INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN PROGRESSIVE EDUCATION & DEVELOPMENT

OPEN ACCESS JOURNAL

Vol 14, Issue 4, (2025) E-ISSN: 2226-6348

Pre-service Teachers' Intention to Use Artificial Intelligence Research during 2005–2025: A Review Based on Bibliometric Analysis

Fu Qiang[1,2], Hamidah Mohamad[1], Cheok Mui Yee[1], Mao Chunyu[2]

[1]Universiti Tun Abdul Razak, Malaysia, [2]Jilin Engineering Normal University, China

DOI Link: http://dx.doi.org/10.6007/IJARPED/v14-i4/26712

Published Online: 25 October 2025

Abstract

This study offers a comprehensive bibliometric overview of research on pre-service teachers' intention to adopt artificial intelligence (AI) in education from 2005 to 2025. Using the Web of Science Core Collection, 522 records were initially retrieved and 477 peer-reviewed articles were retained after PRISMA-aligned screening. CiteSpace (LLR clustering, burst detection, co-citation networks) and VOSviewer/RAWGraphs were employed to map publication trends, intellectual structures, and collaborative patterns. Results show three temporal waves: (1) 2004–2010 foundations in TAM, UTAUT, and TPB; (2) 2011–2017 emphasis on digital competence, self-efficacy, and teacher readiness; and (3) 2018–2025 acceleration of AI-specific themes—ethics, trust, explainability, and pedagogical innovation. Core clusters revolve around technology acceptance constructs (perceived usefulness/ease, attitude, intention), digital competence frameworks, and AI-enabled instructional design. Author and source co-citation analyses highlight enduring methodological anchors (e.g., PLS-SEM standards) and the dominance of journals such as *Computers & Education*, *Computers in Human Behavior*, and the emergent *Computers and Education: Artificial Intelligence*. Geographically, China, the United States, and several European countries lead in productivity and centrality, reflecting an increasingly interdisciplinary and collaborative landscape. Practically, findings point to the necessity of embedding holistic AI literacy—technical, pedagogical, and ethical—into teacher education, while addressing affective barriers like anxiety. Limitations include the single-database scope and the quantitative nature of bibliometrics; future research should triangulate with qualitative syntheses, track policy impacts longitudinally, and examine equity dimensions (gender, region, institutional type) in AI adoption.

Keywords: Pre-service Teachers, Artificial Intelligence, Technology Acceptance, Digital Competence, Bibliometric Analysis, Citespace, Teacher Education

Introduction

Rapid advances associated with the Fourth Industrial Revolution have positioned artificial intelligence (AI) as a principal engine of educational change (Wang & Fan, 2025; Munaye et al., 2025). Generative large language models such as ChatGPT have moved from pilots to routine classroom and teacher-education use, provoking both pedagogical opportunities and ethical concerns (Bae et al., 2024; Wang & Fan, 2025). Empirical studies report gains in adaptive feedback and assessment efficiency, yet warn of overreliance and superficial engagement without careful scaffolding (Ramnarain et al., 2024; Munaye et al., 2025). Across AI in Education—intelligent tutoring, automated feedback, adaptive environments, and predictive analytics—effectiveness ultimately depends on sound pedagogical alignment (Zohdi et al., 2024; Sahar & Munawaroh, 2025). Realizing these benefits hinges on teachers' preparedness, institutional support, and credible AI information (Hazzan-Bishara et al., 2025; Bakhadirov et al., 2024). Pre-service teachers are pivotal because their current beliefs, competencies, and perceived value of AI will shape near-future classroom enactments (Acquah et al., 2024; Runge et al., 2025). Recent work models their intentions with TAM-, TPB-, and UTAUT-based constructs (e.g., perceived usefulness, attitude, subjective norm, perceived behavioral control) (Zhang et al., 2023; Ramnarain et al., 2024). Extensions increasingly incorporate AI self-efficacy, trust, perceived risk, or AI-TPACK to capture nuanced determinants of adoption (Sun et al., 2025; Hazzan-Bishara et al., 2025). Findings often highlight perceived usefulness and social influence as robust drivers, whereas ease of use and anxiety show mixed effects across contexts (Bakhadirov et al., 2024; Acquah et al., 2024).

Nevertheless, evidence remains fragmented, dominated by small-sample surveys or qualitative cases that limit cumulative insight (Bae et al., 2024; Zhang et al., 2023). Population-specific bibliometric syntheses focusing on pre-service teachers are scarce; most reviews scan higher education broadly or take narrative approaches (Sahar & Munawaroh, 2025; Zohdi et al., 2024). Bibliometric techniques implemented via tools such as CiteSpace and VOSviewer enable transparent, replicable mapping of prolific authors, collaborations, citation structures, and thematic evolution (Bajpai et al., 2025).

Accordingly, this study analyzes literature on pre-service teachers' intention to adopt AI from 2005–2025, revealing trajectories, clusters, and gaps to inform curriculum design, teacher preparation, and policy for responsible AI integration (Runge et al., 2025; Ramnarain et al., 2024).

Given the increasing relevance of AI in teacher education and the critical role of pre-service teachers as future implementers of technology, this study aims to answer the following research questions:

①What are the publication trends and knowledge structures in the research on pre-service teachers' intention to use AI from 2005 to 2025?
②Who are the most influential authors, institutions, and countries contributing to this field?
③What are the major research themes, theories, and methodological trends, and how have they evolved over time?

This bibliometric review seeks to address these questions by providing the first systematic, large-scale mapping of global research (2005–2025) on pre-service teachers' AI adoption intention, thereby offering a comprehensive overview of the field. It not only reveals a three-stage thematic evolution from foundational technology acceptance theories to AI-specific ethical and pedagogical integration and identifies emerging research clusters and transnational collaborative networks, but also translates these structural insights into a valuable knowledge map and practical pathways, ultimately delivering both theoretical and practical implications for researchers, policymakers, and educators engaged in teacher preparation and educational innovation.

Literature Review

The digitalization of education has redefined what it means to be a future teacher: beyond pedagogical proficiency, pre-service teachers must demonstrate robust digital competence and technological adaptability (Koehler & Mishra, 2009; Tondeur et al., 2017; Wang & Zhao, 2021; Scherer et al., 2018). Propelled by big data, machine learning, and especially generative AI such as ChatGPT, AI-enhanced learning environments have shifted from vision to routine practice, compelling teacher education programs to embed AI-related knowledge, skills, and ethical considerations explicitly in their curricula (Luckin & Holmes, 2016; Holmes et al., 2019; Adiguzel et al., 2023; Bae et al., 2024; Sun et al., 2025; Wang & Fan, 2025). Yet institutions frequently lack systematic strategies for this preparation, which can foster uncertainty, resistance, or anxiety among pre-service teachers (Hodges et al., 2024; Alenezi, 2021; Alabdulaziz, 2021; Agogo & Hess, 2018; Ertmer & Ottenbreit-Leftwich, 2010). Because classroom practice is deeply shaped by attitudes and experiences formed during initial training, insufficient exposure to AI risks superficial or reluctant adoption later on (Ertmer & Ottenbreit-Leftwich, 2010; Scherer et al., 2018; Ramnarain et al., 2024; Runge et al., 2025).

To explain and predict such uptake, research has relied on established acceptance frameworks. The Technology Acceptance Model (TAM) posits perceived usefulness and perceived ease of use as proximal determinants and has been repeatedly validated with teachers and pre-service teachers (Davis, 1989; Teo, 2010, 2011; Šumak et al., 2011; Bai et al., 2021). The Unified Theory of Acceptance and Use of Technology (UTAUT) extends this with performance expectancy, effort expectancy, social influence, and facilitating conditions, emphasizing contextual moderators like institutional support and culture (Venkatesh et al., 2003; Sánchez-Prieto et al., 2015; Al-Emran et al., 2020; Nistor et al., 2012; Runge et al., 2025). Parallelly, the Theory of Planned Behavior (TPB) highlights attitudes, subjective norms, and perceived behavioral control, and hybrid TAM–TPB models often yield stronger predictive power in teacher education (Ajzen, 1991; Teo, 2010; Wang et al., 2020; Acquah et al., 2024). Recent extensions integrate AI-specific constructs—trust, ethical concerns, transparency, and AI-TPACK—to capture the adaptive, decision-making nature of AI tools (Choung et al., 2022; Dillenbourg et al., 2021; Sun et al., 2025; Hazzan-Bishara et al., 2025). However, findings remain mixed: some studies stress perceived usefulness (Teo, 2011; Bai et al., 2021; Li et al., 2022), others foreground attitude (Hamidi & Chavoshi, 2018), subjective norm (Park, 2009), or self-efficacy/anxiety (Scherer et al., 2018; Agogo & Hess, 2018; Zhang et al., 2023), while continuance intentions hinge on expectation confirmation and perceived outcomes (Tian et al., 2024).

Despite rapid growth, reviews of this domain are fragmented—often narrative or narrowly systematic, focused on niches such as adaptive learning, assessment, or STEM, and reliant on manual coding that constrains objectivity and replicability (Zawacki-Richter et al., 2019; Martin et al., 2020; Roll & Wylie, 2016; Zhai et al., 2020; Pedro et al., 2019; Raffaghelli & Stewart, 2020). Bibliometric approaches overcome these limits by enabling large-scale, transparent mapping of collaboration networks, co-citation structures, and thematic evolution (Chen et al., 2012; Van Eck & Waltman, 2010; Martins et al., 2022; Agbo et al., 2021;

Zhan et al., 2022; Chen et al., 2020; Zohdi et al., 2024; Sahar & Munawaroh, 2025). Accordingly, this study conducts a comprehensive bibliometric review (2005–2025) of research on pre-service teachers' intention to adopt AI, charting thematic trajectories, identifying key actors and networks, synthesizing theoretical applications and extensions, and exposing underexplored variables—such as trust, ethics, and emotional factors—to inform future empirical work, curriculum design, and policy for AI-integrated teacher education (Ramnarain et al., 2024; Runge et al., 2025; Hazzan-Bishara et al., 2025; Wang & Fan, 2025).

Methods

Although studies on pre-service teachers' intention to use AI are growing, the field still lacks a quantitatively grounded overview that reveals its intellectual structure, thematic shifts, and collaboration networks; therefore, we employ bibliometric analysis (Pritchard, 1969; Hawkins, 2001; De Bellis, 2009; Garfield, 2006). Bibliometrics—"the application of mathematical and statistical methods to books and other media of communication"—enables objective mapping of publication trends, influential authors, and citation dynamics (Pritchard, 1969; Garfield, 2006). We used the Web of Science Core Collection for its high-quality indexing and standardized metadata suited to visualization tools (Van Eck & Waltman, 2010; Huong & Quy, 2025). A Topic Search combined three blocks of terms—target population (e.g., "pre-service teacher*"), technological focus (e.g., "artificial intelligence"), and behavioral constructs (e.g., "intention* to use")—with limits on language (English), document type (articles, reviews), and timeframe (January 2005–July 2025), yielding 522 records (Table 1). A two-stage manual screening (titles/abstracts, then full texts) removed tangential items, following PRISMA 2020 to ensure transparency and reproducibility; 477 publications remained (Page et al., 2021). To avoid distortions in co-citation and keyword analyses, we standardized author names, journal titles, and keywords, resolving spelling and format variants (Taskin & Al, 2019; Hawkins, 2001). The cleaned dataset was analyzed in VOSviewer and CiteSpace to generate co-citation clusters, keyword bursts, and collaboration networks (Van Eck & Waltman, 2010). Compared with conventional systematic reviews or meta-analyses that emphasize effect sizes (e.g., Chen et al., 2022), this approach uncovers large-scale structural evolution and knowledge fronts in the domain.Table 1 Summary of data source and selection

Category	Specific standard requirements
Research database	Web of Science Core Collection
Searching period	January 2005 to July 2025
Language	English
Searching keywords	TS=(("pre-service teacher*" OR "student teacher*" OR "teacher education student*" OR "education student*" OR "prospective teacher*" OR "future teacher*" OR "teacher candidate*" OR "education major*" OR "student* in teacher education") AND (("artificial intelligence" OR AI OR "educational technology" OR "digital tool*" OR "emerging technolog*") AND ("adoption intention*" OR "intention* to use" OR "behavioral intention*" OR "technology acceptance" OR "technology adoption" OR willingness OR attitude* OR readiness OR perception* OR acceptance OR usage OR belief*)))
Document types	Articles， Review articles
Data extraction	Export with full records and cited references in plain text format
Sample size	522 (Before manual screening)

Results

Descriptive information

The eligible articles in this study originate from 97 countries and regions. Figure 1 presents the distribution of publications among the top contributing countries, with Spain leading the productivity (n = 88), followed by China (n = 71), USA (n = 61), Turkey (n = 57), and Germany (n = 22). These five countries account for the majority of research output related to pre-service teachers' intention to adopt artificial intelligence in education.

However, in terms of centrality, which reflects a country's importance within the international collaboration network, the highest centrality value was observed in Spain (0.44), indicating its pivotal role in connecting different regions and research clusters. China (0.23) and India (0.12) also demonstrated relatively high centrality, suggesting growing influence in shaping global research conversations.

In addition to centrality, the analysis also identified countries with significant citation bursts, indicating emerging or sustained interest in the topic over time. Notably, Turkey experienced the strongest burst (9.03) during the period 2009–2020, while the USA had a burst strength of 6.36 between 2004 and 2021, and Spain showed a more recent burst (5.61) from 2020 to 2023.

Overall, while traditional research hubs such as the USA and China continue to dominate the field in terms of output, newer contributors like Malaysia, Saudi Arabia, and India are gaining prominence, reflecting the global diversification of research on AI adoption in teacher education.

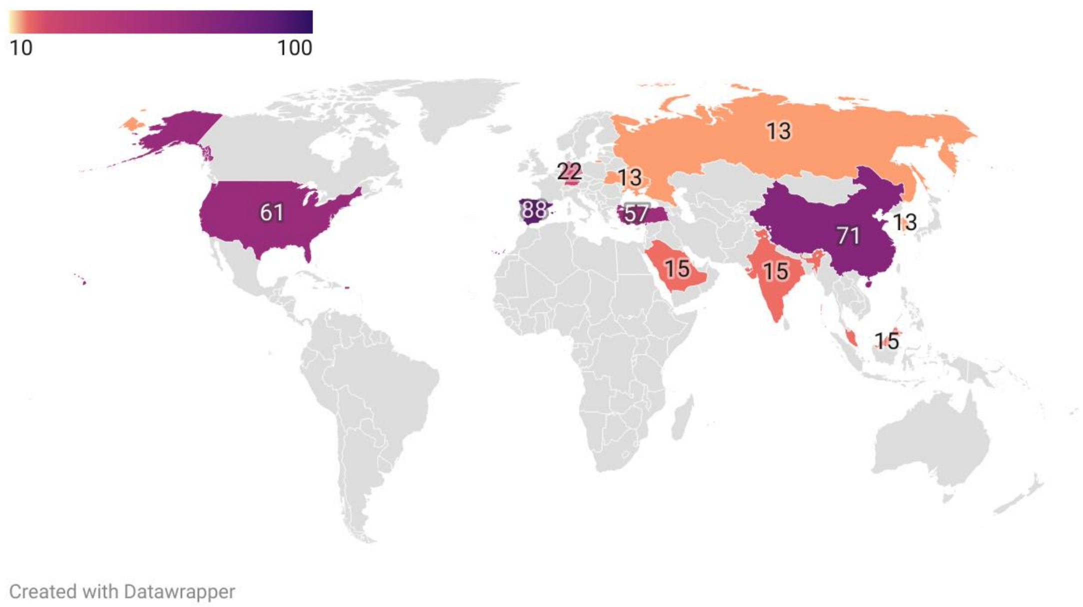

Figure 1 Top 10 contributed countries

Among the studies reviewed, several core research themes were identified, as summarized in Table 1. The most prominent subject area was ICT and Information Systems (n = 420), characterized by keywords such as *information technology*, *adoption*, and *technology acceptance model*, highlighting a sustained interest in infrastructure and system-level adoption of AI tools. This was followed by Psychological Constructs (n = 357) and Attitudes and Motivation (n = 335), which included frequent terms such as *beliefs*, *attitudes*, *self-efficacy*, and *teacher education*, reflecting the strong influence of behavioral and pedagogical constructs in explaining AI adoption.

Other notable domains included Educational Technology and Classroom Integration, which emphasize teaching contexts, digital platforms, and practical implementation strategies. Clusters such as Technology Acceptance Models, Teacher Education, and Digital Competence—though smaller in volume—point to important theoretical and skills-based concerns shaping the research agenda.

Together, these themes indicate that the literature on pre-service teachers' intention to adopt AI spans both technological systems and human-centered variables, grounded in models like TAM and UTAUT, and enriched by emerging focuses on digital pedagogy and instructional readiness.

Table 1
Distribution of literature in subject areas according to keyword frequency

Rank	Subject area	# of keywords	Related keywords (in descending order)
1	ICT and Information Systems	420	information technology; adoption; preservice teachers; teachers; intention; user acceptance; determinants; model; extension; technology acceptance model
2	Psychological Constructs	357	beliefs; acceptance model; classroom; pedagogical content knowledge; technology integration; design; competence; pre-service teachers; science; tpack
3	Attitudes and Motivation	335	attitudes; technology; acceptance; teacher education; self efficacy; performance; gender; digital tools; literacy; students
4	Educational Technology	231	educational technology; higher education; computational thinking; k 12; blended learning; social media; data mining; feature extraction; computational modeling; digital natives
5	Classroom Integration & Practice	226	ict; integration; information; perceptions; experience; challenges; teacher training; behavior; skills; efficacy
6	Technology Acceptance Models	147	knowledge; student teachers; conceptions; impact; classrooms; distance education; digital skills; improving classroom teaching; mathematics; digital technology
7	Teacher Education	124	education; online; distributed knowledge; asynchronous discussion board; knowledge construction; sociocultural theory; initial teacher education; social learning; trust; adult learning
8	Digital Competence	105	framework; digital competence; computer use; professional development; achievement; computer attitudes; educational beliefs; curriculum; internet; strategy

Research Topics and Trends

Keyword Co-occurrence Network

To uncover the intellectual structure of the research on pre-service teachers' intention to adopt artificial intelligence (AI), a keyword co-occurrence analysis was conducted using CiteSpace. This method enables the identification of frequently co-occurring terms in the literature, providing insight into dominant research topics and their interconnections within the field.

The resulting network visualization revealed a total of 129 keyword nodes and 780 co-occurrence links, representing the thematic backbone of the literature corpus. As shown in Figure 2, high-frequency keywords such as "artificial intelligence" (n = 88), "higher education" (n = 80), "educational technology" (n = 78), "education" (n = 76), and "technology" (n = 58) occupy central positions within the network, indicating their widespread presence and foundational status in this research domain.

In addition to technological terms, the network also reveals a strong pedagogical and psychological orientation. Keywords such as "pre-service teachers" (n = 51), "beliefs" (n = 45), "user acceptance" (n = 41), "pedagogical content knowledge", and "self-efficacy" demonstrate that the literature is deeply rooted in teacher cognition, instructional design, and behavioral theory.

The centrality values further illustrate the structural importance of certain nodes. For example, “educational technology” and “model” recorded the highest centrality scores (0.19 and 0.14, respectively), suggesting they act as conceptual bridges linking multiple research clusters. These keywords not only appear frequently but also connect otherwise distinct thematic areas, thereby exerting influence on the overall knowledge structure.

Moreover, the temporal distribution of keywords—ranging from 2003 to 2021—demonstrates the sustained and evolving interest in this topic. Earlier research centered around foundational constructs such as *technology acceptance* and *ICT use*, while more recent studies increasingly focus on *digital competence*, *AI-based tools*, and *student perceptions*, indicating a shift from generalized technology integration to more specific AI-driven educational innovations.

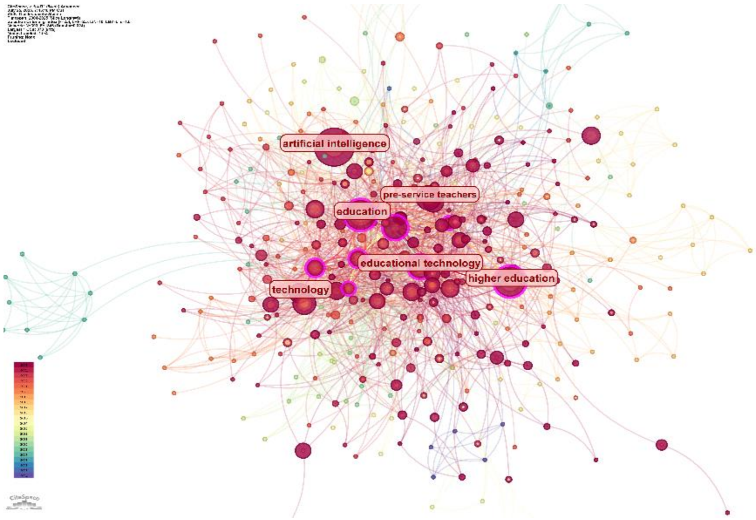

Figure 2 Keyword Co-occurrence Network of Pre-service Teachers’ AI Adoption Research (2005–2025)

The co-occurrence network reveals a multidimensional and interconnected knowledge base grounded in technological, pedagogical, and psychological constructs. This finding supports the notion that AI adoption in teacher education is not a singularly technical issue, but rather an interdisciplinary concern embedded within broader educational and behavioral frameworks.

Thematic Clustering and Knowledge Structure

To explore the underlying conceptual structure of literature related to pre-service teachers’ intention to use artificial intelligence (AI), a clustering analysis of co-occurring keywords was conducted using CiteSpace. The resulting network, based on the Log-Likelihood Ratio (LLR) algorithm, identified 11 distinct thematic clusters, each representing a focused research area within the broader domain (see Figure 3).

The largest and most central cluster was #0 “technology acceptance”, which aggregated keywords related to behavioral intention, acceptance models (e.g., TAM, UTAUT), and adoption patterns. This cluster reflects the dominant theoretical foundation underpinning the literature, emphasizing cognitive variables such as *perceived usefulness*, *perceived ease of use*, and *behavioral intention*.

Cluster #1 "digital tools" includes keywords such as *digital literacy*, *technology integration*, and *online learning*, indicating a growing emphasis on the operational dimension of digital competence in teacher education. This aligns closely with #4 "computer attitude", which explores affective and psychological constructs such as *attitudes toward technology*, *anxiety*, and *self-efficacy*.

Cluster #2 "teacher training" and #3 "pre-service teachers" jointly represent the pedagogical core of the field. These clusters highlight the intersection of professional development, teacher education curricula, and the role of AI in preparing future educators.
Other noteworthy clusters include:

#5 "higher education": focusing on the institutional setting in which most studies are conducted, with attention to *university-based teacher education* and *digital transformation*.
#6 "professional development": examining the continuous learning and upskilling of educators in AI-enhanced environments.
#7 "artificial intelligence": a technology-centered cluster highlighting specific AI tools, algorithms, and implementation strategies in educational settings.
#8 "primary education" and #9 "virtual change agent": reflecting emerging but less dominant areas, such as AI's impact on early childhood education and transformative roles in digital pedagogy.
#10 "cloud computing": associated with infrastructure and technical enablers of AI deployment in teaching and learning.

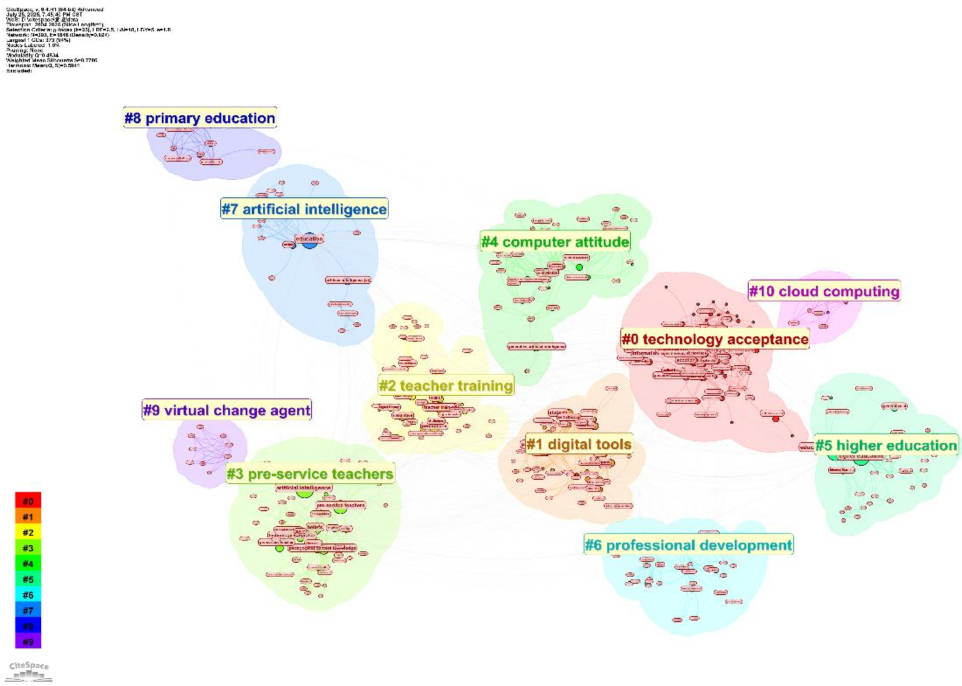

Figure3. Thematic Cluster Visualization of Co-occurring Keywords

The network layout reveals a well-connected structure, with Cluster #0 (technology acceptance) and Cluster #1 (digital tools) occupying central positions and bridging several peripheral topics. This suggests that behavioral models and technological readiness serve as conceptual anchors for related discussions on pedagogy, institutional context, and teacher identity.

Taken together, these findings point to a multidimensional research landscape, where psychological theories, digital competencies, and AI applications coalesce. This thematic diversity underscores the complexity of AI adoption in teacher education and highlights the importance of integrating theory, technology, and pedagogy in future research agendas.

Temporal Evolution of Research Themes

The timeline visualization (Figure 4) reveals the chronological progression and lifespan of key thematic clusters related to pre-service teachers' intention to use artificial intelligence (AI) in educational contexts between 2005 and 2025. This timeline view enables a granular analysis of how specific research topics have emerged, evolved, and waned over time, offering insights into the developmental trajectory of the field.

The earliest thematic cluster, #0 "technology acceptance", has remained consistently influential across the entire study period. Keywords such as *user acceptance*, *Technology Acceptance Model*, and *intention* appeared as early as 2005 and have continued to be central in discussions of AI adoption. This confirms the foundational role of behavioral theories in guiding early-stage research and their sustained relevance in contemporary educational technology studies.

The cluster #1 "digital tools" emerged gradually around 2010, gaining increasing attention in the post-2015 period. This reflects the growing diversification of educational technologies and their integration into teacher training programs. Frequent terms in this cluster include *blended learning*, *computational thinking*, and *digital literacy*, indicating a shift toward tool-based pedagogical strategies.

Cluster #3 "pre-service teachers" exhibits a sharp rise in activity after 2018, with node bursts becoming particularly evident between 2020 and 2023. This trend aligns with global policy efforts to enhance digital readiness in teacher education programs. Prominent terms in this cluster include *teacher beliefs*, *teaching practices*, and *pre-service teacher education*, indicating a robust research focus on psychological and instructional aspects of technology adoption.

#2 "teacher training" and #4 "computer attitude" clusters also show sustained activity across the timeline, particularly during the mid-2010s. These clusters emphasize affective and pedagogical variables such as *self-efficacy*, *perceptions*, and *technology integration*. The continuous presence of these clusters underscores the centrality of teacher dispositions in shaping technology acceptance.

Clusters #5 "higher education" and #6 "professional development" appear as relatively stable thematic areas, reflecting institutional contexts in which AI-related adoption is most actively studied. These clusters have seen moderate yet consistent activity across the entire period, especially in research focusing on curriculum design, capacity building, and policy alignment within teacher education faculties.

More recent clusters, such as #7 “artificial intelligence” and #10 “cloud computing”, demonstrate an upward trajectory in the years following 2020. The emergence of terms like *generative AI*, *large language models*, and *AI-driven feedback systems* indicates a clear thematic pivot toward intelligent technologies in educational research. These newer clusters suggest a reorientation of the field toward automation, personalization, and data-informed teaching practices.

Finally, clusters #8 “primary education” and #9 “virtual change agent” appear more isolated and temporally bounded, reflecting specialized or experimental lines of inquiry that have not yet become mainstream in the broader discourse.

Collectively, this timeline view illustrates the layered and dynamic nature of research on AI adoption among pre-service teachers. It reveals a clear evolution from general models of technology acceptance toward more complex, tool-specific, and context-sensitive themes. Notably, the convergence of “teacher beliefs”, “AI integration”, and “professional development” post-2020 signals a mature and increasingly nuanced research direction, bridging theoretical and applied perspectives in teacher education.

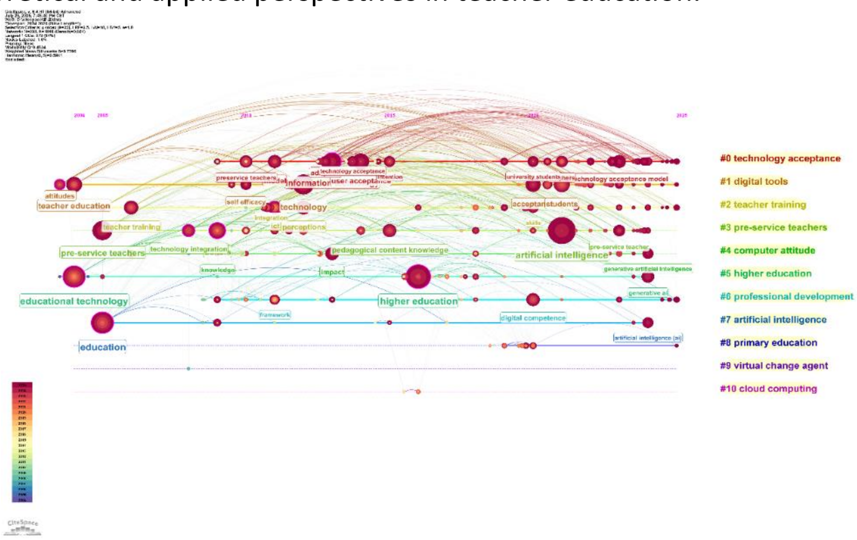

Figure 4 Timeline View of Thematic Cluster Evolution (2005–2025)

Top Keywords with the Strongest Citation Bursts (2005–2025)
Citation burst analysis helps identify emerging or intensifying research themes over time, revealing keywords that have received a sudden surge of attention within a specific period. As shown in Table 2, the top keywords with the strongest citation bursts from 2005 to 2025 include *educational technology*, *ict*, *students*, *performance*, *digital tools*, and *framework*.

Among them, “educational technology” stands out with the highest burst strength (4.71) during the period 2018–2021, suggesting that this field experienced a sharp increase in research interest, possibly influenced by the global shift to online and blended learning environments in the post-pandemic era (Zhao et al., 2023).

The keyword “ict” (burst strength = 4.72) also shows strong citation growth from 2016 to 2021, reflecting a broader emphasis on digital integration and infrastructure development in teacher education, especially in developing regions (UNESCO, 2021). Similarly, “students” (burst = 4.66) and "digital tools" (burst = 3.18) both show bursts beginning in 2021, pointing to a research shift toward understanding student experiences and the adoption of specific digital resources in AI-enhanced learning contexts.

In contrast, "performance" (burst = 3.21, 2021–2022) and "framework" (burst = 3.26, 2016–2020) suggest more theoretical contributions—such as the development or refinement of conceptual models related to digital competence, technology integration, and evaluation mechanisms (Redecker, 2017).

Overall, the burst detection results indicate an increasing convergence of practical implementation (e.g., *digital tools*, *ICT*, *students*) and theoretical framing (e.g., *framework*, *educational technology*) in the research landscape of pre-service teachers' technology adoption. This pattern reflects the evolving complexity of the digital transition in teacher education.

Table 2
Top Keywords with the Strongest Citation Bursts (2005–2025)

Rank	Keyword	Burst Strength	Burst Begin	Burst End	Centrality	Year of First Appearance
1	Educational Technology	4.71	2018	2021	0.19	2004
2	ICT	4.72	2016	2021	0.12	2011
3	Students	4.66	2021	2023	0.02	2021
4	Performance	3.21	2021	2022	0.03	2012
5	Digital Tools	3.18	2021	2023	0.03	2021
6	Framework	3.26	2016	2020	0.04	2011

his section provided a comprehensive exploration of research topics and thematic trends concerning pre-service teachers' intention to use artificial intelligence (AI) in education. Through keyword co-occurrence analysis, it was revealed that the field predominantly focuses on concepts such as *artificial intelligence*, *educational technology*, *digital literacy*, and *technology acceptance*. Thematic clustering further identified major research domains, including *teacher education*, *digital tools*, *teacher training*, and *professional development*, reflecting the evolving priorities in teacher preparation programs.

The timeline visualization clarified how early studies were centered on *educational technology* and *teacher training*, while recent years witnessed a sharp increase in themes such as *AI integration*, *technology acceptance models*, and *generative artificial intelligence*. Furthermore, burst keyword detection indicated that topics such as *students*, *digital tools*, and *performance* have experienced sharp increases in attention in the past five years, signifying emerging research frontiers. Overall, the longitudinal and structural patterns observed in this section provide valuable insights into the shifting academic landscape surrounding AI adoption in teacher education.

Intellectual Structure of the Field

Author Co-citation Analysis

Author co-citation analysis (ACA) is a well-established bibliometric technique for uncovering a field's intellectual structure and core knowledge base (White & McCain, 1998; Chen et al., 2012). Using CiteSpace, our ACA mapped the authors most frequently co-cited in studies on pre-service teachers' intention to adopt AI (2004–2025), revealing a dense, mature network anchored by classic technology-acceptance, behavioral-intention, and methodological scholars. The top nodes—Venkatesh V. (n = 87) and Davis F. D. (n = 86)—reflect the enduring centrality of TAM and UTAUT in AI adoption research (Davis, 1989; Venkatesh et al., 2003). Ajzen's (1991) TPB similarly remains foundational for modeling attitudes, subjective norms, and perceived behavioral control. Hair J. F. (n = 71) is extensively cited for PLS-SEM guidelines and rigor in structural modeling (Hair et al., 2014), while Mishra P. (n = 46) signals the influence of TPACK-related work on teacher digital competence (Koehler & Mishra, 2009). Education-focused adoption researchers such as Teo T. and Tondeur J. frequently appear for their contributions to teacher ICT acceptance and competency frameworks (Teo, 2011; Tondeur et al., 2017). Bandura's social cognitive theory underpins self-efficacy constructs, and Fornell and Larcker's criteria guide validity assessment in SEM models (Bandura, 1986; Fornell & Larcker, 1981). Zawacki-Richter's work highlights AI and online learning in higher education, broadening the contextual lens (Zawacki-Richter et al., 2019). Notably, newer voices like Strzelecki (2024) and Chiu (2023) have entered the top ranks, indicating a post-COVID shift toward fresh perspectives on generative AI and classroom implementation.

Table 3

Top 10 Co-cited Authors in the Field of AI Adoption in Pre-service Teacher Education (2004–2025)

Rank	Author	Year	Co-citation Count	Centrality
1	Venkatesh, V.	2015	87	0.00
2	Davis, F. D.	2008	86	0.00
3	Hair, J. F.	2014	71	0.00
4	Ajzen, I.	2006	64	0.00
5	Mishra, P.	2009	46	0.00
6	Teo, T.	2011	45	0.00
7	Bandura, A.	2010	42	0.00
8	Hwang, G. J.	2021	42	0.00
9	Fornell, C.	2023	41	0.00
10	Ertmer, P. A.	2008	41	0.00

These findings demonstrate that the intellectual foundation of this research field is strongly anchored in classic theories of behavioral intention and educational technology adoption. At the same time, new contributors are emerging, suggesting that the field is evolving dynamically with increased attention to AI, digital transformation, and teacher education in the post-pandemic era.

Document Co-citation Analysis

Document co-citation analysis (ACA) is a standard bibliometric technique for revealing a field's intellectual structure and core knowledge base (White & McCain, 1998; Chen et al., 2012). Using CiteSpace on 477 articles about pre-service teachers' intention to adopt AI (2004–

2025), we identified the works most frequently co-cited as theoretical or methodological anchors. The network is dense and mature: Venkatesh et al. (2003) and Davis (1989) dominate for TAM/UTAUT foundations; Ajzen (1991) anchors TPB-based inquiries; Hair et al. (2014) guide PLS-SEM rigor; and Mishra and colleagues' TPACK work continues to shape discussions of teacher digital competence (Koehler & Mishra, 2009). Bandura (1986) underpins self-efficacy constructs, while Fornell and Larcker (1981) remain indispensable for discriminant validity. Zawacki-Richter et al. (2019) broaden the lens to AI in higher education systems.

Table 4 lists the ten most co-cited documents. Kasneci et al. (2023) leads with 27 citations, reflecting its timely synthesis of ethical, pedagogical, and systemic implications of AI for teacher preparation and policy. Zhang et al. (2023) follows (n = 25) with a data-driven framework for AI readiness among educators. Baidoo-Anu et al. (2023) (n = 24) links digital literacy to emerging technologies in teacher education. Dwivedi et al. (2023) and Çelik (2023) (each n = 21) contribute to theoretical integration—extending TAM/TPB and digital competence perspectives—and methodological refinements for AI adoption studies. The concentration of 2023 publications at the top signals a rapid consolidation of foundational knowledge post-COVID-19, as scholarship pivots toward ethics, readiness, and instructional transformation. Overall, the co-citation patterns indicate an emergent yet consolidating knowledge base, where classic acceptance and behavioral theories intersect with contemporary concerns about AI governance, transparency, and teacher capacity-building.

Table 4
Top 10 Most Frequently Co-Cited Articles

Author	Citations
Kasneci E (2023)	27
Zhang CM (2023)	25
Baidoo-Anu D (2023)	24
Celik I (2023)	21
Dwivedi YK (2023)	21
Cotton DRE (2024)	20
Strzelecki A (2024)	19
Lim WM (2023)	19
Strzelecki A (2024)	18
Chan CKY (2023)	18

Source Journal Co-citation Analysis

The source journal co-citation analysis identifies the core outlets that underpin research on pre-service teachers' intention to adopt AI. Using CiteSpace, 477 journals appeared in the co-citation network; the top 10 (Table 5) show both high frequency and notable betweenness centrality, signalling their pivotal roles in shaping the field's knowledge structure (Chen et al., 2012; Van Eck & Waltman, 2010). *Computers & Education* ranks first (282 citations; centrality = 0.19), long recognized as a leading venue for technology-enhanced learning, digital literacy, and acceptance-model studies (e.g., Davis, 1989; Teo, 2011; Venkatesh et al., 2003). *Computers in Human Behavior* and the *British Journal of Educational Technology* also occupy central positions, bridging human–computer interaction, psychology, and pedagogical innovation—domains crucial for constructs such as perceived usefulness, attitude, and technology anxiety (Teo, 2011; Venkatesh et al., 2003). The rise of *Sustainability* (Basel) (143 citations) reflects growing interest in sustainable digital competence and policy alignment within AI-enhanced education (Sahar & Munawaroh, 2025). The presence of *Educational Technology Research and Development* and *Interactive Learning Environments* underscores sustained attention to design-based research and practical implementation in teacher education. Notably, the recently launched *Computers and Education: Artificial Intelligence* (2022) already ranks eighth, highlighting the rapid consolidation of AI-focused scholarship. Collectively, these patterns reveal an interdisciplinary, dynamic foundation in which established educational technology journals coexist with emergent AI-centric outlets, indicating a maturing yet still evolving research landscape.

Table 5
Top 10 Most Frequently Co-Cited Journals

Rank	Journal Name	Citation Count	Year	Centrality
1	Computers & Education (COMPUT EDUC)	282	2004	0.19
2	Educational Information Technology (EDUC INF TECHNOL)	217	2018	0.05
3	Computers in Human Behavior (COMPUT HUM BEHAV)	187	2008	0.12
4	British Journal of Educational Technology (BRIT J EDUC TECHNOL)	166	2008	0.17
5	Sustainability-Basel	143	2020	0.03
6	Interactive Learning Environments (INTERACT LEARN ENVIR)	133	2015	0.07
7	Educational Technology Research and Development (ETR&D-EDUC TECH RES)	133	2005	0.10
8	Computers and Education: Artificial Intelligence	122	2022	0.02
9	International Journal of Educational Technology in Higher Education (INT J EDUC TECHNOL H)	122	2020	0.06
10	Education Sciences (EDUC SCI)	112	2021	0.02

Intellectual Structure of the Field

CiteSpace's LLR clustering of 477 co-cited documents reveals a coherent yet evolving intellectual structure for research on pre-service teachers' intention to adopt AI, anchored by several major knowledge communities (Chen et al., 2012; White & McCain, 1998). The largest cluster centers on technology-acceptance theorizing—TAM and UTAUT—built on Davis (1989), Venkatesh & Davis (2000), and Venkatesh et al. (2003), and adapted to teacher contexts by Teo (2011); these works foreground perceived usefulness, ease of use, attitude, and intention as core determinants. A second cluster focuses on digital literacy/competence, with Ilomäki et al. (2016) and Spante et al. (2018) defining educators' digital skills and linking them to AI readiness—an idea reinforced by evidence that competence moderates acceptance relationships (Wang & Zhao, 2021; Scherer et al., 2018). A third, rapidly growing cluster groups Artificial Intelligence in Education (AIEd) studies that address ethical, pedagogical, and institutional issues—e.g., explainability, bias, and governance—exemplified by Holmes et al. (2021) and Zawacki-Richter et al. (2019), and energized by post-COVID contributions such as Kasneci et al. (2023) and Zhang et al. (2023). Another cluster draws on the Theory of Planned Behavior, where Ajzen's (1991) constructs—subjective norm and perceived behavioral control—are often hybridized with TAM to boost explanatory power in teacher education (Arpaci et al., 2020; Nistor et al., 2012). Finally, a cluster on pedagogical innovation and teacher training synthesizes design-based work on microteaching, flipped classrooms, and simulations, now increasingly AI-augmented (Tondeur et al., 2012), and underpinned by methodological staples for SEM rigor (Hair et al., 2014; Fornell & Larcker, 1981) and by broader competence frameworks like TPACK (Koehler & Mishra, 2009). Cross-cluster bridges—Bandura's (1986) self-efficacy, for instance—signal a dual imperative: cultivate positive beliefs about AI while building the digital and ethical capacity to implement it (Sahar & Munawaroh, 2025). Together, the clusters depict a maturing landscape where classic behavioral theories intersect with contemporary concerns over competence, ethics, and instructional design, offering clear guidance for curriculum and policy aimed at responsible AI integration in teacher preparation.

Temporal Evolution of the Knowledge Base

Understanding how the field has evolved over time clarifies when key theories, themes, and outlets gained traction. Analyzing publication years of the most frequently co-cited documents, authors, and journals in 477 WoS records (2005–2025) shows three broad phases. 2004–2010: Theoretical foundations. Core behavioral models—TAM, UTAUT, and TPB—dominate, with Davis (1989), Venkatesh et al. (2003), and Ajzen (1991) providing the conceptual backbone for later AI-adoption studies. Early co-citation hotspots include *Computers & Education* and *Computers in Human Behavior*, which hosted many model-driven investigations (see Table 5).

2011–2017: Digital competence and readiness. Focus shifts toward teachers' and students' digital literacy/self-efficacy, extending acceptance models with competence constructs. Teo (2011) and Bandura's social cognitive work (1986) gain prominence, while journals such as *British Journal of Educational Technology* and *Educational Technology Research and Development* become more central, reflecting concern for preparedness and ICT integration in teacher education.

2018–2025: AI integration and pedagogical innovation. AI in Education (AIEd) becomes a distinct domain; widely co-cited papers like Zawacki-Richter et al. (2019) and Holmes et al. (2021) address ethical, pedagogical, and institutional implications of AI. Newer outlets—*Sustainability*, *Education Sciences*, *Interactive Learning Environments*, and *Computers and Education: Artificial Intelligence*—rise in co-citation frequency, signaling interdisciplinary engagement with sustainability, policy, and emerging AI tools. Methodological staples such as Fornell and Larcker (1981) and Hair et al. (2014) remain continuously cited for SEM rigor.
Overall, the trajectory moves from foundational theory to competence-building and finally to AI-specific ethics and design concerns. The post-2020 spike in co-cited work mirrors COVID-19's acceleration of digital/AI adoption and the spotlight on online readiness (Dwivedi et al., 2020; Daniel, 2020). This temporal pattern underscores a dual imperative for teacher education programs: foster positive beliefs about AI (usefulness, ease, norms) and develop the digital/ethical capacity to implement it effectively.

Discussion

Summary of Key Findings

Drawing on 477 peer-reviewed articles from the Web of Science Core Collection (2005–2025), this bibliometric review shows a steep post-2018 growth in studies at the intersection of teacher education and AI, mirroring broader EdTech and AIEd surges (Chen et al., 2012;

Zawacki-Richter et al., 2019; Kasneci et al., 2023). Keyword co-occurrence, clustering, and burst detection highlight persistent emphases on behavioral intention and acceptance constructs (TAM/TPB), alongside digital competence and self-efficacy (Davis, 1989; Ajzen, 1991; Venkatesh et al., 2003; Ilomäki et al., 2016; Spante et al., 2018). Thematic clusters converge on technology acceptance, pedagogical integration, anxiety/trust, and readiness for AI-enabled learning (Teo, 2011; Scherer et al., 2018; Wang & Zhao, 2021; Sun et al., 2025). Highly cited documents and journals—*Computers & Education*, *Computers in Human Behavior*, *British Journal of Educational Technology*, and the newer *Computers and Education: Artificial Intelligence*—indicate conceptual consolidation around classic models and growing attention to AI ethics and implementation (Van Eck & Waltman, 2010; Holmes et al., 2021). Geographically, China, the United States, and several European nations show leading productivity and centrality, evidencing a collaborative, interdisciplinary field spanning education, psychology, and information systems (Zhang et al., 2023; Ramnarain et al., 2024; Runge et al., 2025; Sahar & Munawaroh, 2025).

Theoretical Contributions

By mapping fragmented strands, this study quantitatively confirms the dominance of TAM and TPB in modeling pre-service teachers' AI adoption (Davis, 1989; Venkatesh et al., 2003; Ajzen, 1991), corroborating earlier syntheses (Teo, 2011; Al-Emran et al., 2020) while showing how these frameworks are operationalized across contexts and time. The rise of clusters on digital competence, self-efficacy, and AI readiness illustrates theoretical extensions that merge acceptance constructs with capability- and ethics-oriented dimensions (Bandura, 1986; Ilomäki et al., 2016; Acquah et al., 2024; Sun et al., 2025). Burst analyses reveal a shift from generic ICT adoption to issues of algorithmic transparency, trust, and teacher autonomy in AI-mediated classrooms—topics underaddressed in classic TAM/TPB formulations (Choung et al., 2022; Holmes et al., 2021; Kasneci et al., 2023; Zawacki-Richter et al., 2019). This indicates theoretical diversification that integrates educational psychology, critical digital pedagogy, and AI ethics into established acceptance models (Sahar & Munawaroh, 2025; Scherer et al., 2018).

Practical Implications

Practically, the findings call for embedding AI literacy—technical, ethical, and pedagogical—into pre-service teacher curricula (Luckin & Holmes, 2016; Holmes et al., 2021; Sun et al., 2025). The prominence of constructs like self-efficacy, attitude, and anxiety suggests professional development must tackle affective and cognitive barriers, not just skills gaps (Agogo & Hess, 2018; Scherer et al., 2018; Runge et al., 2025). Digital competence frameworks and assessment-driven approaches can standardize implementation across institutions (Ilomäki et al., 2016; Spante et al., 2018; Wang & Zhao, 2021). Rigorous measurement practices—e.g., reliability/validity checks in SEM—should underpin program evaluation and policy decisions (Fornell & Larcker, 1981; Hair et al., 2014). For policy-makers, the interdisciplinarity evident in co-citation patterns signals the need for cross-sector collaboration to ensure responsible, sustainable AI integration in teacher education (Sahar & Munawaroh, 2025; Zohdi et al., 2024).

Limitations and Future Research

This review relies solely on WoS data; omitting Scopus, ERIC, or regional databases may bias coverage (Chen et al., 2012; Taskin & Al, 2019). Bibliometrics reveal structures and trends but cannot capture nuanced pedagogical contexts or lived experiences (Page et al., 2021). Future work should triangulate with systematic reviews or meta-analyses for depth (Daniel, 2020; Dwivedi et al., 2020), conduct longitudinal tracking of post-pandemic shifts and AI policy implementation (Kasneci et al., 2023; Wang & Fan, 2025), and expand cross-cultural analyses to include gender, urban–rural, and institutional disparities—areas largely underexplored here (Zhang et al., 2023; Ramnarain et al., 2024; Runge et al., 2025). Incorporating mixed methods and stakeholder-engaged designs could illuminate how belief structures, competencies, and ethical stances translate into sustained classroom practice.

Conclusion

This bibliometric synthesis analyzed 477 Web of Science articles published between 2005 and 2025 on pre-service teachers' intention to adopt AI, mapping publication trends, intellectual structures, and thematic trajectories.

The field unfolds across three chronological waves: (1) foundational behavioral theorizing (2004–2010), (2) a turn to digital competence and readiness (2011–2017), and (3) intensified AI integration with ethical and pedagogical concerns (2018–2025).

Intellectually, research is anchored in TAM/UTAUT and TPB while intersecting with clusters on digital competence, AIEd ethics/governance, and pedagogical innovation, signaling a mature yet diversified knowledge base.
Cross-national collaboration is strong, with China, the United States, and several European countries leading in productivity and centrality.

Across clusters, a dual imperative emerges: cultivate positive beliefs about AI and build the digital/ethical capacity to enact it responsibly.
Practically, the results call for embedding comprehensive AI literacy—technical, pedagogical, and ethical—into teacher education, while addressing affective barriers such as anxiety and low self-efficacy through targeted professional development and assessment-driven competence frameworks.

Methodologically, the study demonstrates the utility of bibliometric techniques for revealing large-scale structures, yet its reliance on WoS alone and quantitative mappings limits contextual depth; future work should triangulate with systematic reviews/meta-analyses, pursue longitudinal and cross-cultural comparisons, and probe equity-related factors (e.g., gender, locale, institutional disparities).

Overall, the domain is consolidating but still evolving: classic acceptance theories now coexist with emerging concerns about competence, ethics, trust, and instructional design, offering a roadmap for researchers, curriculum designers, and policymakers to move from intention to responsible, sustainable AI integration in teacher preparation.

References

Acquah, B. Y. S., Arthur, F., Salifu, I., Quayson, E., & Nortey, S. A. (2024). Preservice teachers' behavioural intention to use artificial intelligence in lesson planning: A dual-staged PLS-SEM-ANN approach. *Computers and Education: Artificial Intelligence, 7*, 100307. https://doi.org/10.1016/j.caeai.2024.100307

Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *Contemporary Educational Technology*, *15*(3), ep429. https://doi.org/10.30935/cedtech/13152

Agbo, F. J., Oyelere, S. S., Suhonen, J., & Tukiainen, M. (2021). Scientific production and thematic breakthroughs in smart learning environments: a bibliometric analysis. *Smart Learning Environments*, *8*(1). https://doi.org/10.1186/s40561-020-00145-4

Agogo, D., & Hess, T. J. (2018). "How does tech make you feel?" A review and examination of negative affective responses to technology use. *European Journal of Information Systems, 27*(5), 570–599. https://doi.org/10.1080/0960085X.2018.1435230

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alabdulaziz, M.S. COVID-19 and the use of digital technology in mathematics education. *Educ Inf Technol* **26**, 7609–7633 (2021). https://doi.org/10.1007/s10639-021-10602-3

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2020). Towards a conceptual model for examining the impact of knowledge management factors on mobile learning acceptance. *Technology in Society*, *61*, 101247. https://doi.org/10.1016/j.techsoc.2020.101247

Alenezi, M. (2021). Deep Dive into Digital Transformation in Higher Education Institutions. *Education Sciences*, *11*(12), 770. https://doi.org/10.3390/educsci11120770

Arpaci, I., Yardimci Cetin, Y., & Turetken, O. (2020). Predicting the intention to use mobile learning: The moderating role of personal innovativeness. Computers in Human Behavior, 102, 132–143. https://doi.org/10.1016/j.chb.2019.08.034

Bae, H., Hur, J., Park, J., Choi, G. W., & Moon, J. (2024). Pre-service teachers' dual perspectives on generative AI: Benefits, challenges, and integrating into teaching and learning. *Online Learning, 28*(3), 131–156. https://doi.org/10.24059/olj.v28i3.4543

Bajpai, A., Yadav, S., & Nagwani, N. K. (2025). An extensive bibliometric analysis of artificial intelligence techniques from 2013 to 2023. *The Journal of Supercomputing, 81*, 540. https://doi.org/10.1007/s11227-025-07021-3

Bakhadirov, M., Alasgarova, R., & Rzayev, J. (2024). Factors influencing teachers' use of artificial intelligence for instructional purposes. *IAFOR Journal of Education: Technology in Education, 12*(2), 9–29.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Celik, I. (2022). 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

Chen, C., Haupert, S. R., Zimmermann, L., Shi, X., Fritsche, L. G., & Mukherjee, B. (2022). Global prevalence of post-coronavirus disease 2019 (COVID-19) condition or long COVID: a meta-analysis and systematic review. *The Journal of infectious diseases*, *226*(9), 1593-1607. https://doi.org/10.1093/infdis/jiac136

Chen, C., Ibekwe-SanJuan, F., & Hou, J. (2012). The structure and dynamics of co-citation clusters: A multiple-perspective co-citation analysis. *Journal of the American Society for Information Science and Technology, 61*(7), 1386–1409. https://doi.org/10.1002/asi.21309

Chen, X., Xie, H., & Hwang, G. (2020). A multi-perspective study on Artificial Intelligence in Education: grants, conferences, journals, software tools, institutions, and researchers. *Computers and Education Artificial Intelligence*, *1*, 100005. https://doi.org/10.1016/j.caeai.2020.100005

Choung, H., David, P., & Ross, A. (2022). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human–Computer Interaction, 38*(16), 1552–1565. https://doi.org/10.1080/10447318.2022.2050543

Daniel, S. J. (2020). Education and the COVID-19 pandemic. *Prospects, 49*(1–2), 91–96. https://doi.org/10.1007/s11125-020-09464-3

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

De Bellis, N. (2009). *Bibliometrics and citation analysis: From the Science Citation Index to Cybermetrics*. https://cds.cern.ch/record/1254039

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). Opinion Paper: “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Dwivedi, Y. K., Hughes, L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., Gupta, B., Lal, B., Misra, S., Prashant, P., Raman, R., Rana, N. P., Sharma, S. K., & Upadhyay, N. (2020). Impact of COVID-19 pandemic on information systems research: A research agenda. *International Journal of Information Management, 55*, 102197. https://doi.org/10.1016/j.ijinfomgt.2020.102197

Ertmer, P. A., & Ottenbreit-Leftwich, A. T. (2010). Teacher technology change: How knowledge, confidence, beliefs, and culture intersect. *Journal of Research on Technology in Education, 42*(3), 255–284. https://doi.org/10.1080/15391523.2010.10782551

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Garfield, E. (2006). The history and meaning of the journal impact factor. *JAMA, 295*(1), 90–93. https://doi.org/10.1001/jama.295.1.90

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage.

Hamidi, H., & Chavoshi, A. (2018). Analysis of the essential factors for the adoption of mobile learning in higher education: A case study of students of the University of Technology. *Telematics and Informatics, 35*(4), 1053–1070. https://doi.org/10.1016/j.tele.2017.09.016

Hawkins, D. T. (2001). Bibliometrics of electronic journals in information science. *Information Research*, *7*(1). https://dblp.uni-trier.de/db/journals/ires/ires7.html#Hawkins01

Hazzan-Bishara, A., Kol, O., & Levy, S. (2025). The factors affecting teachers' adoption of AI technologies: A unified model of external and internal determinants. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13393-z

Hodges, C. B., Moore, S., Lockee, B. B., Trust, T., & Bond, M. A. (2024). The Difference between Emergency Remote Teaching and Online Learning. In *BRILL eBooks* (pp. 511–522). https://doi.org/10.1163/9789004702813_021

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in Education: Promises and implications for teaching and learning*. http://oro.open.ac.uk/60255/

Huong, V. T. M., & Quy, D. T. M. C. T. T. (2025). Global Research Trends of Instructional Leadership: A Bibliometric analysis from 2002 to 2023. *European Journal of Educational Management*, *8*(0), 91–104. https://doi.org/10.12973/eujem.8.2.91

Ilomäki, L., Paavola, S., Lakkala, M., & Kantosalo, A. (2016). Digital competence—An emergent boundary concept for policy and educational research. Education and Information Technologies, 21(3), 655–679. https://doi.org/10.1007/s10639-014-9346-4

Kasneci, E., Sessler, K., Lachner, A., Dolata, M., Fischer, F., & Lindner, M. A. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Koehler, M., & Mishra, P. (2009). What is Technological Pedagogical Content Knowledge (TPACK). *Contemporary Issues in Technology and Teacher Education*, *9*(1), 60–70. https://www.learntechlib.org/primary/p/29544/article_29544.pdf

Luckin, R., & Holmes, W. (2016). Intelligence Unleashed: An argument for AI in Education. *UCL Knowledge Lab*. http://oro.open.ac.uk/50104/

Martins, J., Gonçalves, R., & Branco, F. (2022). A bibliometric analysis and visualization of e-learning adoption using VOSviewer. *Universal Access in the Information Society*, *23*(3), 1177–1191. https://doi.org/10.1007/s10209-022-00953-0

Munaye, Y. Y., Admass, W., Belayneh, Y., Molla, A., & Asmare, M. (2025). ChatGPT in education: A systematic review on opportunities, challenges, and future directions. *Algorithms, 18*(6), 352. https://doi.org/10.3390/a18060352

Nistor, N., Lerche, T., Weinberger, A., Ceobanu, C., & Heymann, O. (2012). Towards the integration of culture into the Unified Theory of Acceptance and Use of Technology. *British Journal of Educational Technology*, *45*(1), 36–55. https://doi.org/10.1111/j.1467-8535.2012.01383.x

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71. https://doi.org/10.1136/bmj.n71

Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-Learning. *Educational Technology & Society*, *12*(3), 150–162. https://kshec.ac.in/perspectives/technology%20aaceptance%20model%20for%20e%20learning.pdf

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). Artificial intelligence in education : challenges and opportunities for sustainable development. *MINISTERIO DE EDUCACIÓN*. http://repositorio.minedu.gob.pe/handle/20.500.12799/6533

Pritchard, A. (1969). Statistical bibliography or bibliometrics. *Journal of Documentation*, *25*, 348. http://ci.nii.ac.jp/naid/10016754266

Raffaghelli, J. E., & Stewart, B. (2020). Centering complexity in 'educators' data literacy' to support future practices in faculty development: a systematic review of the literature. *Teaching in Higher Education*, *25*(4), 435–455. https://doi.org/10.1080/13562517.2019.1696301

Ramnarain, U., Ogegbo, A. A., Penn, M., Ojetunde, S., & Mdlalose, N. (2024). Pre-service science teachers' intention to use generative artificial intelligence in inquiry-based teaching. *Journal of Science Education and Technology*. https://doi.org/10.1007/s10956-024-10159-z

Roll, I., Wylie, R. Evolution and Revolution in Artificial Intelligence in Education. Int J Artif Intell Educ 26, 582–599 (2016). https://doi.org/10.1007/s40593-016-0110-3

Runge, I., Hebibi, F., & Lazarides, R. (2025). Acceptance of pre-service teachers towards artificial intelligence (AI): The role of AI-related teacher training courses and AI-TPACK within the Technology Acceptance Model. *Education Sciences, 15*(2), 167. https://doi.org/10.3390/educsci15020167

Sahar, R., & Munawaroh, M. (2025). Artificial intelligence in higher education with bibliometric and content analysis for future research agenda. *Discover Sustainability, 6*, 401. https://doi.org/10.1007/s43621-025-01086-z

Sánchez-Prieto, J. C., Olmos-Migueláñez, S., & García-Peñalvo, F. J. (2015). Informal tools in formal contexts: Development of a model to assess the acceptance of mobile technologies among teachers. *Computers in Human Behavior*, *55*, 519–528. https://doi.org/10.1016/j.chb.2015.07.002

Scherer, R., Siddiq, F., & Tondeur, J. (2018). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, *128*, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Spante, M., Hashemi, S. S., Lundin, M., & Algers, A. (2018). Digital competence and digital literacy in higher education research: Systematic review of concept use. Cogent Education, 5(1), 1519143. https://doi.org/10.1080/2331186X.2018.1519143

Šumak, B., Heričko, M., & Pušnik, M. (2011). A meta-analysis of e-learning technology acceptance: The role of user types and e-learning technology types. *Computers in Human Behavior, 27*(6), 2067–2077. https://doi.org/10.1016/j.chb.2011.08.005

Sun, J., Wu, Q., Ma, Z., Zheng, W., & Hu, Y. (2025). Understanding pre-service teachers' acceptance of generative artificial intelligence: An extended technology acceptance model approach. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-025-10495-w

Taskin, Z., & Al, U. (2019). Natural language processing applications in library and information science. *Online Information Review*, *43*(4), 676–690. https://doi.org/10.1108/oir-07-2018-0217

Teo, T. (2010). Examining the intention to use technology among pre-service teachers: an integration of the Technology Acceptance Model and Theory of Planned Behavior. *Interactive Learning Environments*, *20*(1), 3–18. https://doi.org/10.1080/10494821003714632

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education, 57*(4), 2432–2440. https://doi.org/10.1016/j.compedu.2011.06.008

Tian, W., Ge, J., Zhao, Y., & Zheng, X. (2024). AI Chatbots in Chinese higher education: adoption, perception, and influence among graduate students—an integrated analysis utilizing UTAUT and ECM models. *Frontiers in Psychology*, *15*. https://doi.org/10.3389/fpsyg.2024.1268549

Tondeur, J., Aesaert, K., Pynoo, B., Fraeyman, N., & van Braak, J. (2017). Developing a validated instrument to measure preservice teachers' ICT competencies: Meeting the demands of the 21st century. *British Journal of Educational Technology, 48*(2), 462–472. https://doi.org/10.1111/bjet.12380

Tondeur, J., van Braak, J., Siddiq, F., & Scherer, R. (2012). Preparing pre-service teachers to integrate technology: A synthesis of qualitative evidence. Computers & Education, 59(1), 134–144. https://doi.org/10.1016/j.compedu.2011.10.009

Van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics, 84*(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Wang, J., & Fan, W. (2025). The effect of ChatGPT on students' learning performance, learning perception, and higher-order thinking: Insights from a meta-analysis. *Humanities and Social Sciences Communications, 12*, 621. https://doi.org/10.1038/s41599-025-04787-y

Wang, Q., & Zhao, G. (2021). ICT self-efficacy mediates most effects of university ICT support on preservice teachers' TPACK: Evidence from three normal universities in China. *British Journal of Educational Technology, 52*(6), 2319–2339. https://doi.org/10.1111/bjet.13141

White, H. D., & McCain, K. W. (1998). Visualizing a discipline: An author co-citation analysis of information science, 1972–1995. *Journal of the American Society for Information Science, 49*(4), 327–355. https://doi.org/10.1002/(SICI)1097-4571(19980401)49:4<327::AID-ASI4>3.0.CO;2-4

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1). https://doi.org/10.1186/s41239-019-0171-0

Zhan, Z., Shen, W., Xu, Z., Niu, S., & You, G. (2022). A bibliometric analysis of the global landscape on STEM education (2004-2021): towards global distribution, subject integration, and research trends. *Asia Pacific Journal of Innovation and Entrepreneurship*, *16*(2), 171–203. https://doi.org/10.1108/apjie-08-2022-0090

Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: A multigroup analysis. *International Journal of Educational Technology in Higher Education, 20*, 49. https://doi.org/10.1186/s41239-023-00420-7

Zohdi, M., Al-Samarraie, H., & Saeed, N. (2024). Artificial intelligence in education: A bibliometric study on its role in teaching and learning. *The International Review of Research in Open and Distributed Learning, 25*(3), 45–66. https://doi.org/10.19173/irrodl.v25i3.7757