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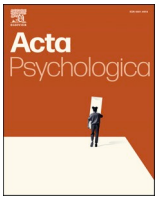



Measuring students' AI competence: Development and validation of a multidimensional scale integrating educational psychology perspectives

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ABSTRACT

The rapid integration of Artificial Intelligence (AI) into K-12 education has created a pressing need to evaluate students' capacity to engage with AI effectively and responsibly. As outlined in UNESCO's AI Competency Framework, AI competence is a multidimensional construct encompassing cognitive (knowledge and skills), affective (values and motivation), ethical (principles and responsibilities), and technical (practical and design-based) dimensions. Without systematic assessment, educators lack the evidence needed to ensure students possess not only technical proficiency but also the critical thinking, ethical awareness, and motivation required in AI-driven learning environments. To address this gap, the present study develops and validates the AI Competence Scale (AICS), a multidimensional instrument grounded in UNESCO's framework and educational psychology principles. The AICS conceptualizes AI competence across four interrelated dimensions-Human-Centred Mindset, Ethics of AI, AI Techniques and Applications, and AI System Design-capturing the interplay between students' knowledge, values, reasoning, and applied skills.

Data were collected from 608 high school students in public secondary schools in Qatar, following a multi-stage process: expert reviews for content validity; exploratory and confirmatory factor analyses for construct validity; reliability testing via Cronbach's alpha and composite reliability; and convergent, discriminant, and nomological validity using AVE, HTMT ratios, and structural equation modeling (SEM). The results confirmed strong psychometric properties, with SEM revealing a significant positive association between AI competence and students' interest in AI-related careers. The validated AICS provides educators, researchers, and policy-makers with a theoretically grounded and empirically robust tool for assessing students' readiness for ethical and informed engagement with AI, supporting curriculum design, targeted interventions, and evidence-based policy in K-12 AI education.

1. Introduction

As Artificial Intelligence (AI) becomes increasingly embedded in K-12 education systems, the demand for students to develop meaningful and responsible AI competence has never been more urgent (Hidayat-ur-Rehman, 2024). Beyond basic technological literacy, AI competence encompasses an understanding of machine learning concepts, ethical considerations, and the ability to apply AI tools in problem-solving contexts (Long & Magerko, 2020; Ng et al., 2021). This competence is vital not only for navigating current digital environments but also for cultivating future-ready, ethically grounded citizens (Wang et al., 2023).

AI competence has been conceptualized in various ways. Some scholars focus on students' AI knowledge, collaborative skills, and capacity for lifelong learning (Huang, 2021), while others emphasize psychological empowerment and the practical use of AI in real-world tasks (Kong et al., 2025). These evolving definitions underscore a shared understanding that AI competence must integrate both technical proficiency and affective readiness, including ethical judgment and self-efficacy (Chiu et al., 2024). To advance this understanding, internationally endorsed frameworks such as UNESCO's AI Competency Framework provide a comprehensive vision. Notably, UNESCO's AI Competency Framework is one of the first K-12-specific guideline,

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offering a globally recognized and policy-aligned foundation for AI education (Filo et al., 2024; UNESCO, 2024). This framework centers not only on digital and technical fluency but also on human-centred values, ethical responsibility, and sustainability principles essential for AI education in the 21st century. Its emphasis on agency, fairness, and accountability aligns closely with key psychological constructs, including motivation, autonomy, and reflective thinking.

Building on this foundation, the present study introduces the AI Competence Scale (AICS), a multidimensional instrument structured around four core competencies: Human-Centred Mindset, Ethics of AI, AI Techniques and Applications, and AI System Design. These dimensions reflect the cognitive, ethical, and affective attributes essential for student readiness in AI-driven contexts. Grounded in educational psychology, specifically Self-Determination Theory (SDT) (Ryan & Deci, 2000) and Social Cognitive Career Theory (SCCT) (Lent et al., 1994), the scale aims to provide a valid and theory-aligned measure for assessing students' preparedness to engage responsibly with AI technologies. By integrating UNESCO's policy-oriented descriptors with SDT and SCCT, this study not only validates the framework's relevance at the high school level but also extends it by embedding psychological aspects such as self-efficacy, moral reasoning, and problem-solving into the operational design of the scale.

2. Literature review

In today's technology-driven world, students' AI competence is generally understood as encompassing both foundational knowledge of AI and the technical skills required to perform AI-related tasks in a responsible manner (Chai et al., 2022). Developing such competence begins with a solid understanding of core AI concepts, which represent the foundational layer of AI literacy (Ng et al., 2022). However, the absence of a psychometrically validated tool that captures the multifaceted nature of AI learning poses a challenge for researchers and educators, as it limits their ability to make informed curriculum and policy decisions. In response to this gap, and building on UNESCO's AI competency framework alongside two prominent motivational theories Self-Determination Theory (SDT) and Social Cognitive Career Theory (SCCT), this review synthesizes empirical findings across four essential dimensions that inform the development of the proposed AI Competence Scale for students: (a) a human-centred mindset, (b) ethics of AI, (c) AI techniques and applications and (d) AI system design.

2.1. Human-centred mindset

Human-centred Artificial Intelligence (AI) emphasizes aligning technological advancement with human values, agency, and well-being (Schmager et al., 2025). Rather than replicating human cognition, this approach focuses on embedding AI systems within ethical, social, and contextual frameworks that respect human dignity and promote societal good. Central to this concept is the idea of augmentation - utilizing AI to enhance human intelligence rather than replace it (Schmager et al., 2025; Shneiderman, 2022). This design philosophy supports cooperative intelligence, where AI systems complement human strengths and promote user-centered interaction that maintains human control (Amershi et al., 2019). As UNESCO (2024) stresses, human-centred AI must uphold human rights, foster inclusion, and support sustainability, ensuring that AI education cultivates learners' capacity to drive innovation that is socially equitable, ethically grounded, and environmentally responsible. Hence, it represents not just a design principle but a humanistic commitment to ensuring AI enhances human agency, creativity, and ethical progress (Miao & Shiohira, 2024).

In education, fostering a human-centred mindset early is widely emphasized. Kim et al. (2021) identified it as the most critical aspect of AI competence, recommending its early introduction to support ethical and purposeful AI engagement. Chiu et al. (2022) added that AI knowledge and readiness cultivate this mindset by helping students apply AI meaningfully while remaining conscious of its human impact. Extending this, Kong et al. (2024) emphasized that metacognitive skills such as reflection and self-regulation are key to enabling learners to make thoughtful decisions when integrating AI into real-world problem-solving.

This approach aligns with SDT, as it supports students' needs for autonomy, competence, and relatedness (Ryan & Deci, 2000). When students view AI as a collaborative partner, they gain control over how it enhances their learning, while connecting with others through shared ethical goals. Similarly, SCCT posits that viewing AI as socially beneficial enhances self-efficacy, outcome expectations, and career aspirations (Lent et al., 1994). Ultimately, human-centred perspectives shape how students perceive empathy, responsibility, and societal benefit in AI use. Embedding this dimension into AI education ensures learners not only use AI effectively but also understand its ethical purpose, preparing them to be responsible, value-driven contributors in an AI-driven world.

2.2. Ethics of AI

As AI technologies increasingly shape societal systems, ethical awareness has emerged as a fundamental component of AI competence. It involves students' ability to critically assess the moral implications of AI systems, including issues such as data privacy, bias, accountability, and transparency (Choi et al., 2024). High-profile cases like the "Lee Luda" chatbot incident underscore the urgent need for learners to develop the ethical reasoning required to navigate such risks (Choi et al., 2024).

Evidence suggests that well-structured ethics education significantly enhances students' moral understanding. Choi et al. (2024) found that a middle school AI ethics program led to substantial gains in students' awareness of fairness, responsibility, and social impact. Kong et al. (2023) similarly emphasized that ethical competence including value judgment and moral reasoning is essential for preparing responsible citizens capable of engaging with AI across disciplines.

From a psychological lens, SDT supports ethical awareness by fulfilling students' need for autonomy in making moral decisions, competence through ethical reasoning skills, and relatedness by considering the societal consequences of AI use (Ryan & Deci, 2000). Likewise, SCCT explains that ethical instruction boosts self-efficacy confidence in one's ability to act responsibly and shapes outcome expectations by helping students foresee the benefits of ethical AI engagement (Lent et al., 1994).

Furthermore, studies show that ethics training increases awareness of embedded biases and discrimination in AI systems (Choi et al., 2024; Modi, 2023), supporting UNESCO's call for human-centred, value-driven AI education. Ethical awareness thus cultivates reflective, morally grounded learners who can use AI not just effectively, but responsibly. Incorporating ethical awareness into AI competence frameworks is not just pedagogically beneficial it is essential. As future AI developers, users, or regulators, students must internalize ethical principles to ensure their engagement with AI remains just, transparent, and socially accountable.

2.3. AI techniques and applications

AI techniques and applications refer to students' ability to understand, use, and adapt technologies like machine learning, natural language processing, neural networks, and data-driven algorithms. This dimension emphasizes both conceptual understanding and practical skills needed to build, evaluate, and apply AI tools in authentic contexts.

Project-based learning has proven effective in developing this competence. Lu and Fan (2023) found that weather prediction projects using machine learning enhanced high school students' algorithmic thinking and technical confidence. Kong et al. (2024) similarly highlighted that hands-on tasks such as visual programming and model training boost engagement and application-level understanding. Reinforcing this, studies have demonstrated that integrating real-world tools

such as mind mapping combined with generative AI chatbots and game-based AI interaction can significantly enhance students' computational thinking and problem-solving abilities (Ye et al., 2025; Edali et al., 2024). Additionally, AI tools like ChatGPT have been shown to improve creative problem-solving performance in students (Urban et al., 2024). These experiences bridge the gap between abstract AI concepts and real-world use, building readiness for AI-integrated academic and career pathways.

Psychologically, SDT supports this dimension by satisfying students' need for competence, autonomy, and intrinsic motivation through exploration and mastery of technical tools (Ryan & Deci, 2000). Students who independently engage with AI applications experience greater confidence and ownership in their learning. SCCT further underscores its relevance. Successful experiences with AI tools foster self-efficacy and strengthen outcome expectations, motivating students to pursue AI-related fields (Lent et al., 1994). For instance, designing a chatbot or training an image classifier can help students envision and set goals aligned with future STEM careers.

Engaging with real-world challenges such as simulating medical diagnoses, developing inclusive language models, or automating environmental tasks enhances students' understanding of AI's social applications and supports ethical reflection and goal setting (Kong et al., 2024). In sum, proficiency in AI techniques and applications equips students with essential technical, cognitive, and motivational capacities needed to thrive in an AI-driven world.

2.4. AI system design

AI system design involves students' ability to conceptualize, prototype, and evaluate AI systems across the full development cycle, problem identification, data preparation, model training, evaluation, and iteration, while considering usability, reliability, and ethical impact. This competence enables students to move beyond tool usage to the creation of AI solutions for real-world challenges.

Wang et al. (2024) demonstrated that project-based curricula covering full-cycle AI development enhanced students' understanding of AI workflows and fostered computational creativity. Tasks such as designing facial recognition or traffic models helped students develop systems thinking and reflect on ethical limitations. Similarly, Huang (2021) highlighted that engaging students in AI design cultivates innovation, reasoning, and collaboration, while Kong et al. (2024) emphasized the interdisciplinary nature of such learning, requiring integration of technical and ethical knowledge.

This design-oriented approach aligns with SDT, as it supports autonomy (decision-making in design), competence (mastery of technical skills), and relatedness (working on socially relevant challenges) (Ryan & Deci, 2000). SCCT also underscores its value complex design experiences enhance self-efficacy, shape outcome expectations, and motivate career aspirations in AI-related fields (Lent et al., 1994). Importantly, students involved in system-level design are more likely to examine bias, transparency, and ethical implications (Wang et al., 2024), aligning with global calls for responsible and inclusive AI innovation. In summary, system design is a crucial part of AI competence, blending technical expertise, creativity, and ethical understanding, equipping students to lead in an AI-driven world.

Collectively, the four core dimensions of AI competence human-centred mindset, ethical awareness, technical proficiency, and system design are deeply grounded in psychological theory and global educational priorities. Drawing on SDT, they nurture students' competence through skill mastery, autonomy via self-directed use and ethical decision-making, and relatedness by emphasizing the societal impact of AI (Ryan & Deci, 2000). Simultaneously, SCCT supports these dimensions by enhancing self-efficacy, shaping positive outcome expectations, and fostering goal setting for future engagement in AI fields (Lent et al., 1994). These theoretical foundations are also echoed in UNESCO's AI education guidelines, which advocate for AI learning that is human-centred, ethically grounded, and inclusive, preparing students not just to use AI, but to shape it responsibly. Thus, this multidimensional framework offers a holistic foundation for developing a valid, future-focused AI Competence Scale that reflects both psychological growth and global policy imperatives.

2.5. Research gap

With the rising integration of AI in education, there is a growing need to assess students' competence in engaging with AI tools meaningfully and responsibly (Park & Kwon, 2024). Although several instruments have emerged to evaluate aspects of AI knowledge, usage, or confidence, many remain fragmented in scope and lack integration of cognitive, affective, ethical, and technical aspect, particularly within a psychological and policy-aligned educational framework.

For example, the Empowerment in Using AI for Problem-Solving (EUAIPS) scale by Kong et al. (2025) assesses students' self-efficacy and meaningful engagement with AI for problem-solving but does not incorporate ethical reasoning or system-level technical competencies. Similarly, the AI Self-Efficacy Scale (AISES) by Wang and Chuang (2024) evaluates confidence across comfort, anthropomorphic interaction, and perceived ease of use but lacks grounding in broader educational psychology constructs such as agency, reflection, or values-based engagement. The Artificial Intelligence Literacy Scale (AILS) by Wang et al. (2023), while offering a broad perspective on AI literacy, is designed for general populations and lacks specificity to secondary learners and theoretical anchoring in motivational or developmental psychology. In a more recent contribution, Lin et al. (2025) conducted a large-scale AI competency survey aligned with the UNESCO AI Competence Framework, capturing students' knowledge, technical skills, system design, and ethical awareness. While the study offers valuable benchmarking data, it is descriptive in nature and lacks psychometric validation. Moreover, the instrument is not grounded in educational psychology theories such as SDT or SCCT, nor does it explore how students' motivational and career-related beliefs influence AI competence development. On the educator side, the AI Competence Educators (AICO_edu) instrument developed by Delcker et al. (2025) evaluates AI competence among teachers but is not applicable to students and does not draw from international standards such as UNESCO's policy framework, which emphasizes ethics, human-centred design, and interdisciplinary integration. To clarify how these existing instruments differ from the present study's contribution, Table 1 provides a comparative overview:

In summary, while current scales contribute valuable insights, they tend to either lack multidimensionality, ignore educational psychology foundations, or remain focused on general or teacher populations. To address this critical gap, the present study adapts globally endorsed UNESCO (2024) AI Competence Framework to develop and validate the AI Competence Scale (AICS). The AICS conceptualizes AI competence across four interrelated dimensions Human-Centred Mindset, Ethics of AI, AI Techniques and Applications, and AI System Design capturing essential cognitive, ethical, technical, and psychological competencies. By aligning with educational psychology theories and international standards, this study offers a robust and psychometrically validated instrument for evaluating high school students' readiness to engage meaningfully and responsibly with AI technologies.

Accordingly, this study investigates the following research questions:

RQ1: To what extent do the competencies identified by the UNESCO AI Competency Framework appropriately reflect the cognitive, affective, and ethical dimensions of students' AI competence?

RQ2: Does the AI Competence Scale (AICS) demonstrate strong psychometric properties, including reliability, construct validity, and predictive validity, in assessing students' AI competence from cognitive, affective, and ethical development perspectives?

Table 1
Comparison of existing AI competence scales and the proposed AICS.

Instrument	Target population	Core dimensions	Focus	Framework base	Limitations addressed by AICS
EUAIPS (Kong et al., 2025)	Students	Impact, self-efficacy, meaningfulness	Psychological empowerment for problem-solving	Metacognition	Lacks ethical/technical coverage
AISES (Wang & Chuang, 2024)	Students	Assistance, anthropomorphic interaction, comfort, skills	AI self-efficacy	Technology Acceptance	Limited to confidence and usage
AILS (Wang et al., 2023)	General users	Awareness, usage, evaluation, ethics	General AI literacy	Digital Literacy & Knowledge, Skills, Attitudes, Values, Ethics (KSAVE)	Not tailored for students; lacks educational psychology grounding
AICO_edu (Delcker et al., 2025)	Teachers	Theoretical knowledge, legal & ethical issues, pedagogy, professionalization	Teachers' perceived AI competence	Empirical & policy models	Focused on teacher training; not student assessment
AI Competency Survey (Lin et al. 2025)	High School Students	AI knowledge, tool use, system design, ethics	Descriptive benchmarking of AI competence	UNESCO AI Competence Framework	No psychometric validation; lacks integration with psychological theory and interrelation of competence dimensions
AICS (present study)	High School Students	Human-centred mindset, ethics of AI, AI techniques & applications, AI system design	AI competence from a cognitive, affective, and ethical lens	UNESCO AI Competence Framework + Educational Psychology	First psychometrically validated student-centered tool integrating psychological and ethical dimensions

3. Methodology

3.1. Research design

The current study employed a quantitative research design using a cross-sectional survey method to develop and validate the AI Competence Scale (AICS). This approach was selected for its efficacy in collecting data from a large sample within a defined time frame (Wang & Cheng, 2020). To enhance representativeness and minimize bias, a two-stage sampling technique was implemented. Given its suitability for scale development, this method facilitated the collection of diverse responses, ensuring broad representation of the target population (Asparouhov & Muthén, 2014). The scale development and validation process adhered to established psychometric guidelines (Churchill, 1979; DeVellis, 2017; Hinkin, 1998), progressing through four systematic steps: scale generation, purification, refinement, and validation testing (Fig. 1).

3.2. Sample and participants

The study sample consisted of high school students enrolled in AI-related courses across multiple schools. To ensure diversity and enhance representativeness, a two-stage sampling strategy was employed for sample selection. Stages refer to the sequential steps in selecting the sample. In Stage 1, stratified random sampling was utilized to select schools from different educational districts, considering demographic and academic diversity to capture a broad cross-section of the target population. In Stage 2, simple random sampling was applied within each selected school to recruit student participants, ensuring that every eligible student had an equal probability of being selected.

Following the establishment of the sampling frame through this systematic two-stage procedure, data collection was conducted across two distinct phases, with phases referring to separate rounds of data collection designed for different psychometric purposes. A total of 822 students participated across both phases. After rigorous data cleaning procedures to remove incomplete and inattentive responses, 608 valid responses were retained for analysis. In Phase 1, a randomly selected group of students participated to provide data for the initial exploration of the AI Competence Scale (AICS) structure via Exploratory Factor Analysis (EFA), utilizing 308 valid responses. In Phase 2, a newly and independently selected cohort provided 300 valid responses. These responses were utilized to conduct Confirmatory Factor Analysis (CFA) and to assess the nomological validity of AI competence scale.

This phased and independent sampling approach ensured that the factor structure was not only explored but also rigorously confirmed on a separate sample, thereby enhancing the psychometric robustness and generalizability of the developed scale. The final sample demonstrated substantial diversity in age, gender, and ethnic background, contributing to the robustness and applicability of the findings across diverse student populations. Detailed demographic information for the participants is provided in Table 2.

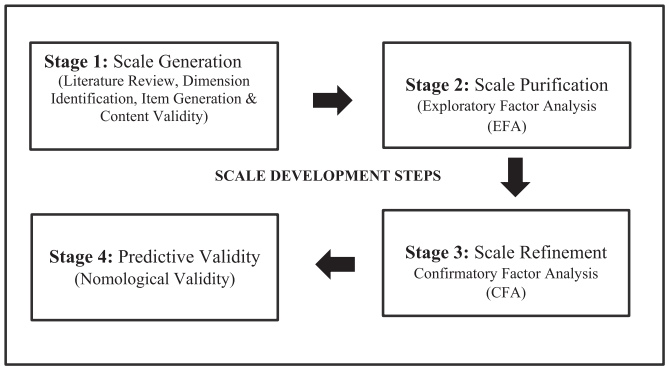

Fig. 1. Stepwise procedure for scale development and validation of the AI competence scale (AICS).

3.3. Procedure for data collection

The data collection was carried out in two systematic phases to ensure the development and validation of the AI Competence Scale (AICS). In the first phase, a pilot study was conducted to explore the underlying factor structure of the initial version of the AICS. The draft questionnaire was distributed to high school students during scheduled

Table 2
Demographic details of high school students utilized for data analysis.

Variables	Parameters	Phase 1		Phase 2	
		N = 308	%	N = 300	%
Age	Under 16 yrs	98	31.82	90	30
	16 yrs–17 yrs	132	42.86	124	41.33
	Above 17 years	78	25.32	86	28.67
Gender	Male	138	44.80	135	45
	Female	170	55.20	165	55
Ethnicity	Nationals	139	45.13	129	43
	Expatriates	169	54.87	171	57

class periods. The responses obtained in this phase were used to perform an Exploratory Factor Analysis (EFA), which informed the refinement and revision of the scale items.

In the second phase, the finalized version of the AICS was administered to a new group of high school students enrolled in AI-related courses. This revised questionnaire included additional items focused on students' interest in AI-related careers, covering aspects such as aspirations, perceived relevance of AI to their future goals, and motivation to pursue AI fields. Data from this phase were subjected to Confirmatory Factor Analysis (CFA) to validate the factor structure of the scale. Additionally, nomological validity testing was conducted to examine the extent to which AI competence, as measured by the AICS, could predict students' interest in pursuing AI-related careers. The analysis yielded strong empirical evidence supporting the scale's nomological validity by establishing a significant relationship between student's AI competence and their career interest.

All data were collected in person, within classroom settings, under the supervision of trained researchers and school staff to ensure uniformity in administration and to address any participant queries. The sampling followed the recommended methodological guideline of maintaining at least a 5:1 ratio of responses to items, supporting the adequacy and reliability of the dataset for both EFA and CFA (Hair et al., 2010). The study adhered strictly to ethical research standards. Approval was obtained from the Qatar University Institutional Review Board (QU-IRB), under approval number QU-IRB 222/2024-EA. Informed consent was collected from both students and their guardians prior to participation. Participation was entirely voluntary, and students were informed of their right to withdraw at any stage. To maintain confidentiality, all responses were anonymized and securely stored.

4. Psychometric evaluation of AI Competence Scale (AICS): development and results

4.1. Step 1: scale generation

4.1.1. Dimension identification

The primary objective was to identify the core dimensions of AI competence essential for developing a comprehensive assessment tool. This phase commenced with an extensive literature review utilizing the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Fig. 2). The data search was performed exclusively from SCOPUS. The search query was formulated as: ((school OR primary OR preparatory OR elementary OR high school OR secondary

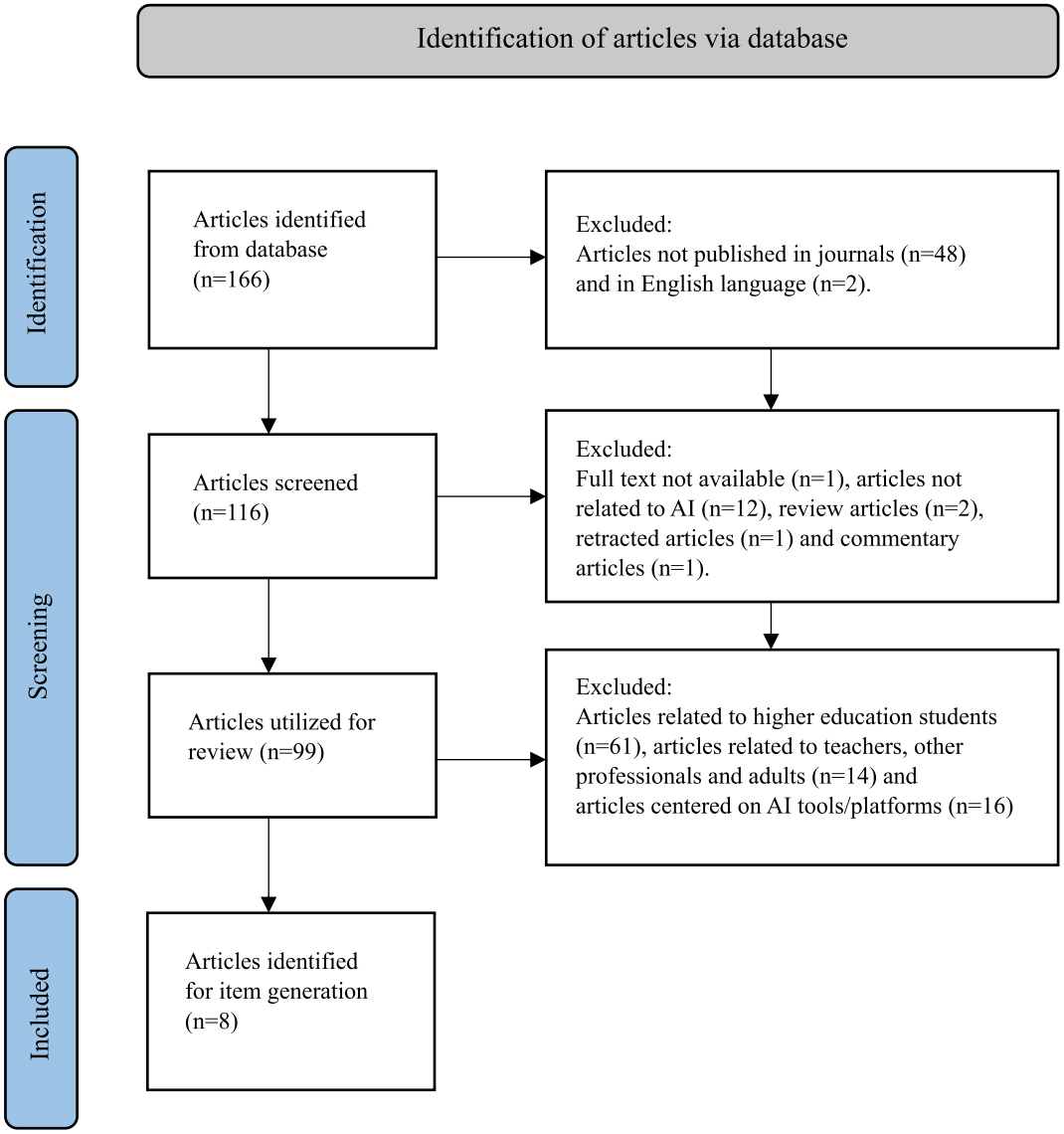

Fig. 2. Flow diagram depicting the screening and selection of articles according to the PRISMA framework.

OR middle school) AND (student* OR learner*) AND (ai OR artificial intelligence) AND competence AND (scale OR measure* OR instrument OR questionnaire OR survey)). Further, the literature search was limited to journal articles published in the English language. Articles were included only if their full text was available, excluding reviews, retracted articles, and commentaries.

As a result, 8 articles were selected that evaluated different aspects of students' AI competence. Additionally, the research team investigated existing international AI literacy frameworks. The team conducted a thorough review of several frameworks, including UNESCO's AI Competency Framework for students, which provided a strong foundation. This framework consists of four key dimensions: Human-Centred Mindset, Ethics of AI, AI Techniques & Applications, and AI System Design (see Table 2). These dimensions aligned well with the existing literature on students' AI competence. Therefore, the research team reached a consensus to adapt these dimensions from UNESCO's framework as they reflect a holistic approach to AI competence, encompassing knowledge, values, skills, and ethical awareness. Accordingly, these four dimensions were adopted to structure the development of the AI Competence Scale (AICS). This adaptation aimed to ensure that the new assessment scale would be relevant, reliable, and aligned with international standards and best practices in AI education.

4.1.2. Mapping identified dimensions to psychological domains

To ensure theoretical clarity and alignment with established learning psychology, each dimension was mapped to one or more psychological domains - cognitive, affective, and ethical based on their descriptions in the UNESCO framework (UNESCO, 2024, pp. 22–25). This mapping ensures that the scale captures the full spectrum of student development as intended by the framework. Specifically:

- Human-Centred Mindset reflects the affective domain, emphasizing values, motivation, identity, and civic responsibility in students' engagement with AI.
- Ethics of AI aligns with the ethical domain, focusing on responsible decision-making, fairness, transparency, privacy, and human rights.
- AI Techniques and Applications and AI System Design correspond to the cognitive domain, emphasizing conceptual understanding, problem-solving, programming, system-level thinking, and tool development. These dimensions also encompass the technical (i.e., practical and design-based) aspects of cognitive competence as emphasized in UNESCO's progression levels particularly the "Apply" and "Create" stages, which focus on designing, building, and optimizing AI systems in real-world contexts.

This theoretical alignment guided the development of items and scale structure. Table 3 summarizes the four dimensions, their definitions, supporting literature, and mapped psychological domains based on UNESCO (2024). By grounding these dimensions in the cognitive, affective, and ethical domains informed by educational psychology, the scale not only retains UNESCO's structural framework but also extends it by theorizing its psychological underpinnings through constructs such as self-efficacy, moral reasoning, and problem-solving. This integration ensures that the AI Competence Scale (AICS) reflects both international policy standards and validated psychological constructs, thereby strengthening its theoretical and practical relevance for high school learners.

4.1.3. Item generation

Following the identification of key dimensions and their theoretical alignment, the next phase involved the systematic generation of scale items to reflect the operational essence of each construct. Grounded in scale development guidelines proposed by DeVellis (2017), Hinkin (1998), and Boateng et al. (2018), the item development process emphasized conceptual clarity, construct relevance, and age-appropriate language suited for high school students.

To ensure comprehensive coverage, each dimension was operationalized into observable indicators that could be measured through students' self-perceptions. These indicators were informed by both theoretical definitions and empirical examples from AI education research. The item wording adhered to best practices such as using first-person statements ("I can…", "I understand…") to reflect self-assessed competence and maintaining simplicity and directness to avoid ambiguity or cognitive overload for adolescent respondents (Clark & Watson, 1995). Care was also taken to avoid double-barreled or negatively worded items, which can introduce measurement error, especially among younger populations (Schmitt & Stuits, 1985).

A total of 35 items were initially generated across the four domains. This number aligns with recommendations for early item pools to be roughly twice the number expected to appear in the final scale, ensuring redundancy for psychometric screening (DeVellis, 2017). Each dimension was represented by 8–10 items to capture sufficient construct variance. All items were formatted using a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This scale length strikes a balance between response sensitivity and respondent burden, as

Table 3
Definitions of the dimensions of students' AI competence with mapped psychological domains (aligned with UNESCO, 2024).

Dimensions	Definitions	References	Mapped psychological domain (UNESCO, 2024)
Human-Centred Mindset	A human-centred mindset focusses on human agency, accountability, interdisciplinary learning, and social good, while empowering students to confidently and effectively engage with AI. It promotes intrinsic motivation, civic identity, and awareness of AI's impact on society.	(Chiu et al., 2022; Huang, 2021)	Affective
Ethics of AI	The ethics of AI involves responsible use of AI, focusing on principles such as human rights, accountability, transparency, non-discrimination, sustainability, and safeguarding personal well-being and privacy. It cultivates students' capacity for moral reasoning (affective) and socially responsible behavior (social impact).	(Huang, 2021; Xia et al., 2023)	Ethical
AI Techniques and Applications	The 'AI techniques and applications' aspect focuses on building foundational AI knowledge, developing programming and data handling skills, and applying these skills to create and customize AI tools, enhancing student's abilities to find solutions through interdisciplinary integration. It enhances students' abilities to create and customize AI tools and solve problems through interdisciplinary integration.	(Huang, 2021; Kong et al., 2024, 2025; Sanusi et al., 2022; Simeunovic & Ruzicic, 2024)	Cognitive (with technical/practical emphasis)
AI System Design	AI system design involves identifying requirements, architecture building, programming, testing, and optimization of AI systems, enabling students to troubleshoot, program, and enhance AI-driven systems effectively, supporting higher-order cognitive skills such as systems thinking, innovation, and solution development	(Chai et al., 2022; Huang, 2021)	Cognitive (with design-based/technical emphasis)

supported by studies showing that 5-point scales provide sufficient reliability and discriminative power for adolescent populations (Revilla et al., 2014). The Likert format was selected to measure degree of agreement rather than frequency or truth-value, making it more suitable for capturing students' self-perceived AI competence.

4.1.4. Content validity

An initial pool of 35 items, designed to comprehensively capture the breadth and depth of the construct, was sent to a panel of ten experts to ensure that each item was both theoretically representative and contextually appropriate for the target population (Haynes et al., 1995). A panel of experts includes faculty members and researchers with specialization in AI and educational technology, who have formally consented to participate. Each expert received a content validation form along with clear operational definitions of the four AI competence dimensions (see Table 3) and was asked to evaluate each item using a 3-point scale: 1 – *Not representative*, 2 – *Somewhat representative*, and 3 – *Clearly representative*. Experts assessed each item based on clarity, alignment with the corresponding construct, and relevance for high school learners. Based on their evaluations, the Item-Level Content Validity Index (I-CVI) was calculated for each item, with a minimum acceptable threshold set at I-CVI $\geq$ 0.78 (Lynn, 1986). To account for chance agreement, *Modified Kappa Statistics (κ)** were also computed, with values above 0.75 considered acceptable (Polit & Beck, 2006).

Following the evaluations, the expert recommended the removal of two items due to concerns related to technical complexity or conceptual vagueness. One item under AI System Design was removed because it used overly technical language ("Students should be able to design neural network pipelines") that was deemed inappropriate for the target population. The second item, listed under Human-Centred Mindset, was removed due to its broad and ambiguous phrasing ("Students should value the future of technology"), which experts felt lacked specificity and did not directly capture self-efficacy or agency. These items did not meet the I-CVI and κ* thresholds and were therefore excluded from the scale.

As a result, the refined version of the scale comprised 33, each demonstrating strong content validity. The Scale-Level Content Validity Index (S-CVI/Ave) exceeded 0.90, indicating high overall agreement among experts on the representativeness of the final items. A detailed breakdown of expert agreement, I-CVI values, and κ* scores is provided in Table 4. This rigorous item refinement process ensured that only conceptually valid and psychometrically sound items were retained for subsequent phases of scale validation.

4.2. Step 2: scale purification

4.2.1. Exploratory factor analysis and construct validity

Following the establishment of content validity, the next step involved purifying the initial item pool and examining the underlying factor structure of the AI Competence Scale (AICS) using Exploratory Factor Analysis (EFA), a crucial procedure for establishing initial construct validity. The finalized 33-item questionnaire was administered during Phase 1 of data collection.

The questionnaires were distributed among 438 high school students, yielding 335 responses, accounting for a response rate of 76.48 %. After cross-checking for serious and complete responses, 27 responses were excluded, resulting in 308 valid responses. This dataset maintained a 5:1 ratio of responses to items, ensuring its appropriateness to further proceed with factor analysis using SPSS version 29 (Hair et al., 2010). To ensure that the data were appropriate for factor analysis, we first conducted the Kaiser-Meyer-Olkin (KMO) test, which confirmed the adequacy of the sampling (Kaiser, 1974). A KMO value closer to 1 is considered excellent, and the results indicated that our sample size was sufficient for analysis. Additionally, we performed Bartlett's test of

Table 4
Content Validity Index (CVI) for AI competence scale items.

Item	N (experts)	No. of agreements (A)	Proportion agreement	I-CVI	K*	Interpretation
Item 1	10	10	1.0	1.0	1.0	Excellent
Item 2	10	10	1.0	1.0	1.0	Excellent
Item 3	10	8	0.8	0.8	0.79	Acceptable
Item 4	10	10	1.0	1.0	1.0	Excellent
Item 5	10	10	1.0	1.0	1.0	Excellent
Item 6	10	10	1.0	1.0	1.0	Excellent
Item 7	10	10	1.0	1.0	1.0	Excellent
Item 8	10	10	1.0	1.0	1.0	Excellent
Item 9	10	10	1.0	1.0	1.0	Excellent
Item 10	10	10	1.0	1.0	1.0	Excellent
Item 11	10	10	1.0	1.0	1.0	Excellent
Item 12	10	10	1.0	1.0	1.0	Excellent
Item 13	10	10	1.0	1.0	1.0	Excellent
Item 14	10	10	1.0	1.0	1.0	Excellent
Item 15	10	10	1.0	1.0	1.0	Excellent
Item 16	10	10	1.0	1.0	1.0	Excellent
Item 17	10	10	1.0	1.0	1.0	Excellent
Item 18	10	10	1.0	1.0	1.0	Excellent
Item 19	10	8	0.8	0.8	0.79	Acceptable
Item 20	10	10	1.0	1.0	1.0	Excellent
Item 21	10	10	1.0	1.0	1.0	Excellent
Item 22	10	10	1.0	1.0	1.0	Excellent
Item 23	10	10	1.0	1.0	1.0	Excellent
Item 24	10	10	1.0	1.0	1.0	Excellent
Item 25	10	8	0.8	0.8	0.79	Acceptable
Item 26	10	10	1.0	1.0	1.0	Excellent
Item 27	10	10	1.0	1.0	1.0	Excellent
Item 28	10	10	1.0	1.0	1.0	Excellent
Item 29	10	10	1.0	1.0	1.0	Excellent
Item 30	10	10	1.0	1.0	1.0	Excellent
Item 31	10	10	1.0	1.0	1.0	Excellent
Item 32	10	10	1.0	1.0	1.0	Excellent
Item 33	10	10	1.0	1.0	1.0	Excellent

S-CVI/Ave based on I-CVI: 0.982; S-CVI/UA (Universal Agreement): 0.909.

sphericity, and its significance confirmed that the correlations between items were suitable for factor analysis (Table 5).

We identified the underlying factor structure through Exploratory Factor Analysis (EFA) using Principal Component Analysis (PCA) with varimax rotation. This methodological approach was chosen to enhance the interpretability of the factor loadings (Tabachnick & Fidell, 2013). During the EFA, we systematically removed items with low factor loadings (<0.40). A criterion of 0.40 was set as the minimum acceptable factor loading for item retention. During this process, one item was removed from the dataset for failing to meet this loading threshold. The item "*I frequently use AI tools outside of school for fun and entertainment*" did not load significantly on any of the four factors. While behaviorally relevant, the item was determined to reflect informal exposure rather than core competence, thus weakening its alignment with the theoretical structure of the scale. This criterion ensured that only items with strong associations with the identified factors were retained. As a result, the scale was refined to a robust set of 32 items, which were selected to accurately reflect the underlying dimensions and provide a reliable measure for subsequent data collection (see Table 6).

The EFA results supported a four-factor structure: Human-Centred Mindset, Ethics of AI, AI Techniques and Applications, and AI System Design. The Human-Centred Mindset dimension included items reflecting students' attitudes toward AI applications and their conceptual understanding, pivotal for effective AI integration in education. Items under Ethics of AI assessed students' awareness regarding ethical considerations, responsible AI use, and societal implications. The AI Techniques and Applications dimension encompasses items evaluating students' logical reasoning and problem-solving abilities utilizing AI tools, critical in today's digital landscape. Finally, AI System Design items gauged technical competencies required for interacting with and managing AI technologies, aligning with UNESCO's AI competency framework.

4.3. Step 3: scale refinement

4.3.1. Confirmatory factor analysis, reliability, and validity assessment

Following the exploration of factors through EFA, the questionnaire was administered to a new cohort of high school students in Phase 2 to validate the emerging factor structure. The survey was distributed among 384 high school students enrolled in an AI course, out of which 374 responses were received, accounting for a response rate of 97.39 %. Among the 374 responses returned, 74 responses were eliminated due to non-seriousness. The remaining 300 responses were deemed suitable for Confirmatory Factor Analysis (CFA). This dataset maintained a 5:1 item-to-response ratio. The result of CFA indicated a good model fit (Table 7). The chi-square statistic was significant, with the chi-square to degrees of freedom ratio below 3, supporting the model's fit. The Comparative Fit Index (CFI) and Tucker Lewis Index (TFI) values were above 0.90, indicating a good fit. The Root Mean Square Error Approximation (RMSEA) indicates a good fit, and the Standardized Root Mean Square Residual (SRMR) value indicates an excellent fit for the model (Table 7). These values reinforce the validity of the theoretical model as the fit indices meet or exceed the thresholds, which justifies interpreting that the data support the theoretical model. All CFA analyses were conducted using AMOS software (version 29).

4.3.2. Internal consistency (reliability)

The CFA results confirmed the underlying structure of the AI

Table 5
KMO and Bartlett's test results.

Kaiser-Meyer-Olkin measure of sampling adequacy		0.901
Bartlett's test of sphericity	Approximate Chi-square	5071.546
	df	496
	Sig.	<0.001

Table 6
Overview of dimensions, items, and their loadings post exploratory factor analysis using principal component analysis with varimax rotation.

Dimensions	Items code	Items	Loadings
Human-Centred Mindset	HC.1	AI technology is used in various daily life applications such as televisions, refrigerators, washing machines, gaming consoles, etc.	0.721
	HC.2	I believe that learning with AI is an essential skill for my future education.	0.745
	HC.3	I believe that working with AI is an essential skill for my future career.	0.665
	HC.4	Advancements in AI, particularly in robotics, will benefit various industries.	0.722
	HC.5	I can use AI to work on interdisciplinary projects.	0.0711
	HC.6	I believe AI should be developed for social good.	0.607
	HC.7	I understand that source validation is essential when using AI.	0.729
	HC.8	I believe critical thinking is necessary for effectively using AI.	0.679
	HC.9	I know how to act responsibly and safely when learning with AI tools.	0.603
	HC.10	I understand the ethical principles related to AI usage.	0.634
	HC.11	I can obtain useful information using AI technologies, including Siri, Google Assistant, and ChatGPT.	0.712
Ethics of AI	EA.1	I can protect my sensitive and personal content from AI tools	0.812
	EA.2	I can safeguard my well-being when using AI tools	0.766
	EA.3	I know how to act responsibly and safely when learning with AI tools	0.794
	EA.4	When an AI system does something unethical that impacts humans, both the developer and the company are accountable.	0.712
	EA.5	If I come across a website that generates fake news stories using AI, I should take appropriate action to address it.	0.781
AI Techniques and Applications	TA.1	I can easily understand AI-related programming concepts such as loops, variables, and algorithms.	0.665
	TA.2	I can develop AI-based programs using block-based programming languages like Scratch.	0.585
	TA.3	I can identify and debug errors in AI-related program codes.	0.624
	TA.4	I can create simple interactive AI-driven applications, such as chatbots or recommendation systems.	0.643
	TA.5	I can integrate sensors with AI applications for data-driven decision-making.	0.753
	TA.6	I can interpret data collected from sensors to generate AI-based insights.	0.811
	TA.7	I can clean and preprocess large datasets required for AI model training and analysis.	0.698
	TA.8	I can collect and organize data relevant to AI-driven studies or projects.	0.729
	TA.9	I can clean, structure, and prepare collected data for AI applications.	0.782
	TA.10	I can analyze AI-generated data and visualize it using graphs and charts.	0.779
	TA.11	I can identify irregularities and biases in AI datasets to improve model performance.	0.690
AI System Design	SD.1	I can troubleshoot (identify and fix) errors in assembling AI-powered robotic components.	0.593

(*continued on next page*)

Table 6 (*continued*)

Dimensions	Items code	Items	Loadings
	SD.2	I can troubleshoot (identify and fix) errors in AI-driven programming codes used for controlling robots.	0.647
	SD.3	I can program an AI-powered robot to navigate in a specific direction.	0.738
	SD.4	I can program an AI-powered robot to recognize and differentiate colors.	0.803
	SD.5	I can program an AI-powered robot to detect and identify images using AI-based vision systems.	0.757

Competence Scale (AICS), supporting its theoretical framework and enabling further evaluation of its psychometric properties. To assess internal consistency, two measures of construct reliability were employed: Cronbach's alpha (Cronbach, 1951) and Composite Reliability (CR) (Bacon et al., 1995).

The Cronbach's alpha values for the four dimensions ranged from 0.860 to 0.952, well above the commonly accepted threshold of 0.70, indicating excellent internal consistency across all subscales. Similarly, CR values ranged between 0.832 and 0.952, exceeding the recommended minimum of 0.70, thereby confirming the construct reliability of each dimension (see Table 8). These results suggest that the items within each construct consistently reflect the intended latent variable, and the scale as a whole demonstrates strong reliability.

4.3.3. Convergent and discriminant validity

To assess the construct validity of the AI Competence Scale (AICS), both convergent and discriminant validity were examined.

Convergent validity was evaluated using the Average Variance Extracted (AVE) for each dimension (Fornell & Larcker, 1981). As shown in Table 6, AVE values ranged from 0.50 to 0.66, exceeding the minimum recommended threshold of 0.50, which suggests that each construct explains a substantial proportion of variance in its respective items.

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio of correlations (Henseler et al., 2015). The HTMT values for all pairs of constructs ranged from 0.051 to 0.725, remaining well below the conservative threshold of 0.85 (Ahmad et al., 2024). These results indicate that each dimension of the AICS captures distinct aspects of AI competence with minimal conceptual overlap (see Table 9). Together, the AVE and HTMT results provide strong empirical support for the construct validity of the instrument, confirming that its dimensions are both internally coherent and conceptually distinct.

4.4. Step 4: nomological validity

As part of rigorous scale development, establishing nomological validity is essential to demonstrate that a newly developed construct behaves as theoretically expected in relation to other conceptually linked variables within its nomological network (Sultana & Farooq, 2024). To this end, Structural Equation Modeling (SEM) was employed on Phase 2 data (N = 300) to examine whether the AI Competence Scale (AICS) relates, in accordance with theory, to students' interest in pursuing AI-related careers (Maulana et al., 2025). This reflects a theory-driven association derived from Self-Determination Theory (SDT) and Social Cognitive Career Theory (SCCT), rather than a temporal predictive design.

The criterion measure for Career Interest in AI was a unidimensional five-item scale conceptually informed by the AI Career Futures Survey developed by Zhang et al. (2023). While the items were newly constructed, they aligned with Zhang et al.'s constructs of AI-related career awareness and adaptability. Each item was rated on a 5-point Likert scale (1 = *Strongly Disagree* to 5 = *Strongly Agree*) and included sample statements such as: "*I am interested in jobs that involve AI*," and "*If I study AI, I feel that I will easily get a job*." To examine the construct validity of this scale, an Exploratory Factor Analysis (EFA) was conducted using SPSS (v29). The Kaiser-Meyer-Olkin (KMO) measure was 0.85, and Bartlett's Test of Sphericity was significant ($p < 0.001$), indicating sampling adequacy. One dominant factor emerged with eigenvalue >1, explaining 69.8 % of the total variance. All items loaded above 0.70 on the single factor, supporting the unidimensional structure. The scale demonstrated strong internal consistency ($\alpha = 0.89$), confirming its reliability.

To establish preliminary nomological validity, Pearson correlation analyses were conducted between each of the four dimensions of AI competence and students' career interest in AI. The results revealed statistically significant and positive associations across all dimensions (Fig. 3). The AI Techniques and Applications dimension showed the strongest correlation with career interest ($r = 0.510$, $p < 0.001$), followed by the Human-Centred Mindset ($r = 0.352$, $p < 0.001$), AI System Design ($r = 0.324$, $p < 0.001$), and Ethics of AI ($r = 0.219$, $p < 0.001$). These findings indicate that students who demonstrate higher levels of competence across these key areas are more likely to express interest in

Table 8
Reliability assessment for the dimensions of the AI competence scale (AICS).

Sl. no.	Dimension	No. of items	Cronbach's alpha	Composite reliability (CR)	Average variance extracted (AVE)
1	Human-Centred Mindset	10	0.952	0.952	0.66
2	Ethics of AI	5	0.860	0.832	0.55
3	AI Techniques and Applications	11	0.915	0.916	0.50
4	AI System Design	5	0.887	0.890	0.61

Table 9
Discriminant validity assessment for the dimensions of AI competence scale (AICS).

Sl. no.	Dimension	Human-Centered Mindset	Ethics of AI	AI Techniques & Applications	AI System Design
1	Human-Centred Mindset	–			
2	Ethics of AI	0.051	–		
3	AI Techniques and Applications	0.062	0.155	–	
4	AI System Design	0.103	0.056	0.725	–

Table 7
Illustration of CFA results.

Construct	SRMR	TLI	CFI	RMSEA	$\chi 2$	df	P-value	$\chi 2$/df
AI Competence	0.062	0.939	0.943	0.051	767.71	430	0.000	1.785

Note: $P < 0.001$ indicates highly significant.

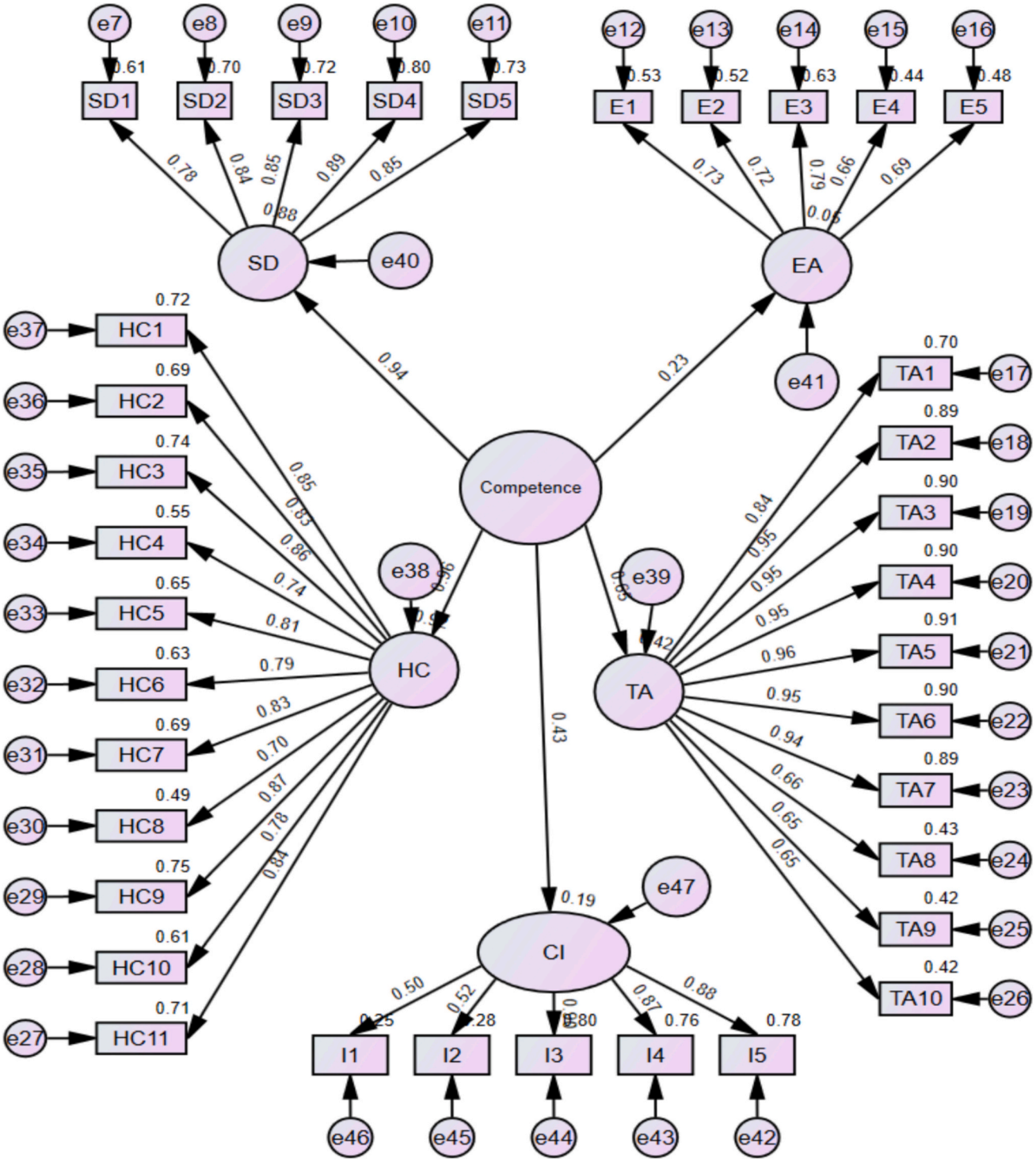

Fig. 3. Structural equation model to assess the nomological validity of AI competence with career interest.

pursuing AI-related careers, thereby reinforcing the theoretical alignment and external validity of the AI Competence Scale.

Building on these findings, a structural equation model was tested using AMOS version 29, where AI Competence was modeled as a second-order latent construct predicting Career Interest. The model showed a good fit to the data, with fit indices meeting recommended thresholds (χ^2/df = 2.58, CFI = 0.953, TLI = 0.950, GFI = 0.879, and RMSEA = 0.051). The standardized regression weight from AI Competence to Career Interest was statistically significant (β = 0.43, p < 0.001), confirming the hypothesized predictive relationship (Table 10).

Table 10
Predictive validity of AI competence scale on students' AI career interest.

Path	Unstandardized estimate	S.E.	C.R.	p-Value	Standardized estimate
Competence → Career interest	0.202	0.021	9.459	<0.001	0.43

Note: SE = standard error; CR = critical ratio; P < 0.001 indicates highly significant.

Furthermore, the psychometric characteristics of the SEM model showed strong composite reliability (CR > 0.88) and average variance extracted (AVE > 0.50) for both constructs. These findings provide strong support for the nomological validity of the AI Competence Scale, confirming its utility in forecasting students' intentions to engage in AI-oriented academic and career trajectories.

5. Discussion

This study develops and validates the AI Competence Scale (AICS), a multidimensional instrument grounded in UNESCO's AI Competency Framework and educational psychology principles, specifically targeting high school students. The findings affirm the scale's psychometric robustness and conceptual soundness, offering a comprehensive tool for assessing students' cognitive, affective, and ethical competencies related to AI. The dimensions identified Human-Centred Mindset, Ethics of AI, AI Techniques and Applications, and AI System Design are firmly rooted in theoretical constructs from Self-Determination Theory (SDT; Deci & Ryan, 2000) and Social Cognitive Career Theory (SCCT; Lent et al., 1994), offering a rich psychological foundation for understanding how students develop competence, motivation, and ethical awareness in AI contexts.

Specifically, the Human-Centred Mindset dimension reflects aspects such as self-efficacy, metacognitive regulation, and autonomous learning, aligning closely with SDT's emphasis on autonomy and competence. According to SCCT, students who perceive themselves as capable of using AI are more likely to pursue AI learning with confidence and agency. The Ethics of AI corresponds to moral reasoning such as Kohlberg's theory of moral development, emphasizing students' progression from rule-based thinking to principled ethical decision-making. This also supports the SDT need for relatedness, encouraging students to consider AI's broader societal impact and moral consequences. The AI Techniques and Applications dimension captures students' ability to engage in technical tasks, aligning with SDT's competence need and SCCT's notion of outcome expectations; it reflects how mastery of AI tools can influence students' beliefs about their future success in technology-related fields. Finally, the AI System Design dimension represents a synthesis of autonomy (design decisions), competence (technical mastery), and relatedness (addressing real-world challenges), mirroring the full spectrum of SDT needs while also enhancing SCCT constructs like self-efficacy and goal setting.

These findings echo prior literature emphasizing the integration of technical skill, ethical reasoning, and psychological readiness in AI education (Chiu et al., 2022; Kong et al., 2024). By validating a four-dimensional structure through factor Analyses, the study affirms that AI competence is a multidimensional construct encompassing technical, ethical, and motivational capacities essential for holistic development. Students who develop a strong human-centred mindset are more likely to perceive AI tools as empowering agents, enhancing their engagement, problem-solving abilities, and ethical use in diverse contexts (Jia & Tu, 2024). Moreover, strengthening students' technical proficiency and system-level design capabilities cultivates adaptability and innovation in an AI-driven society.

Importantly, the SEM results revealed a significant relationship between AI Competence and students' interest in pursuing AI-related careers, affirming the nomological validity of the AICS. This finding is consistent with theoretical expectations drawn from SDT and SCCT, which posit that perceived competence and motivational beliefs are key drivers of students' future-oriented aspirations and career interests. In line with SCCT, career trajectories can also be shaped by a broader interplay of factors such as contextual support and attitudes that work alongside competence to influence students' aspirations.

In summary, the validated AICS not only measures students' current competencies but also serves as a predictor of their preparedness for AI-integrated academic and professional settings. For educators and policymakers, it provides a rigorous, research-based tool for assessing and nurturing AI competence within schools ensuring that teaching practices support students' cognitive, ethical, and technical development simultaneously. Positioned at the intersection of educational psychology and AI literacy, the AICS advances a holistic understanding of learning that encompasses technical proficiency, ethical awareness, and motivational drive. Accordingly, this study establishes a robust platform for designing evidence-based interventions, informing curriculum reform, and guiding future research in the rapidly evolving landscape of AI education

6. Limitations and future research

This study presents a solid and theoretically sound instrument for evaluating AI competence among high school students; however, there are several potential directions for further refinement and expansion. While the use of a cross-sectional design and simultaneous measurements offers a valuable snapshot of the relationship between AI competence and career interest, conducting longitudinal research could build on this foundation to track the evolution of competence over time and unpack predictive pathways leading to future aspirations. Similarly, the sample was drawn from public secondary schools in Qatar, specifically including students actively involved in AI-related courses, which provides rich insights into a particular educational context. Replicating this research across diverse countries, school types, and student backgrounds would enhance its global relevance.

To strengthen this understanding, it's essential to look beyond competence in isolation and to consider its interaction with broader environmental and motivational factors. The SEM analysis in this study focused solely on the direct link between AI competence and AI career interest, overlooking other potential predictors such as institutional or peer support. However, Social Cognitive Career Theory (SCCT) and related literature highlight that environmental factors, like institutional support, can indirectly influence AI competence through attitudes, motivation, and other emotional variables. Future models that incorporate these contextual factors may provide a more comprehensive understanding of how external supports and internal influences work together to shape AI competence and career aspirations.

Additionally, future research could explore SEM models that assess how each dimension of AI competence relates individually to career interest, offering more detailed evidence of criterion validity while complementing the unified second-order structure utilized in this study. Building on these insights, upcoming studies might also evaluate the scale's responsiveness to instructional interventions, apply item response theory for precise measurement, and investigate short-form or adaptive versions suitable for classroom use. To further support collaborative validation efforts, broader dissemination of items, scoring protocols, and anonymized datasets would ensure the AICS continues to evolve as a practical, evidence-based tool for enhancing AI education within K-12 settings.

7. Conclusion

The present study makes a substantial contribution to the intersection of AI education and educational psychology by developing and validating a multidimensional AI Competence Scale (AICS) specifically designed for high school students, grounded in the UNESCO AI Competence Framework. Through a rigorous and systematic process involving exploratory and confirmatory factor analyses, the study established the psychometric soundness of the scale, confirming its reliability, construct validity, and predictive power. The resulting four-dimensional model- comprising Human-Centred Mindset, Ethics of AI, AI Techniques and Applications, and AI System Design- offers a holistic lens for understanding and measuring students' AI competence across cognitive, affective, and ethical domains.

The findings underscore the multifaceted nature of AI competence, emphasizing that technical proficiency alone is insufficient for meaningful engagement with AI technologies. A balanced integration of

critical thinking, ethical awareness, self-efficacy, and design-based problem-solving- key constructs within educational psychology- is essential. The demonstrated predictive validity linking AI competence with students' career interests further reinforces the scale's practical utility, highlighting its dual role as both an assessment and diagnostic tool supporting students' academic growth and psychological readiness for future AI-driven careers.

Additionally, the AICS provides a vital instrument for curriculum developers, educators, and policymakers to evaluate, refine, and enhance AI learning experiences. Its comprehensive structure enables tailored interventions, informed instructional designs, and targeted curriculum reforms that nurture responsible, motivated, and future-ready learners. By aligning with international standards and addressing critical gaps in existing assessment tools, this scale lays a foundational framework for guiding AI education initiatives at the secondary level and potentially across the broader K-12 spectrum, while advancing research on students' psychological development in AI learning contexts.

CRediT authorship contribution statement

Zubair Ahmad: Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Almaas Sultana:** Writing – review & editing, Writing – original draft, Methodology. **Nafilah Abdul Latheef:** Writing – review & editing. **Nitha Siby:** Data curation. **Abdellatif Sellami:** Writing – review & editing. **Saddam Akber Abbasi:** Writing – review & editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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