ZKG INTERNATIONAL
ISSN / eISSN 2366-1313
Publisher: BAUVERLAG BV GMBH,
AVENWEDDER STR 55, GUTERSLOH, GERMANY, 33311
Volume 25-Issue 1-(2025)

Exploration of the Artificial Intelligence Literacy Framework for University Teachers: A Qualitative Study

Abstract

This study focuses on the extensive application of artificial intelligence (AI) in the field of education and the urgent need to improve the AI literacy of college teachers. Grounded theory and the analytic hierarchy process are employed to construct a framework for the AI literacy of college teachers. Through the analysis of 65 core documents and the data from 12 respondents with diverse backgrounds, a literacy framework consisting of five dimensions, namely knowledge and skills, technological application, ethical responsibility, teaching innovation, and professional development, is refined. The analytic hierarchy process is used to determine the weights of indicators at all levels. The study finds that the dimension of technological application has a relatively high weight, while the weights of other dimensions are relatively evenly distributed. This research provides a scientific basis for the assessment of the AI literacy of college teachers. However, it has limitations such as not delving deeply into subject differences and lacking empirical analysis. This study lays a foundation for promoting college teachers to enhance their AI literacy and facilitating the digital transformation of higher education.

Keywords: College Teachers; Artificial Intelligence Literacy; Grounded Theory; Analytic Hierarchy Process

1.Introduction

With the advancement of the Fourth Industrial Revolution, artificial intelligence (AI), as its core driving force, is profoundly reshaping social structures, knowledge logic, and educational systems (Schwab, 2024; Milberg, 2024). As a key subsystem of society, education is undergoing deep transformations in teaching tools, instructional spaces, and pedagogical concepts under the rapid development of AI technologies (Kandlhofer et al., 2016; Ng et al., 2021; Holmes & Tuomi, 2022). Increasingly, countries are incorporating AI literacy into their national education strategies, emphasizing the cultivation of future citizens who can understand, apply, and critically evaluate AI systems (UNESCO, 2021). The application of AI in the field of education is becoming increasingly widespread, and it is being used extensively for personalized learning recommendations, automated assessment, and the generation of instructional content (Antoninis et al., 2023). At the same time, it has triggered a series of student development issues such as overreliance (Zhang et al., 2024), decreased learner autonomy (Nguyen et al., 2023), and academic integrity concerns (Perkins et al., 2024). As key guides in students' development within AI-embedded environments, teachers' levels of AI literacy directly influence the ways, depth, and value orientation in which students use AI tools (Pinski & Benlian, 2024). Existing studies have pointed out that teachers' lack of AI-related knowledge, ethical awareness, and pedagogical integration capabilities has, to some extent, limited their effective use of AI technologies in classroom instruction (Zhao et al., 2022). If such competency deficiencies persist over time, they may, on a broader scale, impact the realization of educational equity and quality.

As the cornerstone of cultivating high-level talent, universities rely heavily on the AI literacy levels of their faculty members to determine whether they can effectively nurture students with robust AI competencies, thereby directly influencing the quality and direction of talent cultivation (Wang Yijun et al., 2022; Li Yan et al., 2025). However, existing research on AI literacy has primarily focused on student groups, K–12 teachers, or pre-service teachers (Ng et al., 2021; Ding et al., 2024), while showing relatively little attention to the structural framework, dimensional weighting, and assessment mechanisms specific to university faculty. Especially at a time when AI is rapidly entering classroom practices, teachers are facing increasing challenges in capability reconstruction, identity adjustment, and ethical decision-making. There is an urgent need for a literacy framework with stronger contextual adaptability and structural coherence. This study is proposed in response to this research gap, aiming to provide both theoretical support and empirical evidence for the development of university teachers’ AI literacy.

The expansion of AI technologies is further widening the gap of intelligence access and application—commonly referred to as the “intelligent divide” (Yang, 2023). In educational settings, this divide affects teachers’ ability to enhance instructional quality through technology and also hinders progress toward the global goals of equitable and inclusive education, as outlined in the United Nations Sustainable Development Goals (Soomro et al., 2020). Designing AI literacy education frameworks and content for teachers is an effective strategy to improve their understanding and use of intelligent tools, thereby strengthening their AI literacy and helping to bridge the intelligent divide among educators (Sun & Li, 2024).

Based on this context, this study focuses on university teachers in China and employs grounded theory to systematically identify the core dimensions of teacher AI literacy in AI-embedded environments. In addition, the analytic hierarchy process (AHP) is used to assign weights to each dimension, resulting in a five-dimensional evaluation model of AI literacy. Unlike previous studies, this research conducts multi-level investigations into the university faculty group, constructing an evaluation system from the perspectives of instructional practice, technological integration, and ethical guidance, while quantifying the relative importance of each dimension within the framework. By emphasizing data-driven insights and contextual relevance, this study seeks to offer both a theoretical foundation and practical reference for teacher literacy assessment and AI education training systems.

2.Literature review

2.1 Concepts Related to Artificial Intelligence Literacy

Informatization, digitalization, and intelligentization are three critical stages in technological development (Xue Shumin et al., 2024). Across different stages, related concepts such as information literacy, digital literacy, and AI literacy have emerged, which are considered as evolutionary extensions of information literacy (Guo Yajun et al., 2025). Information literacy, which gained prominence with the growing complexity of the information environment and advances in information technology, became widely used in the 1990s. Its definition focuses on the ability to process and utilize information, emphasizing the capacity to acquire, evaluate, and apply information from various sources (Bawden, 2001). The "Seven Pillars" model proposed by SCONUL in the UK identified seven core competencies for higher education students: recognizing information needs, identifying suitable sources, devising search strategies, retrieving and accessing information, comparing and evaluating sources, organizing and applying information, and synthesizing and constructing knowledge (Martin & Grudziecki, 2006). Early concepts of information literacy emphasized tool usage—how to use tools to acquire information.

Entering the 21st century, with the emergence of new digital technologies, a more integrated literacy framework has followed. Digital literacy was proposed by Gilster (1997), who defined it as the ability to understand and use information from digital resources. Some scholars argue that digital literacy is not only the effective use of digital resources but also a specific mode of thinking or cognitive pattern (Eshet, 2002). The concept of literacy has gradually evolved from a tool-oriented to a mindset-oriented perspective. Digital literacy not only involves operating software or devices but also includes cognitive, psychomotor, sociological, and emotional skills essential in digital environments (Eshet, 2004). It is viewed as a fundamental requirement for life in the digital age and as a framework that integrates various forms of literacy and skills (Lankshear & Knobel, 2008).

As AI technologies continue to evolve across multiple dimensions, the competencies individuals need to adapt to society must also change. In increasingly complex AI environments, the focus of individual literacy has shifted from acquiring information to understanding and applying it, and now to using technological tools effectively, creatively, and critically in specific contexts. Accordingly, the concept of "AI literacy" has emerged.

2.2 Frameworks of AI Literacy

AI literacy has been recognized as a crucial interdisciplinary competence relevant to various aspects of people's lives (Ng & Chu, 2021). Due to the rapid development of new algorithms, models, and especially generative AI, enhancing AI literacy has become increasingly challenging (Cox, 2024). Consequently, the definition of AI literacy is still evolving, and no universally accepted definition currently exists (Laupichler et al., 2022). Existing definitions of AI literacy mainly focus on two aspects. The first emphasizes technical understanding and application abilities. Early studies focused on the technical foundations of AI, explaining the operational mechanisms of AI through concepts such as automata and intelligent agents, thereby providing a theoretical basis for understanding AI (Kandlhofer et al., 2016). This perspective laid the groundwork for subsequent research, which expanded the connotation of AI literacy. Later studies shifted toward the interaction between individuals and AI, proposing that AI literacy includes the ability to critically evaluate, collaborate with, and use AI, encompassing cognition, application, and ethical assessment of AI systems (Long & Magerko, 2020; Pinski & Benlian, 2023). This shift reflects a move from focusing on AI itself to emphasizing individuals' practical competence in AI-embedded contexts.

The second perspective incorporates ethical and sociocultural dimensions, defining AI literacy as the ability to use AI effectively and ethically in daily life, covering understanding, application, evaluation, creation, and ethical cognition. It emphasizes the moral responsibility individuals bear in the age of AI technologies (Wang et al., 2023; Ng et al., 2021; Yin, 2024; Celik, 2023a). This expands the research scope from individual-level and technical perspectives to include moral reasoning and sociocultural factors. The sociocultural dimension highlights how personal trust, attitudes, and cultural environments influence the development of AI literacy (Heyder & Posegga, 2021).

Many scholars have proposed AI literacy definitions tailored to specific groups. For instance, some define AI literacy for K–12 students as the ability to acquire and use AI-related knowledge and skills (Dai et al., 2020; UNESCO, 2022). For non-technical personnel, such as in-service and pre-service teachers, it refers to the ability to understand and responsibly use AI-enhanced systems (Ding et al., 2024). In the context of working professionals, AI literacy is seen as a set of four core competencies: technical, occupational, human-machine interaction, and learning (Cetindamar et al., 2022). Regarding K–12 teachers, some researchers developed the Intelligent-TPACK framework, integrating AI tools into pedagogical knowledge and including technological knowledge, pedagogical knowledge, content knowledge, and their intersections (Celik, 2023b). These studies reflect the differing AI literacy needs across various groups.

In the educational field, scholars have constructed multiple frameworks for AI literacy. From a curriculum design perspective, one framework for middle school students includes five modules: awareness, knowledge, interaction, empowerment, ethics, and impact, providing practical pathways for cultivating AI literacy (Chiu et al., 2022). For university students of various disciplinary backgrounds, AI literacy is defined as including conceptual understanding, application for evaluation, and solving real-world problems, emphasizing both conceptual grasp and practical application at the higher education level (Kong et al., 2021). For the general public, especially non-computer science majors, AI literacy is defined as the ability to understand, use, monitor, and critically reflect on AI applications, thus broadening the educational research scope (Laupichler et al., 2022).

In summary, while existing research on AI literacy has made notable progress, several gaps remain. In particular, there is still no unified definition, and the logical relationships and weighting among the various components are unclear. Therefore, it is necessary to develop AI literacy frameworks tailored to different populations and educational settings, and to design and validate reliable tools for measuring AI literacy across groups.

2.3 AI Literacy of University Teachers

Although the application of AI in education has received increasing attention, current studies mainly focus on student groups, with relatively few addressing teachers. The digital transformation of higher education is a complex process requiring sophisticated change management strategies and the involvement of diverse stakeholders. Teachers, as key stakeholders, play a critical role in this transformation (McCarthy et al., 2023). As early as 2019, scholars began calling for more educators to participate in AI-related research (Zawacki-Richter et al., 2019). Baker (2019) also explored educational AI tools from the teacher's perspective, suggesting that such tools could reduce workload, offer insights into student progress, and support instructional innovation through automation, personalized feedback, and pedagogical enhancement. However, this also raises the bar for teachers' competencies.

Chiu (2023) surveyed 88 teachers and school leaders from 30 primary and secondary schools and found that most participants had high interest in learning about generative AI applications and viewed them as useful in the classroom. At the same time, they expressed concerns about ethical and reliability issues posed by these technologies. Participants emphasized that teachers should possess robust AI literacy, including understanding how generative AI works and managing ethical challenges to effectively support instruction.

Despite the overall positive attitude of teachers toward intelligent technologies, their AI literacy levels remain insufficient. In the emerging educational ecosystem, teachers must confront challenges such as AI-integrated teaching environments, interdisciplinary content focused on competencies, digitally native learners, and open public education services (Wu Di et al., 2020). With the integration of AI technologies, the traditional ecosystem of higher education is undergoing profound changes. Standards for faculty capabilities and professional requirements are being redefined, and human–AI collaboration is becoming the new norm in academic professions. AI literacy is thus becoming an essential skill for educators to navigate professional transformations in the intelligent era (He Feixia, 2022).

Therefore, to facilitate the smooth digital transformation of higher education and ensure that teachers can effectively fulfill their roles in the intelligent era, it is imperative to develop a scientifically sound and practically oriented AI literacy framework for university teachers. Such a framework will provide clear developmental directions for teachers, help enhance their professional competencies, and serve as a robust basis for institutions to assess faculty capabilities and design training programs—ultimately contributing to the comprehensive improvement of higher education quality.

3.Methodology

3.1 Research Design

This study adopts a grounded theory qualitative research method, combined with the analytic hierarchy process (AHP), to construct a framework for university teachers' AI literacy. Although previous research has addressed AI literacy, a clear framework specific to university teachers remains lacking, and there is an absence of systematic synthesis based on practical experience. For research questions in which the structure is unclear and concepts need to be inductively extracted from empirical data, grounded theory provides a suitable analytical path (Bowers & Creamer, 2021; Apramian et al., 2016; Allen, 2010). Grounded theory, proposed by Strauss and Corbin (1998), emphasizes the construction of categories through step-by-step coding, and the establishment of structural relationships among them, eventually leading to a theoretical model. In this study, the research team did not predefine any structural model but directly conducted open, axial, and selective coding on interview transcripts and literature sources to extract key concepts and summarize structural dimensions. NVivo software was used to assist with the coding process and category organization.

After the theoretical structure was formed, the AHP method was applied to sort the framework dimensions and calculate their weights. AHP utilizes expert judgment to construct pairwise comparison matrices, and through consistency checks, derives the relative weights of each dimension to support structural optimization and practical application (Saaty, 1990; Thanassoulis et al., 2017; Saaty & Vargas, 2012). Through the combination of "data construction + weight ranking," the model possesses both practical grounding and logical hierarchical structure.

3.2 Data Sources

The data for this study comprises two parts: (1) 65 core Chinese and English academic articles, and (2) interview transcripts from 12 higher education professionals (see Table

1). The literature was retrieved from the CNKI and Web of Science (WOS) core databases, using keywords such as “AI literacy” and “teacher AI competence.” After screening, 65 studies with structural extraction value were selected. All literature was treated as primary data and entered the grounded theory coding process, rather than being used solely as background references. The interviewees came from diverse types of universities, academic disciplines, and professional ranks. The interviews focused on teachers’ understanding of AI, teaching application experiences, and the challenges they face. All data were collected with informed consent and were uniformly transcribed and coded. Both literature and interview data were subjected to the grounded theory coding process and contributed to the category and model construction. These dual data sources form the basis for triangulation validation.

3.3 Analytical Methods

This study employs a combined approach of grounded theory and AHP for data analysis. The data set includes 65 core Chinese and English academic articles and 12 interview transcripts from higher education practitioners. The grounded theory analysis follows the Straussian school’s three-stage coding process (Stough & Lee, 2021; Matavire & Brown, 2013; Sui et al., 2025).

In the open coding phase, the research team used NVivo 12 to analyze the data line by line, generating 179 initial labels that were then summarized into 26 primary concepts. In the axial coding phase, based on the “phenomenon–context–strategy–outcome” framework, relationships among concepts were reorganized and integrated into five dimensions: knowledge and skills, technology application, ethical responsibility, instructional innovation, and professional development. In the selective coding phase, “AI literacy of university teachers” was identified as the core category, and structural relationships among the five dimensions were established, resulting in the final model. The coding process adopted constant comparative analysis until no new concepts emerged, achieving theoretical saturation (Conlon et al., 2020).

Subsequently, the AHP method was employed to assign structural weights to the five dimensions. Twelve experts in AI and education were invited to complete pairwise comparison forms. Using the 1–9 scale method, they rated the relative importance of each AI literacy dimension, forming judgment matrices (Thanassoulis et al., 2017; Saaty & Vargas, 2012). To reduce subjective bias, Python was used to calculate the geometric mean weight vectors of each expert's matrix. The consistency of the matrices was checked using the formula CR = CI/RI, where RI is the average consistency index of randomly generated matrices of the same size. A consistency ratio (CR) of less than 0.1 indicates acceptable consistency; if CR > 0.1, the matrices were adjusted accordingly (Pant et al., 2022). Consistency ratios were calculated, and matrices with CR ≥ 0.1 were excluded. The final weights were obtained by calculating the arithmetic mean of the valid expert weights that passed the consistency check.

Table 1 Information of the Respondents

Serial No.	The Identity of the Respondents	academic discipline and major	academic rank	years of teaching	The Type of the University Attended
1	college teacher	Computer Science and Technology	professor	20	Research - oriented Comprehensive University
2	college teacher	Education	professor	18	Normal University
3	college teacher	Chinese Language and Literature	associate professor	12	Comprehensive University
4	college teacher	Electronic Information	associate professor	10	University of Science and Technology
5	college teacher	Economics	Lecturer	6	University of Finance and Economics
6	college teacher	Biology	Lecturer	5	Agricultural University
7	college teacher	Art and Design	Teaching Assistant	3	Art University
8	college teacher	Clinical Medicine	associate professor	15	Medical University
9	Academic Affairs	-	Mid -	8	Comprehensive

	Office staff		level		University
10	teaching tutoring	-	High - level	25	Normal University
11	college teacher	Mathematics	professor	22	University of Science and Technology
12	college teacher	English	Lecturer	7	Language University

4.Results

4.1 Open Coding

After labeling the relevant content of the textual materials, concept extraction was carried out. Through the analysis of the phenomena represented by the labels, a total of 26 concepts were assigned, including conceptual cognition, technical principles, interdisciplinary integration, etc. During the concept extraction process, concepts with similar meanings in their content expressions were merged; and concepts that were extremely rare or contradictory to other concepts were deleted.（Table 2）

4.2 Axial coding

The task of axial coding is to connect the relatively independent concepts obtained from open coding and explore the internal forms and associations among these concepts. In this study, through the exploration of relationship types such as causal, temporal, semantic, situational, and functional relationships, and based on the internal connections between concepts and the objects of cross-border activities, the concepts obtained from open coding were correlated.（Table 3）

4.3 Selective Coding

After systematically analyzing the conceptual categories discovered through axial coding, it is necessary to further explore the logical connections among these conceptual categories. That is, through selective coding, it is required to summarize and extract a core category that can govern and explain all the phenomena, so as to form a complete explanatory framework.（Table 4）

Table 2 Results of Open Coding

conceptualize	marker	Excerpts from the Interview Content
Conceptual cognition	Assessment framework; Technical knowledge;	When teaching convolutional neural networks, I noticed students often become

	Three waves; Know What; Four - dimensional literacy; Conceptual definition; K1 Basic Cognition	"parameter tuners" instead of grasping the essence of feature extraction.
Technical principle	Basic Layer of Data Processing; Technical Logic of AIED; Knowledge of the Technical Layer; Decision-making Process; Knowledge of SK Steps; Technical Lifecycle; ML Steps	In the mathematical modeling class, I require students to derive the mathematical proofs of AI algorithms, like analyzing the convergence of gradient descent, to understand the importance of technical principles over mere trial-and-error tuning.
Interdisciplinary integration	Interdisciplinary Thinking; Intersection of Technology and Social Sciences; Integration of Multidisciplinary Theories; General Knowledge; Interdisciplinary Field; Interdisciplinary Courses	When using AI to analyze A Dream of Red Mansions' character relationships, students need both sociological network analysis skills and classical literature knowledge. Weak foundations limit scientific evaluation and lead to superficial use of technology.
Tool foundation	Digital and Intelligent Skills; Multimedia Tools; Programming Knowledge; Platform Selection; Tool Promotion; VR/AR; TK Technical Knowledge; Prompt Engineering; Tool Application	Data acquisition and processing skills with AI are the basis of teachers' digital and intelligent literacy.
Cutting - edge tracking	Stanford Report; Transformation of Knowledge Production; Lifelong Learning; Self-renewal; Technological Iteration; Orientation towards Social Welfare	I track AI protein prediction papers on BioRxiv weekly, but the lack of AlphaFold's commercial rights in the school library disconnects teaching from practice.
Tool operation	Analysis of Learning Situation; High-level Decision-making; Immersive Teaching; Online Tools; Intelligent Design; Role Boundary; Application Ability; Teaching Design; Teaching Enhancement	The AI speech evaluation system asks teachers to master phoneme annotation, a task that should be for technicians. Half of the lesson preparation time is now for tool operation, cutting into teaching content design.
Data processing	Analysis of Learning Situation; Data Acquisition; Full-cycle Data; Ternary Data Analysis; Data-driven Decision-making; Data-driven; Precision Teaching	Medical imaging data needs manual verification of AI annotations. Last week, the system mislabeled vascular calcification as tumors, which could mislead teaching.
System development	Product Transformation; Programming Development; Intelligent Tutoring System; Open Development; Technical Application; Innovative Practice; Intelligent System Design	Developing the intelligent teaching plan system revealed a gap between teachers' needs and technical implementation. For example, teachers want progressive difficulty adjustment, but engineers prefer one-size-fits-all algorithms.
Human - machine collaboration	Role Transformation; Human-machine Interaction; Technological Integration; Human-machine Knowledge Production; Fine Management; Collaborative Design; Collaborative Ability	In econometrics, AI is for data cleaning, and students do parameter selection and model interpretation, enabling them to use technology and keep critical thinking.
Scenario innovation	Integration of Multiple Spaces; VR Simulation; Virtual Laboratory; Intelligent Environment; Experiential Learning; Scenario Innovation; Environmental Creation	A teacher used AI for a UN climate change negotiation simulation. While innovative and highly scored, we must guard against technology-dominated performative teaching.
Fault handling	Critical Assessment; Algorithm Fairness; Ethical Evaluation; Risk Management; Practical Problem-solving	When the smart classroom system crashed, an old teacher taught with a blackboard and was praised. We now include technical failure emergency plans in teacher training, stressing that teaching doesn't rely on equipment.
Privacy protection	Security Principles; Data Governance; Information	Medical case teaching with real patient data has a dual desensitization mechanism: AI

	Ethics; Risk Prevention; Privacy Regulations; Data Security; Privacy Policy; Compliant Use	blurring first, then manual review by attending physicians. This is an ethical bottom line.
Algorithm fairness	Fairness; Algorithm Bias; Matthew Effect; Data Transparency; Algorithm Review; Ethical Guidelines; Fairness Reflection; Technological Justice	Finding an AI teaching assistant system recommended low-difficulty content to rural students, we rewrote the recommendation logic with the technical team. Educational equity should be in algorithm design, not patched later.
Social impact	Social Responsibility; Labor Values; Sociality; Social Literacy; Cultural Reflection; Social Embeddedness	An AI ethics module in the IoT course lets students analyze the social costs of intelligent monitoring systems. A student's thesis was adopted by the city government, showing the link between technical education and social responsibility.
Legal compliance	Regulatory Oversight; Governance Mechanism; Intellectual Property Rights; Citation Standards; Legal Practice	When using AI for macroeconomic forecasts, data sources and algorithm limitations must be stated. A student was flagged for academic misconduct for directly citing AI results without declaration.
Humanistic care	Creative Labor; Human - Machine Trust; Emotional Communication; Humanistic Consciousness; Child Protection; Responsive Ethics; Inclusive Design	An AI poem generator can mimic Li Bai's boldness but not the loneliness in "Raising my cup, I invite the moon". I asked students to compare machine and human creations to feel the irreplaceable emotional resonance.
Model reconstruction	Multi - mode Coupling; Dynamic Learning; Blended Teaching; Innovation of Teaching Activities; Model Innovation; Blended Instruction; Field Innovation	CAD teaching has shifted to a dual-track mode of "AI-assisted design + traditional drawing", balancing spatial imagination training and complex surface design efficiency by finding the right tech integration point.
Resource creation	Upgrading of Learning Materials; Knowledge Graph; Intelligent Resources; Resource Integration; Resource Development; Personalized Push; Resource Screening	Using Stable Diffusion for architectural concept diagrams and manual material adjustment saves 60% of initial design time. But the school won't allow AI works in teaching achievement exhibitions, calling for policy innovation.
Evaluation reform	Intelligent Diagnosis; Teaching Reflection; Comprehensive Quality Evaluation; Multi - level Diagnosis; Data Analysis; Evaluation Ethics; Authentic Evaluation	The supervision team is creating a three-dimensional AI teaching evaluation: technical appropriateness (30%), student participation (40%), and humanistic value (30%), avoiding overemphasis on technical advancement.
Precise intervention	One - to - One System; Cognitive Map; Potential Assessment; Child Personalization; Differential Design; Path Planning; Adaptive Teaching	The AI learning situation system identified three students faking experimental data due to postgraduate entrance exam pressure. After technical identification, teachers' humanistic intervention is needed.
Collaborative network	Diverse Support; Cross - regional Exchange; Inter - school Collaboration; Resource Sharing; Community Co - construction; Cross - border Integration; Collaborative Literacy	I led the establishment of an intercollegiate AI mathematical modeling alliance for algorithm and case sharing. But inconsistent data interface standards prevent 30% of resource sharing, highlighting coordination issues.
Independent learning	Lifelong Learning; Pre - service Training; Information Training; Seminar; Lifelong Learning; Self - motivation; Continuous Update	Using ChatGPT for personalized learning paths led to "AI dependence". We now require weekly handwritten reflection reports to balance autonomy and technology.
Research - teaching transformation	Scientific Research Innovation; Teaching Research; Product Development; Empirical Research; Scientific Research Output; Reflection and Improvement; Academic Leadership	Last year, 37% of the school's AI teaching and research results couldn't be applied in class, as research chases innovation while teaching needs stability. A "teaching applicability" pre-examination mechanism is being piloted.
Technical leadership	Integrated Practice; Principal Leadership; School-Enterprise Cooperation; Leadership in the Field;	As the director of a provincial key lab, I demand that all research projects have a teaching transformation module, like turning industrial robot research into undergrad experiments

	Organizational Empowerment	to foster teachers' and students' technical leadership thinking.
Cross - boundary collaboration	Multiple Subjects; Combination of Production, Education and Research; Interdisciplinary Design; Multidisciplinary Perspectives; Team Collaboration; Professional Integration; Cross-domain Curriculum	When developing an AI-assisted diagnosis system with the computer school, engineers simplified medical requirements into a function list. A dual-leader system was adopted to keep technical implementation clinical.
Lifelong adaptation	Relearning; Lifelong Coverage; Technical Sensitivity; Cognitive Update; Learning Culture; Agile Response; Adaptive Literacy	I started learning Python at 55 and can now make simple educational data visualization tools. Teachers who can't overcome "technology fear" can't help students face an uncertain future.

Table 3 Results of Axial Coding

realm	concept	realm connotation
Knowledge - and - Skills Dimension	Conceptual cognition Technical principle Interdisciplinary integration Tool foundation Cutting - edge tracking	One should master core AI concepts like machine learning and generative AI, understand technical classifications (e.g., strong/weak AI) and their development paths. Comprehend algorithm logics (e.g., supervised/unsupervised learning), data training processes, and model evaluation methods. Integrate interdisciplinary knowledge of AI, pedagogy, psychology, and computer science to design cross-disciplinary solutions. Be familiar with the functional scopes and interfaces of mainstream AI tools like ChatGPT and intelligent evaluation systems. Keep up with AI tech trends (e.g., multimodal large models, AIGC) via academic papers and industry reports.
Technological - Application Dimension	Tool operation Data processing System development Human - machine collaboration Scenario innovation Fault handling	The application of AI technology covers diverse practical aspects. One should be skilled in using AI tools for teaching tasks like design, resource creation, and assignment marking. Have the ability to clean, annotate, and visually analyze data, and devise personalized teaching strategies based on learning data. Actively engage in developing simple AI teaching apps such as intelligent question banks and auto Q&A bots. In classroom management and research collaboration, assign appropriate roles to humans and AI, like using AI for lesson prep and student behavior analysis. Strive to build virtual-real integrated teaching environments like VR labs and metaverse classrooms for immersive learning. Also, be able to diagnose issues like model biases and data irregularities in AI tools and implement emergency solutions promptly.
Ethical - Responsibility Dimension	Privacy protection Algorithm fairness Social impact Legal compliance Humanistic care	The scope of AI ethical responsibilities mainly includes: strictly complying with the Personal Information Protection Law, standardizing the collection of students' data, and ensuring the security of data storage and transmission; keenly identifying and correcting biases in AI systems, such as scoring discrimination and unequal resource push; comprehensively evaluating the potential impacts of AI on aspects like the employment structure and teacher-student relationships, and proposing targeted risk mitigation strategies; consciously adhering to the copyright norms of AI-generated content, and effectively avoiding academic misconduct such as using AI to write papers; during the application of technology, paying attention to

		maintaining the warmth of education, for example, conducting emotional design of AI feedback and providing support to vulnerable groups.
Teaching - Innovation Dimension	Model reconstruction Resource creation Evaluation reform Precise intervention Collaborative network	The scope of AI teaching innovation covers several key aspects. Actively design new teaching models such as "AI + Project-based Learning" and "Flipped Classroom 2.0" to inject new vitality into teaching. Make full use of AI to generate dynamic teaching materials, adaptive question banks, and virtual experimental resources to enrich the supply of teaching resources. Use AI to implement intelligent process evaluation, conduct learning behavior analysis, and build ability profiles to achieve accurate assessment. Carry out differentiated teaching based on student portraits, adapt to cognitive levels, recommend learning paths, and meet personalized needs. Build a collaborative platform for teachers, AI, and experts to promote the sharing of innovative cases and best practices and drive the development of teaching innovation.
Professional - Development Dimension	Independent learning Research - teaching transformation Technical leadership Cross - boundary collaboration Lifelong adaptation	The scope of AI professional development mainly encompasses that teachers should formulate AI learning plans, actively participate in learning activities such as MOOCs and workshops and complete no less than 30 hours of training on an annual average basis. They should be eager to publish papers on the application of AI in education and apply for relevant topics, ensuring an average annual output of at least one research achievement. Teachers need to take the initiative to promote AI education pilot projects within the school to help young teachers upgrade their technical abilities, actively engage in school-enterprise cooperation like jointly developing intelligent teaching systems or joining interdisciplinary teaching and research teams, and establish a dynamic knowledge update mechanism to keep pace with the rapid iteration of AI through means such as subscribing to technical bulletins and joining professional communities.

Table 4 Results of Selective Coding

realm	level	logical consistency
Knowledge - and - Skills Dimension	Concept, Principle, Tool, Interdisciplinarity	The dimension of knowledge and skills focuses on basic cognition.
Technological - Application Dimension	Tool Usage, Development, Human-Machine Collaboration, Scenario Innovation	The dimension of technical application emphasizes practical operation.
Ethical - Responsibility Dimension	Privacy, Equity, Law, Humanities	The dimension of ethical responsibility restricts the boundaries of technology.
Teaching - Innovation Dimension	Mode, Resource, Evaluation, Intervention	The dimension of teaching innovation promotes educational transformation.
Professional - Development Dimension	Learning, Research, Collaboration, Leadership	The dimension of professional development ensures

continuous adaptation.

4.4 Determination of the Weights of First-level Indicators Based on the Analytic Hierarchy Process (AHP)

According to the implementation principles of the Analytic Hierarchy Process and based on the finally constructed artificial intelligence literacy framework, this study established a hierarchical structure model（Figure 1）。The artificial intelligence literacy framework at the first layer is the target layer, the first-level indicators at the middle layer are the criterion layer, and the second-level indicators at the last layer are the indicator layer.The study found that due to its close association with artificial intelligence practices, the dimension of technological application has a significantly higher weight than other dimensions, accounting for 34.8%. The weights of the dimensions of knowledge and skills, ethical responsibility, teaching innovation, and professional development are relatively evenly distributed, accounting for 21.0%, 18.1%, 16.1%, and 10.0% respectively.（**Error! Reference source not found.**）

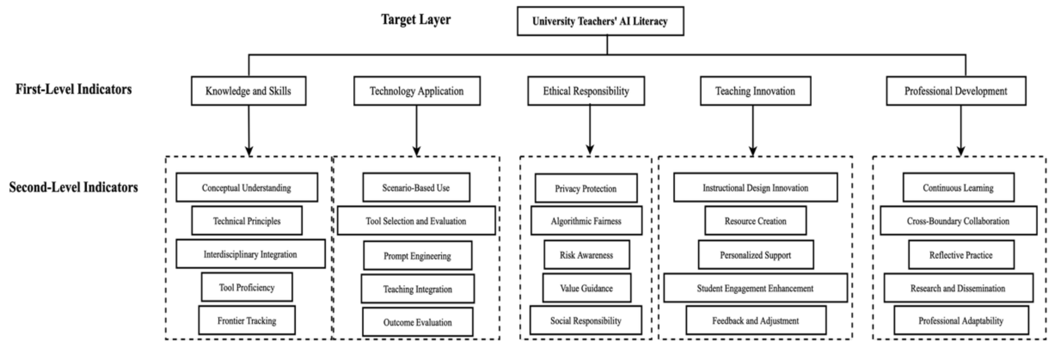

Figure 1 Hierarchical Structural Model of Artificial Intelligence Literacy Framework for University Teachers

5.Discussion

This study constructs a framework of AI literacy for university teachers, comprising five major dimensions: knowledge and skills, technology application, ethical responsibility, instructional innovation, and professional development. This framework reflects a systematic logic that progresses from cognitive understanding to practical application, and ultimately to value reflection and continuous growth. It not only responds to the three-dimensional model of AI literacy proposed by Ng and Chu (2021), which includes “understanding, application, and evaluation,” but also expands it by incorporating the dimensions of ethical responsibility and professional development. It further addresses the lack of "instructional innovation" in the AI literacy structure within adult education, as observed by Laupichler et al. (2022), thus demonstrating theoretical adaptability and extensibility within the context of higher education faculty. In addition, the systematic review by Zawacki-Richter et al. (2019) on AI research in education pointed out that academic attention has been overly concentrated on technical functions, with insufficient focus on ethics, culture, and the evolving role of teachers. The structural enhancement of the "ethical responsibility" and "professional development" dimensions in this study fills this theoretical gap.

The knowledge and skills dimension provides teachers with the cognitive foundation to understand core AI concepts, master technological principles, and integrate interdisciplinary knowledge. The technology application dimension emphasizes the deep integration of AI tools into teaching practice, serving as a key intermediary for enabling AI-enhanced instruction. The ethical responsibility dimension regulates teachers' value judgments and awareness of boundaries in using AI, encompassing issues such as privacy protection, algorithmic fairness, and social responsibility, thereby reflecting the moral tensions and risk management requirements in AI education. The instructional innovation dimension focuses on new teaching paradigms, resource generation, and personalized intervention practices based on AI technologies. The professional development dimension highlights continuous learning, cross-disciplinary collaboration, and lifelong adaptation for teachers in the intelligent era. This aligns with the core ideas of "ethical integration and professional growth synergy" emphasized in Celik's (2023b) concept of "Intelligent TPACK."

Park and Choo (2024) have pointed out that prompt engineering has become a core skill for educators to interact effectively with generative AI systems. The ability to design instructional tasks and assessment strategies based on structured prompting is becoming an essential component of AI literacy for teachers. This perspective supports this study's inclusion of AI tool comprehension and usage strategies in the dimensions of knowledge and skills and technology application.

The five dimensions form an interconnected, supportive chain. According to the AHP results, the technology application dimension received the highest weight, indicating that teachers currently place the greatest emphasis on the functional attributes of AI as teaching tools. In contrast, the relatively lower weights assigned to ethical responsibility and professional development align with the findings of Zhao et al. (2022), which observed weakened ethical and developmental awareness in the AI literacy structure of K–12 teachers. This suggests a similar developmental shortcoming among university teachers in China. Reconstructing teachers' ethical awareness and professional development mechanisms on the basis of technological empowerment is one of the structural challenges revealed in this study.

Holmes and Tuomi (2022) also noted in their study that AI is reshaping the professional identity of teachers, with their professionalism, instructional authority, and educational control being redefined. This necessitates the incorporation of stronger ethical reflection and identity adaptation mechanisms into the AI literacy system—an approach that aligns closely with the logic of this study's framework.

Methodologically, this study employs grounded theory combined with AHP. In contrast to the dominant use of literature analysis and expert consultation in current AI literacy research, this approach offers a bottom-up construction of the framework based on teachers' practical experiences. It enhances the contextual adaptability and data-driven nature of the model. To some extent, this study also responds to the calls from international organizations such as UNESCO (2021) and OECD (2022) for the development of AI literacy models suited to diverse cultural contexts. Using Chinese universities as its context, the study builds on teachers' lived experiences and practical challenges to propose a framework that goes beyond a purely technical logic, instead emphasizing a triadic structure of ethics, practice, and development. This contributes to the diversification of global educational AI research.

Nevertheless, this study has certain limitations. First, the sample is confined to Chinese universities, and the number of interviewees is limited. Therefore, it does not fully represent the global teaching community's AI literacy structure. Future studies should expand to other regions and educational systems to enable cross-cultural validation. Second, although AHP provides a quantitative basis for the importance of each dimension, the structural validity of secondary indicators within dimensions still requires empirical verification through scale development and confirmatory factor analysis. Finally, the differences in AI literacy structures among teachers with different disciplinary backgrounds remain an important area for future research.

6.Conclusion

Based on the teaching practices of university faculty, this study constructs an AI literacy framework comprising five key dimensions: knowledge and skills, technology application, ethical responsibility, instructional innovation, and professional development. Using the analytic hierarchy process (AHP), the study further clarifies the relative importance of each dimension. The framework emphasizes the integration of structural coherence and contextual adaptability, aiming to provide an operable basis for teacher development and educational decision-making. Building upon existing three-dimensional models of AI literacy, this study extends the framework by incorporating ethical norms and professional development, thereby enhancing its completeness and practical relevance in the context of higher education.

In contrast to prior research that has largely focused on students or K–12 teachers, this study pays closer attention to the specific challenges university faculty face in areas such as technology integration, role reconstruction, and capacity development. It provides structured support for future directions in teacher training, assessment system development, and policy formulation. Nevertheless, this study's sample remains limited in scope. Future research should further validate the framework's applicability and stability across different cultural contexts and educational levels. Additionally, large-scale survey instrument development is recommended to promote the standardization and broader application of the AI literacy framework.

7.Data availability

The data utilised in this study came from different higher education institutions of education workers and it was agreed between the researcher and the participants during the interviews that the data could not be shared publicly or disseminated freely. However, upon reasonable request and with permission, the datasets generated and/or analysed during this study are available from the corresponding author.

8.Reference

Allen, L. M. (2010). A critique of four grounded theory texts. The Qualitative Report, 15(6), 1606-1620.

Antoninis, M., Alcott, B., Al Hadheri, S., April, D., Fouad Barakat, B., Barrios Rivera, M., ... & Weill, E. (2023). Global Education Monitoring Report 2023: Technology in education: A tool on whose terms?.

Apramian, T., Cristancho, S., Watling, C., & Lingard, L. (2016). (Re)Grounding grounded theory: a close reading of theory in four schools. Qualitative Research, 17(4), 359-376. https://doi.org/10.1177/1468794116672914

Baker, T., Smith, L., & Anissa, N. (2019). Exploring the future of artificial intelligence in schools and colleges.

Bawden, D. (2001), "Information and digital literacies: a review of concepts", Journal of Documentation, Vol. 57 No. 2, pp. 218-259. https://doi.org/10.1108/EUM0000000007083

Bowers, A. W., & Creamer, E. G. (2020). Core principles of grounded theory in a systematic review of environmental education for secondary students. International Journal of Social Research Methodology, 24(6), 713–726. https://doi.org/10.1080/13645579.2020.1818414

Celik, I. (2023)a. Exploring the determinants of artificial intelligence (Ai) literacy: Digital divide, computational thinking, cognitive absorption. Telematics and Informatics, 83, 102026.https://doi.org/10.1016/j.tele.2023.102026

Celik, I. (2023)b. Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. Computers in human behavior, 138, 107468. https://doi.org/10.1016/j.chb.2022.107468

Cetindamar, D., Kitto, K., Wu, M., Zhang, Y., Abedin, B., & Knight, S. (2022). Explicating AI literacy of employees at digital workplaces. IEEE transactions on engineering management, 71, 810-823.

Chiu, T. K. F. (2023). The impact of Generative AI (GenAI) on practices, policies and research direction in education: a case of ChatGPT and Midjourney. Interactive Learning Environments, 32(10), 6187–6203. https://doi.org/10.1080/10494820.2023.2253861

Chiu, T. K., Meng, H., Chai, C. S., King, I., Wong, S., & Yam, Y. (2022). Creation and evaluation of a pretertiary artificial intelligence (AI) curriculum. IEEE Transactions on Education, 65(1), 30-39.

Conlon C, Timonen V, Elliott-O'Dare C, O'Keeffe S, Foley G. Confused About Theoretical Sampling? Engaging Theoretical Sampling in Diverse Grounded Theory Studies. Qualitative Health Research. 2020;30(6):947-959. https://doi.org/10.1177/1049732319899139

Cox, A. (2024). Algorithmic Literacy, AI Literacy and Responsible Generative AI Literacy.

Journal of Web Librarianship, 18(3), 93–110. https://doi.org/10.1080/19322909.2024.2395341

Dai, Y., Chai, C. S., Lin, P. Y., Jong, M. S. Y., Guo, Y., & Qin, J. (2020). Promoting students' well-being by developing their readiness for the artificial intelligence age. Sustainability, 12(16), 6597.https : //doi.org/10.3390/su12166597

Ding, L., Kim, S., & Allday, R. A. (2024). Development of an AI literacy assessment for non-technical individuals: What do teachers know?. Contemporary Educational Technology, 16(3), ep512. https://doi.org/10.30935/cedtech/14619

Eshet, Y. (2002). Digital literacy: A new terminology framework and its application to the design of meaningful technology-based learning environments (pp. 493-498). Association for the Advancement of Computing in Education (AACE).

Eshet, Y. (2004). Digital Literacy: A Conceptual Framework for Survival Skills in the Digital era. Journal of Educational Multimedia and Hypermedia, 13(1), 93-106. Norfolk, VA: Association for the Advancement of Computing in Education (AACE). Retrieved April 1, 2025 from https://www.learntechlib.org/primary/p/4793/.

Glaser, B., & Strauss, A. (1999). Discovery of Grounded Theory: Strategies for Qualitative Research (1st ed.). Routledge. https://doi.org/10.4324/9780203793206

Guo Yajun, Kou Xuying, Feng Siqian, Liu Kunfeng & Xu Ruichao. (2025). Artificial intelligence literacy: connotation analysis and evaluation standard construction. Library Forum (02), 42-50.

He Feixia. (2022). Challenges and opportunities: the diversified development of university teachers' academic career in the era of artificial intelligence. Exploration of Higher Education (02), 22-27. https://doi:CNKI:SUN:GJTA.0.2022-02-003.

Heyder, T., & Posegga, O. (2021). Extending the foundations of AI literacy. In ICIS (Vol. 9, pp. 1-9).

Kandlhofer, M., Steinbauer, G., Hirschmugl-Gaisch, S., & Huber, P. (2016, October). Artifi cial intelligence and computer science in education: From kindergarten to university. I n 2016 IEEE frontiers in education conference (FIE) (pp. 1-9). IEEE. doi: 10.1109/FI E.2016.7757570.

Kong, S. C., Cheung, W. M. Y., & Zhang, G. (2021). Evaluation of an artificial intelligen ce literacy course for university students with diverse study backgrounds. Computers a nd Education: Artificial Intelligence, 2, 100026.https://doi.org/10.1016/j.caeai.2021.100026

Lankshear, C., & Knobel, M. (Eds.). (2008). Digital literacies: Concepts, policies and practices (Vol. 30). Peter Lang.

Laupichler, M. C., Aster, A., Schirch, J., & Raupach, T. (2022). Artificial intelligence literacy in higher and adult education: A scoping literature review. Computers and Education: Artificial Intelligence, 3, 100101. https://doi.org/10.1016/j.caeai.2022.100101

Li Yan, Sun Lingyun, Jiang Quanyuan, Chen Limeng, Yang Yang & Wu Fei. (2025). Artificial intelligence literacy and improvement strategies for college teachers. Open Education Research (01), 23-33. https://doi:10.13966/j.cnki.kfjyyj.2025.01.003.

Lintner, T. A systematic review of AI literacy scales. npj Sci. Learn. 9, 50 (2024). https://doi.org/10.1038/s41539-024-00264-4.

Long, D., & Magerko, B. (2020, April). What is AI literacy? Competencies and design co nsiderations. In Proceedings of the 2020 CHI conference on human factors in computi ng systems (pp. 1-16). https://doi.org/10.1145/3313831.3376727

Martin, A., & Grudziecki, J. (2006). DigEuLit: Concepts and Tools for Digital Literacy Development. Innovation in Teaching and Learning in Information and Computer Sciences, 5(4), 249–267. https://doi.org/10.11120/ital.2006.05040249

Matavire, R., & Brown, I. (2013). Profiling grounded theory approaches in information sys tems research. European Journal of Information Systems, 22(1), 119–129. https://doi.or g/10.1057/ejis.2011.35

McCarthy, A. M., Maor, D., McConney, A., & Cavanaugh, C. (2023). Digital transformation in education: Critical components for leaders of system change. Social sciences & humanities open, 8(1), 100479. https://doi.org/10.1016/j.ssaho.2023.100479

Ng, D. T. K., & Chu, S. K. W. (2021). Motivating Students to Learn AI Through Social Networking Sites: A Case Study in Hong Kong. Online Learning, 25(1), 195-208.

Ng, D. T. K., Leung, J. K. L., Chu, K. W. S., & Qiao, M. S. (2021). AI literacy: Definition, teaching, evaluation and ethical issues. Proceedings of the association for information science and technology, 58(1), 504-509.

Ng, D. T. K., Luo, W., Chan, H. M. Y., & Chu, S. K. W. (2022). Using digital story writing as a pedagogy to develop AI literacy among primary students. Computers and Education: Artificial Intelligence, 3, 100054. https://doi.org/10.1016/j.caeai.2022.100054

Nguyen, A., Ngo, H.N., Hong, Y. et al. Ethical principles for artificial intelligence in education. Educ Inf Technol 28, 4221–4241 (2023). https://doi.org/10.1007/s10639-022-11316-w

Pant, S., Kumar, A., Ram, M., Klochkov, Y., & Sharma, H. K. (2022). Consistency Indice s in Analytic Hierarchy Process: A Review. Mathematics, 10(8), 1206. https://doi.org/1 0.3390/math10081206

Perkins, M., Roe, J., Postma, D. et al. Detection of GPT-4 Generated Text in Higher Education: Combining Academic Judgement and Software to Identify Generative AI Tool Misuse. J Acad Ethics 22, 89–113 (2024). https://doi.org/10.1007/s10805-023-09492-6

Pinski, M., & Benlian, A. (2024). AI literacy for users–A comprehensive review and futur e research directions of learning methods, components, and effects. *Computers in Hum an Behavior: Artificial Humans*, 100062. https://doi.org/10.1016/j.chbah.2024.100062

Saati, T. (1994). Fundamentals of decision making and priority theory with the AHP. Pitsburg: RWS Publication.

Saaty, T. L. (1990). How to make a decision: the analytic hierarchy process. European journal of operational research, 48(1), 9-26.https://doi.org/10.1016/0377-2217(90)90057-I

Saaty, T.L., Vargas, L.G. (2012). The Seven Pillars of the Analytic Hierarchy Process. In: Models, Methods, Concepts & Applications of the Analytic Hierarchy Process. International Series in Operations Research & Management Science, vol 175. Springer, Boston, MA. https://doi.org/10.1007/978-1-4614-3597-6_2

Soomro, K.A., Kale, U., Curtis, R. et al. Digital divide among higher education faculty. Int J Educ Technol High Educ 17, 21 (2020). https://doi.org/10.1186/s41239-020-00191-5

Stough, L. M., & Lee, S. (2021). Grounded Theory Approaches Used in Educational Research Journals. International Journal of Qualitative Methods, 20. https://doi.org/10.1177/16094069211052203

Sui, M., Yang, Y. & Zhou, M. The educational structure of digital artisans: a qualitative study based on grounded theory. Humanit Soc Sci Commun 12, 357 (2025). https://doi.org/10.1057/s41599-025-04530-7

Sun Rong & Li Baiyang. Research on a new digital divide identification framework under the background of generative artificial intelligence (GAI). Library and Information Knowledge .

Su Wencheng, Guo Haoran, Lu Zhangping, Pan Ying & Liu Guifeng.(2024) Construction and effectiveness verification of the evaluation index system of artificial intelligence literacy of college students in China. Library Construction .

Thanassoulis, E., Dey, P. K., Petridis, K., Goniadis, I., & Georgiou, A. C. (2017). Evaluating higher education teaching performance using combined analytic hierarchy process and data envelopment analysis. Journal of the Operational Research Society, 68(4), 431–445. https://doi.org/10.1057/s41274-016-0165-4

UNESCO. K-12 AI curricula. A mapping of government-endorsed AI curricula [EB/OL].[2024-02-19].https://unesdoc.unesco.org/ark:/48223/pf0000387029_chi.

Wang Yijun, Wang Yingmei & Yang Youran. (2022). Content system and development path of artificial intelligence literacy education in colleges and universities. Heilongjiang Higher Education Research (02), 26-31.

Wang, B., Rau, P. L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. Behaviour & Information Technology, 42(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

Wu Di, Zhou Chi & Chen Min. (2020). Research on the evaluation of teachers' information literacy in the "Internet +" era. China Audio-visual Education (01), 56-63+108.

Xue Shumin, Yan Yingying & Xu Mengjie. (2024). Teacher AI literacy: Teacher preparation in the era of artificial intelligence - An analysis based on the UNESCO “AI CFT” framework and seven policy documents. Teacher Education Research (04), 105-113.

Yang Feng. (2023). Intelligence gap generation of generative artificial intelligence. Library

Construction (04), 22-24. https://doi:10.19764/j.cnki.tsgjs.20230859.

Yin Kaiguo. (2024). Artificial intelligence literacy: background, concept definition and constituent elements. Library and Information (03), 60-68. https://doi:CNKI:SUN:BOOK.0.2024-03-007.

Zawacki-Richter, O., Marín, V.I., Bond, M. et al. Systematic review of research on artificial intelligence applications in higher education – where are the educators?. Int J Educ Technol High Educ 16, 39 (2019). https://doi.org/10.1186/s41239-019-0171-0

Zhang Qiufang, Liu Ruoyu & Xie Yuxin. (2024). Risks and avoidance approaches of generative AI in higher education applications. Journal of Mudanjiang Education College (01), 41-45. doi:CNKI:SUN:MDJJ.0.2024-01-012.

Zhao, L., Wu, X., & Luo, H. (2022). Developing AI literacy for primary and middle school teachers in China: Based on a structural equation modeling analysis. Sustainability, 14(21), 14549. https://doi.org/10.3390/su142114549

Park, J., & Choo, S. (2024). Generative AI Prompt Engineering for Educators: Practical Strategies. Journal of Special Education Technology, 0(0). https://doi.org/10.1177/01626434241298954

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. European journal of education, 57(4), 542-570. https://doi.org/10.1111/ejed.12533

UNESCO. (2021). AI and Education: Guidance for Policymakers. Paris: United Nations Educational, Scientific and Cultural Organization.

OECD. (2022). Harnessing the power of AI and emerging technologies: Background paper for the CDEP ministerial meeting. OECD Digital Economy Papers, No. 340.

Schwab, K. (2024). The Fourth Industrial Revolution: what it means, how to respond1. In Handbook of research on strategic leadership in the Fourth Industrial Revolution (pp. 29-34). Edward Elgar Publishing. https://doi.org/10.4337/9781802208818.00008

Milberg, T. (2024, April). The future of learning: How AI is revolutionizing education 4.0. World Economic Forum. https://www.weforum.org/stories/2024/04/future-learning-ai-revolutionizing-education-4-0/