) and Rotgans and Schmidt (2011). It examined the extent to which participants invested cognitive effort in learning through behaviours such as linking new knowledge with prior understanding, participating in discussions and applying concepts to real-life contexts.

CTS were measured using six items adapted from Chien et al. (2020) and Kim et al. (2025). The scale assessed tendencies to question assumptions, evaluate alternative viewpoints and make evidence-based judgements.

All subscales demonstrated strong internal consistency, with Cronbach's alpha values above the recommended threshold of 0.70 (Nunnally & Bernstein, 1994), supporting measurement reliability. In addition, item selection and adaptation were grounded in SCT (Bandura, 2001), ensuring content validity and conceptual coherence across constructs.

Data analysis

The statistical analysis was conducted using SPSS and AMOS. Confirmatory factor analysis (CFA) was first performed in AMOS to establish the reliability and validity of the measurement model. Subsequently, the hypothesised mediation relationships were examined using Hayes' (2022) PROCESS macro (Model 6) with 5,000 bootstrap re-samples and 95% confidence intervals. PROCESS was selected because the primary objective of the study was to estimate specific indirect effects and the sequential mediation pathway using bias-corrected bootstrapping, which provides a robust and widely accepted approach for mediation testing. In addition, PROCESS allows straightforward estimation and interpretation of direct, indirect and total effects within observed-variable models. Thus, AMOS was employed to validate the measurements, whereas PROCESS was used for parsimonious, theory-driven testing of the proposed mediation mechanisms.

Results

Descriptive statistics

Descriptive statistics, including means, standard deviations and bivariate correlations among the primary variables, are presented in Table 1, and reliability and factor loadings of constructs are presented in Table 2. The mean scores across the core constructs indicated moderate to high levels of agreement among participants: PAIC (M = 3.98, SD = 0.67), DL (M = 3.93, SD = 0.71), CE (M = 3.82, SD = 0.83) and CTS (M = 3.87, SD = 0.79). Pearson correlation coefficients revealed significant, positive associations among all key variables. Specifically, PAIC was strongly correlated with DL (r = 0.57, p < 0.001), CE (r = 0.41, p < 0.01) and CTS (r = 0.52, p < 0.001). The relationships among the mediators and the outcome variable were also statistically significant, affirming the theoretical alignment of the proposed model. Control variables, including university type, faculty type and gender, showed no significant correlations with the primary constructs.

Table 1
Mean, standard deviations and correlations of the constructs

Variables	*M*	*SD*	1	2	3	4	5	6	7
1: University	10.14	3.68							
2: Faculty	5.26	2.28	0.06						
3: Gender	1.61	0.49	0.04	0.06					
4: PAIC	3.98	0.67	0.07	0.09	0.03	**0.83**			
5: DL	3.93	0.71	0.10*	0.09	0.05	0.57***	**0.82**		
6: CE	3.82	0.83	0.08	0.05	0.02	0.41**	0.39**	**0.80**	
7: CTS	3.87	0.79	0.07	0.08	0.06	0.52***	0.42**	0.44**	**0.80**

Note. N = 464. Diagonal values (in bold) are the square roots of AVE.
*p < 0.05.**p < 0.01. ***p < 0.001.

Table 2
Reliability and factor loadings of constructs

Constructs	Factor loading	SD	Sources
PAIC, α = 0.92 AVE = 0.69 CR = 0.92	**	**	
I can explain AI and distinguish it from other digital technologies.	0.91	0.29	Chee et al. (2024); Chiu et al. (2024); Tenberga & Daniela (2024); Yuan et al. (2024)
I can recognise AI tools in daily life and describe what they do.	0.88	0.32	
I understand how AI uses data, learns, and predicts.	0.84	0.36	
I can evaluate AI-generated content for bias and accuracy.	0.80	0.39	
I understand AI ethics, including privacy, bias, and transparency.	0.78	0.42	
I use AI to improve efficiency in research, content creation, and data tasks.	0.76	0.44	
I use AI for personalised learning and skill development.	0.73	0.47	
I understand AI's impact on education and society.	0.70	0.52	
DL, α = 0.91 AVE = 0.68 CR = 0.91			
I use digital tools effectively to learn new things.	0.92	0.25	Dalgıç et al. (2024); Deschênes (2024)
I can search for information online using AI tools.	0.85	0.29	
I can recognise and avoid scams, phishing, and harmful online activity.	0.79	0.37	
I have the technical skills to use digital technologies for work and create outputs.	0.73	0.43	
My digital skills help me collaborate better with colleagues on projects and tasks.	0.71	0.47	

Constructs	Factor loading	SD	Sources
CE, α = 0.85 AVE = 0.65 CR = 0.86			
I connect new knowledge with what I already know.	0.88	0.33	Greene (2015); Rotgans & Schmidt (2011)
I look for extra resources beyond what is provided.	0.85	0.36	
I keep trying to solve difficult problems.	0.80	0.39	
I apply what I learn to real-life situations.	0.76	0.46	
I discuss ideas with others to improve my understanding.	0.72	0.49	
I track my progress and set goals for learning.	0.71	0.53	
CTS, α = 0.86 AVE = 0.65 CR = 0.87			
I consider different ways to understand what I learn.	0.87	0.32	Chien et al. (2020); Kim et al. (2025)
I compare different opinions to decide what makes sense.	0.84	0.36	
I support my opinions with reasons and evidence.	0.82	0.38	
I question situations and problems when facing new challenges.	0.78	0.41	
I ask deep questions to understand complex issues.	0.74	0.44	
I draw conclusions from data and generate new ideas.	0.72	0.52	

Note. N = 464. General α = 0.89. Kaiser–Meyer–Olkin measure = 0.909. Bartlett's test of sphericity = 855,503. $p < 0.001$. Cumulative % of variance = 78.12. M = 3.90.

Preliminary results

CFA

CFA was performed using AMOS to assess the construct validity of the measurement model. The hypothesised four-factor model, comprising PAIC, DL, CE and CTS, demonstrated a good fit to the data: $\chi^2(372) = 773.76$, $\chi^2/df = 2.08$, comparative fit index (CFI) = 0.93, Tucker–Lewis index (TLI) = 0.92, incremental fit index (IFI) = 0.92, standardised root-mean-square residual (SRMR) = 0.06, root mean-square-error of approximation (RMSEA) = 0.05. These indices met the recommended thresholds for model adequacy (Hair et al., 2010). Comparative analyses with alternative models (three-factor, two-factor and one-factor solutions) confirmed the superior fit of the four-factor structure (Table 3), thereby supporting the distinctiveness of the constructs and alleviating concerns regarding common method bias.

Table 3

The results of CFA

Measurement model	χ2	df	χ2/df	CFI	TLI	IFI	SRMR	RMSEA
Four-factor model: PAIC (DL) (CE) and CTS	773.76	372	2.08	0.93	0.92	0.92	0.06	0.05
Three-factor model: PAIC (DL + CE) and CTS	1712.52	402	4.26	0.88	0.86	0.84	0.12	0.11
Two-factor model: PAIC (DL + CE + CTS)	2187.08	428	5.11	0.83	0.82	0.80	0.15	0.13
One-factor model: (PAIC + DL + CE + CTS)	3100.82	454	6.83	0.74	0.70	0.73	0.18	0.14

Note. N = 464.

Reliability and validity of measures

The internal consistency of all constructs was assessed using Cronbach's alpha, all of which exceeded the recommended threshold of 0.70, indicating strong reliability: PAIC (α = 0.92), DL (α = 0.91), CE (α = 0.85), CTS (α = 0.86). Composite reliability (CR) values ranged from 0.86 to 0.92, and average variance extracted (AVE) values ranged from 0.65 to 0.69, satisfying the criteria for convergent validity. Discriminant validity was verified by ensuring that the square root of each construct's AVE exceeded its inter-construct correlations. The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.909, and Bartlett's test of sphericity was significant ($\chi^2 = 855.503$, $p < 0.001$), further validating the factor structure. Collectively, these findings confirm that the measurement model demonstrated both reliability and construct validity.

Control variables

To mitigate potential confounding effects, this study incorporated three control variables: university type, faculty type and gender. Both university type and faculty type were measured as categorical variables representing their respective classifications. Gender was also treated as a categorical variable, distinguishing between male and female participants. These control variables were included in the analysis to ensure a more accurate estimation of the relationships among the primary constructs, PAIC, DL, CE and CTS. The statistical analyses revealed that these control variables had no significant influence on the outcome variables, indicating that the hypothesised model was robust across different institutional contexts and demographic categories.

Common method bias

To mitigate common method bias, procedural and statistical remedies were applied in line with Podsakoff et al. (2012). Procedurally, the survey was conducted independently across multiple universities and faculties to reduce response homogeneity. Reverse-coded items were included to limit patterned responses, and filler items unrelated to the main constructs helped conceal the study purpose and reduce demand characteristics. A marker variable was also included to control for method variance. Statistically, Harman's single-factor test was conducted. The unrotated exploratory factor analysis showed that no single factor explained most of the variance. All factors had eigenvalues greater than 1, and the first factor accounted for less than 30% of the total variance. These results indicate that common method bias is unlikely to threaten the validity of this study's findings.

Hypothesis testing

The hypothesised structural model was tested using the PROCESS macro (Model 6) in SPSS, incorporating a serial multiple mediation analysis. Bootstrapping procedures with 5,000 re-samples were used to assess the significance of direct and indirect effects at the 95% confidence level. Figure 2 and Table 4 present the results. H1 proposed a positive association between PAIC and CTS. The analysis supported this hypothesis, indicating a significant direct relationship ($\beta = 0.18$, $SE = 0.06$, $p < 0.05$). H2 proposed that DL mediates the positive relationship between PAIC and CTS. This indirect effect was significant ($\beta = 0.19$, $SE = 0.02$, 95% CI [0.13, 0.48]), supporting H2. H3 proposed CE as a mediator of the same relationship and was also supported ($\beta = 0.24$, $SE = 0.01$, 95% CI [0.09, 0.56]). H4 proposed a sequential mediation pathway through DL and CE. This indirect effect was significant ($\beta = 0.09$, $SE = 0.01$, 95% CI [0.02, 0.17]), supporting H4. The total relationship between PAIC and CTS was also significant ($\beta = 0.38$, SE = 0.03, $p < 0.01$). All mediation paths remained statistically significant, supporting the notion that DL and CE serve as key psychological mechanisms that transform perceptions of AI competence into higher-order thinking outcomes.

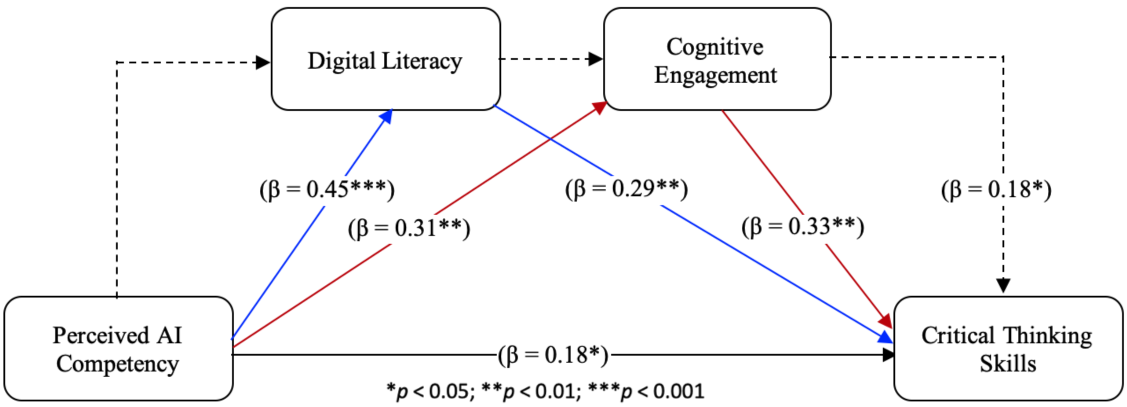

Figure 2. Results of the hypothesised serial mediation model

Table 4
Bootstrap results for direct, conditional and indirect effects

Path	Estimate		SE	
Direct effect				
PAIC → DL	0.45^{***}		0.03	
PAIC → CE	0.31^{**}		0.05	
DL → CE	0.18^{*}		0.07	
CE → CTS	0.33^{**}		0.05	
DL → CTS	0.29^{**}		0.06	
Conditional effect				
PAIC → CTS (Direct effect)	0.18*		0.06	
PAIC → CTS (Indirect effect)	0.20^{**}		0.04	
PAIC → CTS (Total effect)	0.38^{**}		0.03	
Standardised indirect effect using 5,000 bootstrap 95% CI				
	Effect	SE	LL 95% CI	UL 95% CI
PAIC→ DL → CTS	0.19	0.02	0.13	0.48
PAIC→ EC → CTS	0.24	0.01	0.09	0.56
PAIC→ DL → EC → CTS	0.09	0.01	0.02	0.17

Note. LL: lower limit. UL: upper limit. CI: confidence interval.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Discussion and conclusion

This study examined the relationship between PAIC and CTS, with particular attention to the mediating roles of DL and CE. The findings support the proposed model, indicating that PAIC is positively associated with CTS both directly and indirectly through DL and CE. Participants who reported higher levels of PAIC also reported stronger CTS. However, given the cross-sectional design, these findings should be interpreted as associative rather than causal. This aligns with SCT (Bandura, 2001), which posits that self-efficacy in technological contexts fosters cognitive processes such as reasoning, problem-solving and evaluative thinking. Participants who perceived themselves as competent with AI technologies demonstrated higher critical thinking capacities, likely due to greater confidence and autonomy when navigating AI-mediated environments. This is consistent with research by Chiu et al. (2024) and Tenberga and Daniela (2024), who identified AI self-efficacy as a catalyst for strategic reasoning and critical reflection.

DL has emerged as a crucial cognitive tool that mediates the link between AI competency and critical thinking. The results validate previous findings that DL, encompassing technical, evaluative and ethical skills, enhances individuals' ability to interrogate digital content (Eshet, 2012; Memarian & Doleck, 2023; Shatila et al., 2025; Vuorikari et al., 2016). Respondents with high DL were better positioned to critically assess information, recognise bias and synthesise diverse perspectives. The finding also supports the notion that AI competency stimulates digital exploration and, when reinforced by DL, transitions into reflective thinking.

CE was also found to be a significant mediator. This reinforces SCT's view that self-efficacy beliefs motivate individuals to persist, reflect and engage deeply (Bandura, 2001). Participants who felt capable in AI contexts were more cognitively engaged, which translated into better critical thinking outcomes. This pathway reflects findings by Fabian et al. (2022) and Li et al. (2023), who emphasised the role of engagement in activating higher-order cognitive functions in AI-integrated environments.

The serial mediation findings were consistent with the proposed sequence: PAIC was associated with DL, which in turn was associated with CE and CTS. From a theoretical perspective, this ordering is plausible because DL may provide the functional skills needed to navigate digital environments, whereas CE reflects the psychological investment invested during learning tasks. However, because the data are cross-sectional, this temporal ordering cannot be treated as definitive. Alternative configurations, including parallel mediation or different serial sequences, may also be theoretically credible. Accordingly, the findings should be interpreted as supporting the plausibility of the proposed pathway rather than conclusively confirming causal or temporal precedence among the mediators.

In contrast to studies that examined these constructs in isolation (e.g., Ashbourne, 2026; Asonge, 2026; Hatlevik et al., 2018), this research offers a more holistic and integrative framework. However, it must be noted that causality cannot be inferred due to the cross-sectional design. The findings underscore the significance of AI competency in fostering 21st-century cognitive skills, with DL and CE serving as essential pathways. As digital technologies continue to permeate educational and professional spheres, equipping individuals with AI-related competencies and the literacies to engage with them critically becomes paramount. This study not only reinforces theoretical tenets but also presents a validated structural model for future educational and psychological research.

Theoretical implications

This study extends the core assumptions of SCT, particularly self-efficacy in technology-mediated settings (Bandura, 2001). By conceptualising PAIC as a domain-specific form of self-efficacy, it offers a new application of SCT to AI and cognitive development. First, the findings show that PAIC is not only a technical or declarative construct,but also a motivational and metacognitive belief system that strongly predicts higher-order thinking. Unlike earlier studies focusing on general self-efficacy or digital competence (e.g., Audrin & Audrin, 2022; Hatlevik et al., 2018), this study identifies AI competency as a distinct cognitive-affective factor with specific relevance for learning and reasoning.

Second, DL is shown to operate as a mediating cognitive resource, extending SCT's notion of knowledge structures, by converting self-beliefs into meaningful cognitive behaviours. This demonstrates an important intersection between DL frameworks (Hobbs, 2017; Ng, 2012) and SCT, suggesting that DL should be viewed not only as a skill set but also as a mediational mechanism within cognitive theory. Third, CE is interpreted as a behavioural manifestation of agency. Although studies have linked engagement to academic performance (e.g., Fabian et al., 2022; Jimenez-Liso et al., 2022; Li et al., 2023), this research positions it as a theoretical connector between digital competencies and critical thinking, emphasising the role of active mental investment in reflective judgement.

The sequential mediation model further clarifies how PAIC stimulates cognitive development: first through DL, which supports CE, and then through engagement's influence on critical thinking. This layered mechanism enriches SCT by proposing sequential rather than parallel mediation. It also suggests a boundary condition: DL is necessary for CE to effectively enhance critical thinking in AI-mediated environments.

Finally, the results challenge the assumption that technical skills alone are sufficient for developing reasoning abilities. Instead, metacognitive awareness and sustained engagement emerge as essential mediators. Accordingly, critical thinking is framed not simply as an instructional outcome (Carter et al., 2025; Mei et al., 2025), but as an emergent result of reciprocal interactions among self-perceptions, cognitive tools, and behavioural engagement, consistent with a central principle of SCT.

Practical implications

The study offers several practical implications for educators, instructional designers and policymakers seeking to strengthen critical thinking in digitally mediated learning environments. First, the positive association between PAIC and critical thinking suggests that AI literacy should be embedded across curricula rather than confined to technical courses. Integrating AI-related competencies into disciplinary learning can help students develop confidence in using AI tools while applying them to authentic academic problems (Dikhanbayeva, 2025; Medina-Gual et al., 2025; Xu et al., 2025). Second, the findings indicate that hands-on and guided engagement with AI tools is essential. Educators should design learning tasks that require students to test prompts, compare outputs, verify evidence and reflect on the reliability and limitations of AI-generated responses. Such praxis-oriented approaches move learners beyond passive consumption towards active and critical use of AI systems. Studies have shown that structured pedagogical interventions and reflective digital tasks can strengthen higher-order thinking and applied competence in technology-enhanced settings (Ba et al., 2025; Klisc et al., 2017; Medina-Gual et al., 2025).

Third, the mediating role of DL underscores the need for comprehensive capability development that goes beyond basic tool use. Institutions should provide training in information evaluation, online safety, digital ethics and collaborative problem-solving. Frameworks such as DigComp and recent intervention studies have demonstrated that systematic literacy development can improve learners' readiness to engage effectively with emerging technologies (Cui et al., 2026; Redecker, 2017; Vuorikari et al., 2016). Fourth, the role of CE suggests that pedagogical design remains central. Inquiry-based, collaborative and problem-centred learning activities can encourage students to invest greater mental effort, sustain attention and apply reasoning strategies while using AI tools. For example, AI-supported peer feedback, adaptive learning tasks and discussion-based activities may foster deeper engagement and reflective judgement (Ba et al., 2025; Klisc et al., 2017; Zhou & Hou, 2024).

Finally, policymakers and institutional leaders should address equity issues in access to AI learning opportunities. Students from disadvantaged backgrounds may have fewer opportunities to build confidence in AI or DL. Targeted support programmes, faculty development initiatives and inclusive digital infrastructure can help reduce these disparities and ensure that AI integration contributes to broader educational development rather than widening existing gaps. Overall, effective digital transformation (Yang, 2025) requires not only access to AI tools but also pedagogically grounded practices that cultivate reflective, capable and ethically aware learners.

Limitations and future research directions

Despite its contributions, this study has several limitations. First, the cross-sectional design limits causal interpretation and precludes definitive conclusions about the temporal order of the variables. Future longitudinal and experimental studies are needed to clarify causal relationships and developmental trajectories among these constructs. Second, the sample consisted of Generation Z university students in Türkiye, which may limit the generalisability of the findings to other age groups, professional populations or cultural contexts. Educational systems, levels of technological infrastructure and patterns of AI adoption may shape how these constructs are experienced across settings. Replication studies in different countries and demographic groups would strengthen external validity.

Third, the use of self-report measures may introduce social desirability, common method variance and perceptual bias. Future research could incorporate performance-based assessments of critical thinking, behavioural indicators of engagement or objective measures of digital competence. Mixed method approaches may also provide richer insight into how learners experience AI-supported environments. Fourth, while the study focused on DL and CE as key explanatory mechanisms, other relevant variables were not examined. Constructs such as emotional engagement, epistemic beliefs, ethical awareness of AI, learning motivation or prior technological experience may further explain variation in critical thinking outcomes.

Finally, the proposed serial mediation pathway should be interpreted cautiously. Although the findings are consistent with the sequence from PAIC to DL, CE and CTS, competing structures may also be plausible. Future studies should compare alternative models, such as parallel mediation or reversed serial pathways, using longitudinal or experimental designs to determine whether the ordering proposed here represents the most robust explanation.

Author contributions

Mahmut Demir: Conceptualisation, Data curation, Investigation, Methodology, Software, Supervision, Validation, Visualisation, Writing – original draft, Writing – review and editing; **Dilek Ünveren:** Conceptualisation, Data curation, Investigation, Resources, Software, Supervision, Validation, Visualisation, Writing – original draft.

References

Alon, A. T., Rahimi, I. D., & Tahar, H. (2024). Fighting fake news on social media: A comparative evaluation of digital literacy interventions. *Current Psychology*, *43*(19), 17343–17361. https://doi.org/10.1007/s12144-024-05668-4

Ashbourne, A. C. (2026). How artificial intelligence fosters student creativity in higher education: Evidence from a moderated mediation model. *International Journal of Social Sciences and Education Research, 12*(1), 29–43. https://doi.org/10.24289/ijsser.1771902

Asonge, L. (2026). Artificial intelligence readiness and service innovation performance in hospitality: The role of employee digital self-efficacy and psychological safety. *International Journal of Social Sciences and Education Research, 12*(1), 16–28. https://doi.org/10.24289/ijsser.1772005

Audrin, C., & Audrin, B. (2022). Key factors in digital literacy in learning and education: A systematic literature review using text mining. *Education and Information Technologies*, *27*(6), 7395–7419. https://doi.org/10.1007/s10639-021-10832-5

Ba, S., Zhan, Y., Huang, L., & Lu, G. (2025). Investigating the impact of ChatGPT-assisted feedback on the dynamics and outcomes of online inquiry-based discussion. *British Journal of Educational Technology*, *56*(5) 1710–1734. https://doi.org/10.1111/bjet.13605

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology*, *52*(1). https://doi.org/10.1146/annurev.psych.52.1.1

Carter, J. W., Scott, J. T., & Barrett, J. D. (2025). The emotional cost of AI chatbots in education: Who benefits and who struggles? *Computers in Human Behavior: Artificial Human, 5*, Article 100181. https://doi.org/10.1016/j.chbah.2025.100181

Chai, C. S., Koh, J. H. L., & Tsai, C. C. (2013). A review of technological pedagogical content knowledge. *Journal of Educational Technology & Society*, *16*(2), 31–51. https://www.jstor.org/stable/jeductechsoci.16.2.31

Chee, H., Ahn, S., & Lee, J. (2024). A competency framework for AI literacy: Variations by different learner groups and an implied learning pathway. *British Journal of Educational Technology*, *56*(5), 2146–2182. https://doi.org/10.1111/bjet.13556

Chien, S. Y., Hwang, G. J., & Jong, M. S. Y. (2020). Effects of peer assessment within the context of spherical video-based virtual reality on EFL students' English-speaking performance and learning perceptions. *Computers & Education*, *146*, Article 103751. https://doi.org/10.1016/j.compedu.2019.103751

Chiu, T. K., Ahmad, Z., & Çoban, M. (2024). Development and validation of teacher artificial intelligence (AI) competence self-efficacy (TAICS) scale. *Education and Information Technologies*, *30*(5), 6667–6685. https://doi.org/10.1007/s10639-024-13094-z

Cui, H., Dong, H., & Ulanbek, M. (2026). Digital literacy development of vocational college teachers: An industry-integrated TPACK framework and intervention study. *Australasian Journal of Educational Technology, 42*(1), 38–58. https://doi.org/10.14742/ajet.10462

Dalgıç, A., Yaşar, E., & Demir, M. (2024). ChatGPT and learning outcomes in tourism education: The role of digital literacy and individualized learning. *Journal of Hospitality, Leisure, Sport & Tourism Education*, *34*, Article 100481. https://doi.org/10.1016/j.jhlste.2024.100481

Daulay, A. A., Asna, A., & Br Tarigan, D. E. Y. (2026). Determinants of critical thinking in the AI era: The mediating role of self-efficacy in digital literacy and students' social interaction. *Buletin Konseling Inovatif, 6*(1), 44–53. https://doi.org/10.17977/2797-9954.1040

Demir, M., & Demir, Ş. Ş. (2025). Digital technologies and applications in tourist guidance: The dilemma between adopting innovations and career concerns. *Journal of Human Resources in Hospitality & Tourism, 24*(1), 1–25. https://doi.org/10.1080/15332845.2024.2405805

Demir, M., Demir, Ş. Ş., & Aktürk, O. (2024). The effects of distance education capabilities and competencies on learning outcomes during COVID-19 in higher education institutions. *Journal of Hospitality & Tourism Education*, *36*(4), 371–382. https://doi.org/10.1080/10963758.2023.2191966

Deschênes, A. A. (2024). Digital literacy, the use of collaborative technologies, and perceived social proximity in a hybrid work environment: Technology as a social binder. *Computers in Human Behavior Reports*, *13*, Article 100351. https://doi.org/10.1016/j.chbr.2023.100351

Dikhanbayeva, Y. (2025). Has the importance of technology in tourism been realized after Covid-19? Opportunities and challenges. *Journal of Tourism Theory and Research, 11*(1), 1–8. https://doi.org/10.24288/jttr.1514704

Eshet, Y. (2012). Thinking in the digital era: A revised model for digital literacy. Issues in Informing Science and Information Technology, 9, 267–276. https://doi.org/10.28945/1621

Fabian, K., Smith, S., Taylor-Smith, E., & Meharg, D. (2022). Identifying factors influencing study skills engagement and participation for online learners in higher education during COVID-19. *British Journal of Educational Technology*, *53*(6), 1915–1936. https://doi.org/10.1111/bjet.13221

Getenet, S., Cantle, R., Redmond, P., & Albion, P. (2024). Students' digital technology attitude, literacy and self-efficacy and their effect on online learning engagement. *International Journal of Educational Technology in Higher Education*, *21*, Article 3, 1–20. https://doi.org/10.1186/s41239-023-00437-y

Greene, B. A. (2015). Measuring cognitive engagement with self-report scales: Reflections from over 20 years of research. *Educational Psychologist*, *50*(1), 14–30. https://doi.org/10.1080/00461520.2014.989230

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Pearson Education.

Hatlevik, O. E., Throndsen, I., Loi, M., & Gudmundsdottir, G. B. (2018). Students’ ICT self-efficacy and computer and information literacy: Determinants and relationships. Computers & Education, 118, 107–119. https://doi.org/10.1016/j.compedu.2017.11.011

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). The Guilford Press.

Hobbs, R. (2017). *Create to learn: Introduction to digital literacy*. John Wiley & Sons. https://doi.org/10.1002/9781394260201

Jimenez-Liso, M. R., Bellocchi, A., Martinez-Chico, M., & Lopez-Gay, R. (2022). A model-based inquiry sequence as a heuristic to evaluate students’ emotional, behavioural, and cognitive engagement. *Research in Science Education*, *52*(4), 1313–1334. https://doi.org/10.1007/s11165-021-10010-0

Kim, L., Imjai, N., Kaewjomnong, A., Dowpiset, K., & Aujirapongpan, S. (2025). Does experiential learning matter to strategic intuition skills of MBA students? Implications of diagnostic capabilities and critical thinking skills. *The International Journal of Management Education*, *23*(2), Article 101138. https://doi.org/10.1016/j.ijme.2025.101138

Klisc, C., McGill, T., & Hobbs, V. (2017). Use of a post-asynchronous online discussion assessment to enhance student critical thinking. *Australasian Journal of Educational Technology, 33*(5), 63–76. https://doi.org/10.14742/ajet.3030

Laakso, N. L., Korhonen, T. S., & Hakkarainen, K. P. (2021). Developing students’ digital competences through collaborative game design. *Computers & Education*, *174*, Article 104308. https://doi.org/10.1016/j.compedu.2021.104308

Li, W., Huang, J.-Y., Liu, C.-Y., Tseng, J. C. R., & Wang, S.-P. (2023). A study on the relationship between student’ learning engagements and higher-order thinking skills in programming learning. *Thinking Skills and Creativity*, *49,* Article 101369. https://doi.org/10.1016/j.tsc.2023.101369

Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: Serial mediating roles of self-efficacy and cognitive engagement. *Frontiers in Psychology*, *14*, Article 1285392. https://doi.org/10.3389/fpsyg.2023.1285392

Liu, Z., Gao, Y., Zhang, N., Long, T., Liu, S., & Peng, X. (2024). Effects of self-regulated learning on cognitive engagement and learning achievement in online discussions. *Current Psychology*, *43*(35), 28147–28162. https://doi.org/10.1007/s12144-024-06445-z

Medina-Gual, L., Medina-Velázquez, L., & Parejo, J. L. (2025). A tridimensional model of AI literacy: An empirical analysis of student performance and demographic patterns in higher education. *Australasian Journal of Educational Technology, 41*(5), 37–55. https://doi.org/10.14742/ajet.10596

Mei, P., Brewis, D. N., Nwaiwu, F., Sumanathilaka, D., Alva-Manchego, F., & Demaree-Cotton, J. (2025). If ChatGPT can do it, where is my creativity? generative AI boosts performance but diminishes experience in creative writing. *Computers in Human Behavior: Artificial Humans, 4*, Article 100140. https://doi.org/10.1016/j.chbah.2025.100140

Memarian, B., & Doleck, T. (2023). ChatGPT in education: Methods, potentials, and limitations. *Computers in Human Behavior: Artificial Humans, 1*(2), Article 100022. https://doi.org/10.1016/j.chbah.2023.100022

Morgan, A., Sibson, R., & Jackson, D. (2022). Digital demand and digital deficit: Conceptualising digital literacy and gauging proficiency among higher education students. *Journal of Higher Education Policy and Management*, *44*(3), 258–275. https://doi.org/10.1080/1360080X.2022.2030275

Ng, W. (2012). Can we teach digital natives digital literacy? Computers & Education, 59(3), 1065–1078. https://doi.org/10.1016/j.compedu.2012.04.016

Nouri, J., Zhang, L., Mannila, L., & Norén, E. (2020). Development of computational thinking, digital competence and 21st century skills when learning programming in K-9. *Education Inquiry*, *11*(1), 1–17. https://doi.org/10.1080/20004508.2019.1627844

Nunnally J. C., & Bernstein I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.

Pattemore, M., & Gilabert, R. (2023). Using eye-tracking to measure cognitive engagement with feedback in a digital literacy game. *The Language Learning Journal*, *51*(4), 472–490. https://doi.org/10.1080/09571736.2023.2207582

Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. Educational Psychology Review, 16(4), 385–407. https://doi.org/10.1007/s10648-004-0006-x

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*(1), 539–569. https://doi.org/10.1146/annurev-psych-120710-100452

Redecker, C. (2017). European framework for the digital competence of educators: DigCompEdu. Publications Office of the European Union. https://doi.org/10.2760/159770

Reeve, J., & Tseng, C. M. (2011). Agency as a fourth aspect of students' engagement during learning activities. Contemporary Educational Psychology, 36(4), 257–267. https://doi.org/10.1016/j.cedpsych.2011.05.002

Rotgans, J. I., & Schmidt, H. G. (2011). Cognitive engagement in the problem-based learning classroom. *Advances in Health Sciences Education*, *16*, 465–479. https://doi.org/10.1007/s10459-011-9272-9

Shatila, K., Aránega, A. Y., Soga, L. R., & Hernández-Lara, A. B. (2025). Digital literacy, digital accessibility, human capital, and entrepreneurial resilience: A case for dynamic business ecosystems. *Journal of Innovation & Knowledge, 10*(3), Article 100709. https://doi.org/10.1016/j.jik.2025.100709

Siddiq, F., Scherer, R., & Tondeur, J. (2016). Teachers' emphasis on developing students' digital information and communication skills (TEDDICS): A new construct in 21st-century education. Computers & Education, 92–93, 1–14. https://doi.org/10.1016/j.compedu.2015.10.006

Sienkiewicz-Małyjurek, K., & Zyzak, B. (2025). Overcoming social and ethical challenges of AI through organizational resilience. A PLS-SEM approach. *Telematics and Informatics, 96*, Article 102210. https://doi.org/10.1016/j.tele.2024.102210

Tenberga, I., & Daniela, L. (2024). Artificial intelligence literacy competencies for teachers through self-assessment tools. *Sustainability*, *16*(23), Article 10386. https://doi.org/10.3390/su162310386

Vuorikari, R., Punie, Y., Carretero, S., & Van den Brande, G. (2016). DigComp 2.0: The digital competence framework for citizens. Update phase 1: The conceptual reference model (EUR 27948 EN). Publications Office of the European Union. https://doi.org/10.2791/11517

Xu, J., Shen, R., Li, J., & Hu, D. (2025). Artificial intelligence literacy among Chinese Master of Education students: Current situation, influencing factors and generative pathways. *Australasian Journal of Educational Technology, 41*(6), 1–17. https://doi.org/10.14742/ajet.10656

Yang, X. (2025). Digital transformation of tourism education: Technologies, opportunities, challenges, and future research agenda. *Journal of Tourism Theory and Research, 11*(1), 38–46. https://doi.org/10.24288/jttr.1516114

Yaşar, E. (2022). The effect of employer brand on workplace selection in the hospitality industry. *Journal of Tourism Theory and Research*, *8*(2), 29–36. https://doi.org/10.24288/jttr.1096279

Yuan, C. W., Tsai, H. Y. S., & Chen, Y. T. (2024). Charting competence: A holistic scale for measuring proficiency in artificial intelligence literacy. *Journal of Educational Computing Research*, *62*(7), 1675–1704. https://doi.org/10.1177/07356331241261206

Zhang, L., Wang, S., Wu, H., Zhang, S., Xv, M., Liu, L., & Shu, Y. (2025). Preparation before collaboration matters: An interactive system coupled with a four-phase pedagogy for collaborative reading. *Interactive Learning Environments*, *33*(10), 6102–6123. https://doi.org/10.1080/10494820.2025.2491628

Zhou, C., & Hou, F. (2024). Can AI empower L2 education? Exploring its influence on the behavioural, cognitive and emotional engagement of EFL teachers and language learners. *European Journal of Education*, *59*(4), Article e12750. https://doi.org/10.1111/ejed.12750

Zhu, X., Chen, A., Ennis, C., Sun, H., Hopple, C., Bonello, M., Bae, M., & Kim, S. (2009). Situational interest, cognitive engagement, and achievement in physical education. *Contemporary Educational Psychology*, *34*(3), 221–229. https://doi.org/10.1016/j.cedpsych.2009.05.002

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