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Artificial intelligence in pre-service teacher education: Bibliometrics analysis

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ABSTRACT

This study conducts a comprehensive bibliometric analysis to evaluate how research on artificial intelligence (AI) integration in pre-service teacher education has evolved from 2020 to 2025. Using Bibliometrix 5.0 in R, I analyzed 3,623 papers from Web of Science (1,823) and Scopus (1,800). The data reveal that following ChatGPT's launch in 2022, publications increased dramatically, with Scopus exhibiting an annual growth rate of 41.38% compared to Web of Science's 18.83%. Germany and Finland demonstrate the highest citation impact per article, while China shows the lowest citation density despite high publication volume. Generative AI and ChatGPT emerge as the most frequently discussed topics. Thematic mapping reveals a paradigmatic shift from traditional TPACK models toward emerging AI-TPACK frameworks. However, a significant gap persists between technical AI concepts and their practical implementation in educational settings. Web of Science statistics show that new "motor themes" are developing in education, but Scopus has not yet found a distinct core topic. For future research, I recommend enhanced interdisciplinary collaboration, integration of AI literacy curricula in teacher preparation programs, and development of more inclusive AI policies. Overall, this analysis provides researchers, educators, and policymakers with comprehensive insights into this rapidly evolving field.

Keywords: artificial intelligence, pre-service teacher education, bibliometric analysis, teacher preparation, AI literacy, generative AI

INTRODUCTION

The rapid expansion of AI and the release of generative AI systems like ChatGPT in late 2022 have revolutionized education and created unprecedented challenges for teacher preparation programs worldwide (Chiu, 2023; Rudolph et al., 2023). It's important to train future instructors to perform successfully in classrooms with a lot of AI technologies, such personalized learning, automated grading, and smart tutoring (UNESCO, 2024). The shift from earlier technological models to AI-focused ones, like TPACK to AI-TPACK, highlights how AI makes teaching more complicated (Celik, 2023; Mishra et al., 2023). Teachers need to know more than just how to use technology; they also need to understand AI ethics, bias, and the effects of algorithmic decisions in education (Baker & Hawn, 2022; Ng et al., 2023).

Even though many people now see AI's power in education, studies about using AI in teacher training are scattered and lack a clear overview. While individual studies have examined technology acceptance (Sun et al., 2024; Zhang et al., 2023), attitude change (Lucas et al., 2025; Yang et al., 2024), and competence frameworks (UNESCO, 2024) comprehensive analyses remain limited. However, comprehensive studies mapping the field's intellectual structure, collaboration networks, and thematic evolution remain scarce. Furthermore, existing literature exhibits significant geographic and linguistic biases while providing insufficient analysis of cross-database and cross-regional research variations. Although the field has experienced rapid growth following ChatGPT's emergence, systematic efforts to identify emerging trends, key contributors, and future research directions remain absent.

This study addresses these gaps. Using both Web of Science and Scopus records from 2020–2025, it runs a full bibliometric analysis of AI in teacher education. The study aims to:

(1) Map the field's intellectual structure and temporal evolution,

(2) Identify key contributors, institutions, and collaboration networks,

(3) Analyze thematic development and emerging trends, and

(4) Provide evidence-based recommendations for future research directions.

Through systematic bibliometric methods, this analysis provides educators, researchers, and policymakers with comprehensive, data-driven insights into the field's evolution—particularly following the generative AI revolution—while offering guidance for teacher preparation programs and research priorities.

LITERATURE REVIEW

Pedagogical Foundations for AI-Ready Teacher Education

There has been a lot of theoretical and empirical progress in the pedagogical foundations for AI-ready teacher education. Research has converged around several key themes demonstrating how pre-service teachers should prepare for AI-integrated classrooms.

The AI literacy and digital skills of pre-service teachers

Recent research shows that teachers of the future need to be very good in AI as well as general digital skills. While many pre-service teachers demonstrate comfort with standard AI tools, they lack foundational AI knowledge (Yang et al., 2024). This gap shows that new instructors may not be ready, which could make them more likely to be affected by AI in schools in ways they didn't mean to. Researchers have therefore asked that AI literacy be added to teacher education programs so that teachers can comprehend, apply, and assess AI tools in a critical and moral way (Guan et al., 2025). For instance, a narrative inquiry with 141 preservice teachers using ChatGPT over three weeks indicated that while AI can make learning more personal and make lesson planning easier, the participants were worried about academic integrity and data security (Karataş & Yüce, 2024). Prospective teachers' AI literacy should be addressed within a conceptual readiness framework with relation to digital citizenship, perceived threats related to AI, and AI-supported innovation; ethical, competency, vision, and cognitive dimensions should be incorporated into education programs (Özüdoğru & Durak, 2025). This finding is in line with research from Nigeria that used structural equation modeling on 529 pre-service teachers to show that knowledge of AI is a strong predictor of good outcomes in the areas of AI use, detection, ethics, creation, and problem-solving (Ayanwale et al., 2024a). This mix of promise and danger shows how important it is for teacher preparation programs to include ethics in their AI literacy training. In response, programs like UNESCO's AI Competency Framework for Teachers (UNESCO, 2024) have started to spell out what teachers need to know, be able to do, and value in the age of AI. Indeed, recent evidence highlights that risks such as privacy, security, and exam integrity are significant among teacher candidates and that these threats must be explicitly addressed for the responsible integration of AI in education (Özüdoğru & Durak, 2025).

Technology acceptance models

How people feel about AI technology acceptance theories like TAM and UTAUT (Sun et al., 2025) have often been used to help us understand how teachers feel about instructional AI. TAM-based final syntheses show that, in particular, PU (perceived usefulness), PEU (perceived ease of use), and self-efficacy (SE) significantly predict teacher candidates' intention to use GenAI; in contrast, personal innovativeness and perceived cyber risk have a weak/insignificant direct effect on intention in most models (Liu et al., 2025). Researchers have verified that perceived usefulness and simplicity of use are important factors in teachers' decisions to deploy AI tools in the classroom by using TAM-based questionnaires. For example, a 2023 study of 452 pre-service teachers in Germany (based on TAM3) indicated that perceived usefulness ($\beta \approx 0.50$) and perceived ease of use ($\beta \approx 0.30$) were strong predictors of their intention to employ AI. On the other hand, AI anxiety affected different groups in diverse ways (Guan et al., 2025). Furthermore, a comprehensive GETAMEL study comparing the two countries showed that PEU strongly influenced both PU and attitude, while PU strongly influenced both attitude and usage intention ($\beta \approx 0.21$ - 0.52 range for Turkey/UAE) (Konca et al., 2025). Models based on UTAUT also show the importance of social influence and settings that make things easier. In the very same comparative model, external constructs such as self-efficacy, subjective norm, experience, and perceived pleasure produced indirect effects on PEU/PU; these effects were consistently confirmed in both cultures (Konca et al., 2025). In a recent UTAUT extension, performance expectancy, effort expectancy, social influence, and trust were all linked to faculty members' plans to use AI. On the other hand, privacy concerns had a big negative effect (i.e. teachers who were worried about data privacy were less likely to use AI) (Rana et al., 2024). These frameworks show that making teachers surer of how valuable AI is and resolving their worries (such privacy or gender bias in AI) can make them more likely to adopt it. Professional development can help here: Research shows that targeted training can lower teachers' fear about AI and boost their confidence, which can change their views toward integrating AI in a positive way (Xu et al., 2024).

Integrating AI in classroom practice

New research reveals how teachers may use generative AI systems like ChatGPT in the classroom (Filiz et al., 2025). Designs such as GenAI-supported digital storytelling in classroom integration can meaningfully increase teacher candidates' reflective thinking and metacognition; therefore, GenAI applications should be considered not only as tools but also in conjunction with pedagogical design (Wei et al., 2025). Case studies show that teachers in training utilize ChatGPT to prepare lessons, make assessments, or provide students feedback that is specific to them (Karataş & Yüce, 2024). A lot of individuals think that these kinds of tools make education better and more personal. For instance, they can quickly adjust examples to reflect what students are interested in or give them quick feedback on their work. Teachers are also mindful not to depend too much on AI. People are still afraid about AI-assisted testing because it can offer students erroneous knowledge ("hallucinations"), make them less able to think critically, and create ethical problems. Because of this, experts stress how important it is for teachers to use AI in a reflective way. They need to always think about what AI makes, check facts, and assist students understand what AI can't do.

Learning theories and instructional design frameworks can be used to put these ideas into practice. The TPACK model (Technological, Pedagogical, and Content Knowledge) has been updated to AI-TPACK, which stands for “Intelligent-TPACK.” AI-TPACK updates detail the transformation of teacher knowledge in the AI era by preserving the seven knowledge domains of classic TPACK (CK, PK, TK, PCK, TCK, TPK, TPACK) while emphasizing AI-specific dimensions and the ‘Ethics’ component (Xu et al., 2025). This illustrates that teachers need to know more than just how to use computers. They also need to know how to teach AI and be cognizant of moral issues. Celik’s (2023) study established an AI-TPACK scale and found that teachers’ ability to use AI tools well is linked to their understanding of how such tools may be employed in the classroom. You need to know how to utilize an AI tool and how to use it in the classroom for AI-based teaching to work. Not only do teachers need to know how to employ AI in a lesson, but they also need to know when and why to use it. This is in accordance with what learning theory says: AI tutors can help students learn in a way that is based on their own experiences, and AI analytics can help professors give feedback on formative exams in a way that is based on how students think. On this aspect, ongoing professional development is quite important. Yang et al. (2024) found that a well-planned professional development program on AI in education made teachers far surer that they could teach with AI. Teachers reported that “mastery experiences” with AI tools in the classroom during training (such hands-on practice and seeing exceptional student results) made them more confident that they could employ AI in their future classes. The results are comparable to what other studies have shown in teacher education: that professional development that includes active learning and reflection can influence how teachers think about and utilize technology.

Equity and culturally responsive teaching in the AI era

A key part of good teaching is making sure that AI doesn’t make existing inequalities worse (Baker & Hawn, 2022; Ng et al., 2023). Researchers say that AI systems could be biased in ways that hurt students from underrepresented groups. For instance, if an AI-powered learning system has mostly learned from data from one cultural context, it can make wrong guesses about what pupils from another culture need or not see them at all. Baker and Hawn (2022) looked at a lot of studies and found that educational AI is biased against ethnic minorities, female students, pupils from low-income families, and other groups. They uncovered biases at several points, from training data that wasn’t fair to algorithms that weren’t designed well. They cautioned that AI may make existing educational gaps worse if nothing was done. So, in the context of AI, culturally responsive teaching ideas are being brought back up: instructors are being told to examine whose data and values are behind an AI system and to look for tools that let them adapt to local languages and cultures. A recent review talks about how important it is to have localized datasets and to work with local teachers to create AI solutions (Grab, 2025; Oyetade & Zuva, 2025). For instance, in South Africa, scholars have advocated developing AI-driven educational apps using local languages and contexts to ensure relevance and fairness. Inclusive AI adoption also demands continuous teacher training on bias mitigation and ethics (Oyetade & Zuva, 2025). Encouragingly, strategies like using fairness-aware algorithms and diverse representation in training data have been proposed to mitigate biases in classroom AI. Teachers are seen as key agents in this effort: with proper preparation, they can recognize potential AI biases and adapt or “correct” AI outputs in real time to fit their students’ cultural and individual needs. In summary, pedagogical foundations for AI-ready teachers encompass three pillars: comprehensive AI literacy including ethical considerations, balanced dispositions toward AI integration developed through evidence-based training, and sustained commitment to equity and inclusion in technology-enhanced learning environments.

Attitudes of Pre-Service Teachers Toward Artificial Intelligence

It is crucial for aspiring educators to comprehend artificial intelligence, as its integration into educational institutions is occurring rapidly. Kalniņa et al. (2024) undertook a study in Latvia and found that only 43% of people who desire to be teachers use AI tools. Only 23% of participants used ChatGPT. Conversely, studies in Slovakia (Pokrivcakova, 2023), Nigeria-Finland-South Africa (Sanusi et al., 2024), and the Philippines (Alejandro et al., 2024), demonstrate that most pre-service teachers believe AI enhances learning efficiency and creativity. There are a lot of hopes throughout the world, but not many people are using it yet.

Candidates’ propensity to adopt technology varies from context to context. In a four-week intervention in Germany, attitudes accounted for 46% of the variance in AI adoption (Ayanwale et al., 2024a). In a China-Germany comparative study, perceived usefulness and ease of use were more influential than social pressure (Zhang et al., 2023). When AI education is lacking in faculties of education, neutral attitudes or mild concerns dominate (Lucas et al., 2025). These findings suggest that how useful and accessible we see technology strongly determines our intention to use it in the classroom.

The advantages of AI are quite tangible in the eyes of prospective teachers. Seventy-five percent of Latvian participants reported that AI offers support for students with language barriers, and two thirds reported that it increases accessibility for students with disabilities (Kalniņa et al., 2024). Practical gains such as automatic feedback, differentiated activities and quick lesson planning significantly improve attitude scores (Pokrivcakova, 2023; Walter, 2024). Candidates who perceive their own technical competence as high also increase their enthusiasm for AI (Alejandro et al., 2024). After a five-week literacy course, both knowledge and intention to use increased significantly (Abdulayeva et al., 2025). There is also a widespread perception that tools such as ChatGPT or Copilot facilitate brainstorming and content production (Wulandari & Purnamaningwulan, 2024).

However, concerns about over-dependence remain significant. Most participants in studies by Chung (2024) and Chung and Jeong (2024) expressed concerns that AI might inhibit critical thinking and creativity. According to Kalniņa et al. (2024), 66 percent of respondents were concerned that AI would reduce students’ effort; 59 percent were concerned about the risk of plagiarism; and 58 percent were concerned about weakening problem-solving skills. Ethical issues such as data privacy, academic integrity and the future of the teaching profession are also on the agenda (Eyüp & Kayhan, 2023; Uyanik Aktulun et al., 2024). Zhang et al. (2023) observed that people are anxious about AI, but this doesn’t immediately affect their desire to use it. However, people who think AI is useful and easy to use can calm their fear.

A significant gap exists between AI use in academic settings and practical classroom implementation. There was a minimal link between university use and future use in teaching in Latvia (Kalniņa et al., 2024). Sperling et al. (2024) stress that teacher education programs should not just teach concepts but also give candidates the skills they need to be good teachers, including moral ones. Runge et al. (2025) have also said that systematic, experience-based training is the best way to keep people with good attitudes.

This illustration gives clear advice on how to train teachers. Gatlin (2023) says that courses should include practice sessions focusing on AI. Wang et al. (2024b) and Falebita (2024) say that emotional support and safe chances to try new things can help people feel less anxious. Ramnarain et al. (2024) stress the importance of a balanced approach that puts human contact and critical thinking at the core. It is also very important for teachers to use AI tools as examples. According to Zhang and Zhang (2024) and Sun et al. (2024), showing applicants how faculty members use AI in their classes gives them a sense of control. Mnguni et al. (2024) discovered that working together on AI projects helped candidates think of unique ways to use the technology in the classroom.

This literature review reveals dramatic transformation in pre-service teacher AI education over the past five years, particularly following the emergence of generative AI technologies like ChatGPT. While there has been a theoretical evolution in the field from traditional TPACK models to AI-TPACK frameworks, pre-service teachers' attitudes towards AI technologies seem to oscillate between opportunity and anxiety. Technology acceptance models and pedagogical frameworks are being updated, but technical AI concepts and educational practices are not yet fully bridged. While issues of ethics, equity and inclusion are of increasing importance, the need for systematic mapping is becoming evident due to the rapid growth and diversity in the field. Therefore, this study adopts comprehensive bibliometric analysis approach that needs to be adopted to assess the current state of the literature, its development dynamics, conceptual structure and future directions in the light of objective data.

METHODS

This study employs the bibliometric analysis method to perform a systematic analysis of the academic literature on the use of artificial intelligence in pre-service teacher education. Bibliometric analysis is an approach that reveals the intellectual structure and development dynamics of a particular research field by examining the quantitative characteristics of scientific publications and the relationships between them with mathematical methods (Aria & Cuccurullo, 2017; Donthu et al., 2021). This approach enables objective evaluation of research trends in the rapidly evolving, interdisciplinary field of AI education. In this study, publication volume, citation patterns, inter-author collaborations and conceptual development map in the field were analyzed using data from Web of Science and Scopus databases. The impact of different indexing policies on the results was evaluated comparatively.

Data Collection Process

The data collection process was carried out in two main academic databases to systematically identify the extensive literature on the use of artificial intelligence in pre-service teacher education. Web of Science Core Collection and Scopus databases were selected due to their different indexing policies and coverage areas, thus enabling the literature to be evaluated from a broad perspective.

The search strategy was structured around two main concept groups covering the fields of artificial intelligence technologies and teacher education. The first group includes terms related to artificial intelligence ("artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR "neural network*" OR "natural language processing" OR "computer vision" OR "automated system*" OR "intelligent system*" OR "smart system*"). The second group includes terms related to pre-service teachers and teacher education ("pre-service teacher*" OR "preservice teacher*" OR "student teacher*" OR "teacher candidate*" OR "prospective teacher*" OR "future teacher*" OR "teacher preparation" OR "teacher training" OR "teacher education" OR "initial teacher education" OR "teacher development") (full search query is presented in the **Appendix**).

The time scope of the research was limited between 2020 and early 2025. This period was chosen because it is the period when artificial intelligence technologies started to become widespread in the field of education and the COVID-19 pandemic increased the interest in educational technologies. The initial search yielded 1,823 records from Web of Science and 1,853 records from Scopus. During the data cleaning process, 50 publications without author information were removed from Scopus and 3 duplicate records identified among Scopus database publications were eliminated. As a result, 1,823 records from Web of Science and 1,800 records from Scopus were included in the analysis.

Data Analysis

In the bibliometric analysis process, the R programming language-based Bibliometrix 5.0 package program was used in Posit (2025). The raw data in BibTeX format obtained from both databases were processed according to the standard analysis protocols of the Bibliometrix package (Aria & Cuccurullo, 2017). The Web of Science and Scopus databases were analyzed separately to provide a comparative assessment of the impact of the unique indexing features of each database on the results. The analysis process was carried out under five main categories. First, descriptive statistics such as annual publication numbers, citation statistics and author collaboration indicators were calculated. Second, the most influential authors, sources and institutions were identified using h-index, g-index and m-index values. Third, inter-author and cross-country collaboration networks were visualized using social network analysis methods. In the fourth stage, keyword co-occurrence analysis was conducted, and the conceptual structure of the field was revealed. Finally, thematic maps were created to identify core, engine, emerging and isolated themes in

Table 1. Descriptive statistics based on databases

Description	Wos	Scopus
MAIN INFORMATION ABOUT DATA		
Timespan	2020:2025	2020:2025
Sources (Journals, Books, etc)	902	887
Documents	1823	1800
Annual Growth Rate %	18.83	41.38
Document Average Age	1.87	1.46
Average citations per doc	7.235	8.823
DOCUMENT CONTENTS		
Keywords Plus (ID)	Keywords Plus (ID)	Keywords Plus (ID)
Author's Keywords (DE)	Author's Keywords (DE)	Author's Keywords (DE)
AUTHORS		
Authors	Authors	Authors
Authors of single-authored docs	Authors of single-authored docs	Authors of single-authored docs
AUTHORS COLLABORATION		
Single-authored docs	161	259
Co-Authors per Doc	4.39	3.47
International co-authorships %	23.31	21.78

the research area. The findings are reported through a systematic comparison of results from both databases. This comparative approach revealed how differing database coverage and indexing policies influence results.

FINDINGS

Publications on AI in pre-service teacher education increased substantially between 2020 and 2025 (as shown in **Table 1**). However, growth rates differed between databases. Scopus displays a greater yearly growth rate (41.38 %) than Web of Science (18.83 %), and its papers are slightly younger on average (1.46 years against 1.87). This suggests Scopus captures rapidly emerging literature with more recent publications, while WoS provides broader but more established coverage.

Patterns of citation support this difference. WoS indexes a few more documents overall (1,823 vs. 1,800), however Scopus articles have a higher average effect (8.823 vs. 7.235 citations). The denser citation profile, along with a bigger pool of Keywords Plus terms (5,786 vs. 1,991), suggests that the Scopus corpus has more topical dispersion and possibly more interdisciplinary visibility. WoS, on the other hand, has more Author Keywords (5,881 vs. 4,296), which means that WoS writers provide more detailed self-descriptions, whereas Scopus depends more on phrases that are generated by algorithms.

There are also differences in how authorship is structured. WoS involves more total contributors (5 264 vs 5 008) and promotes somewhat larger research teams (4.39 vs 3.47 co-authors per manuscript) with marginally higher rates of international collaboration (23.31 % vs 21.78 %). But Scopus has a lot more papers with only one author (259 vs. 161). When you look at all these numbers together, they show that WoS likes projects that involve more than one person and often cross borders. On the other hand, Scopus has two sides: it has a lot of collaborative articles and a lot of articles written by one person, which may be because dissertations or early-career studies are entering the literature more quickly.

Overall, WoS has more coverage and stronger signs for collaboration, whereas Scopus has faster growth, newer publications, and more influence per article. Researchers who want to compare both sources should employ triangulation: use WoS to find existing networks and thematic depth, and Scopus to keep an eye on new topics and breakthroughs that are quickly referenced.

Web of Science

Citation intensity decays steadily as the cohort ages. 2020 publications average 16.64 citations, but each subsequent vintage loses roughly two–three citations (in **Figure 1**), falling to 3.88 for 2024 and 0.71 for 2025. Yet mean citations per year remain almost flat from 2020 to 2023 ($\approx$ 2.8 - 3.0), then slip to 1.94 in 2024. This reflects typical citation aging patterns: WoS papers maintain consistent annual citation rates for 3-4 years before declining as the total corpus expands.

Scopus

Early cohorts accumulate markedly more recognition (in **Figure 1**). 2020 articles reach 27.67 citations on average and still collect 4.61 per year. The 2022 and 2023 classes even surpass the 2021 vintage, peaking at 19.48 and 17.47 total citations and, strikingly, 5.82 citations per year in 2023. This spike indicates a burst of highly referenced contributions—possibly systematic reviews or policy-oriented pieces—that resonated unusually quickly. Only with the massive 2024–2025 influx does citation density contract (4.53 and 0.65 citations per article), reflecting both recency and dilution effects.

Across every matched year except 2025, Scopus delivers higher mean impact. In 2020 the gap is dramatic (27.67 vs 16.64 citations), and even by 2024 Scopus still leads (4.53 vs 3.88). Mean citations per year follow the same hierarchy, with Scopus papers receiving roughly one to three extra yearly citations up to 2023. Two mechanisms likely underpin this advantage:

(a) Scopus's broader source list imports citations from conference proceedings and regional journals not indexed in WoS, and

(b) Its faster indexing cycle lets citations accrue sooner.

Figure 1. Number of publications and citations (circle: mean TC/Year, size of circle: mean TC/ article) (Source: Authors' own elaboration)

Table 2. Most influential source

Databases	Source	h_index	g_index	m_index	TC	NP
Wos	IEEE Access	11	18	1.83	366	40
Wos	Sustainability (Switzerland)	10	20	1.67	412	25
Wos	Education And Information Technologies	10	17	2.00	323	56
Wos	Teaching And Teacher Education	8	12	1.33	174	23
Wos	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	7	12	1.40	422	12
Wos	Education Sciences	7	15	1.17	234	33
Wos	Heliyon	6	13	2.00	171	14
Wos	Interactive Learning Environments	5	9	2.50	248	9
Wos	2020 IEEE/Cvf Conference on Computer Vision and Pattern Recognition (Cvpr)	1	1	0.17	518	1
Scopus	Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	10	18	1.67	362	45
Scopus	Education And Information Technologies	9	30	3.00	924	45
Scopus	Education Sciences	9	23	2.25	536	27
Scopus	Proceedings Of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition	9	9	1.50	1075	9
Scopus	Computers And Education: Artificial Intelligence	8	14	1.60	219	19
Scopus	Sustainability (Switzerland)	7	17	1.17	407	17
Scopus	ACM International Conference Proceeding Series	5	9	0.83	104	41
Scopus	Interactive Learning Environments	4	6	2.00	285	6
Scopus	Lecture Notes in Networks and Systems	3	3	0.60	33	52
Scopus	IEEE Transactions on Pattern Analysis and Machine Intelligence	3	3	0.75	582	3
Scopus	Journal Of Applied Learning and Teaching	2	2	0.67	1027	2
Scopus	Information And Learning Science	2	2	2.00	14	2

WoS, in turn, shows a more predictable decay curve and narrower year-to-year fluctuation. For evaluators this implies that WoS yields conservative but stable benchmarks, whereas Scopus portrays a livelier, more volatile citation landscape—valuable for spotting emergent "hit" papers but prone to inflation.

Contribution of the Source

The top five sources identified represent key venues concentrating significant influence on AI research for pre-service teachers (**Table 2**). They fall into three functional groups:

1) Broad open-access mega-journals,
2) Education-centred journals, and
3) Computer-vision or AI proceedings.

Web of Science perspective

IEEE ACCESS and Sustainability head the WoS roster by h- and g-index, confirming their capacity to disseminate AI-in-education work to large, interdisciplinary audiences. Purely educational titles—Education and Information Technologies (EIT), Teaching and Teacher Education, Interactive Learning Environments (ILE), and Education Sciences—exhibit the highest m-indices

Table 3. Most influential authors in AI for pre-service teacher education

Databases	Author	h_index	g_index	m_index	TC	NP
WoS	Li Y	7	19	1.17	367	37
WoS	Zhang Y	9	16	1.50	287	34
WoS	Wang Y	9	18	1.50	353	33
WoS	Chen Z	8	19	1.33	372	26
WoS	Chen Y	5	7	1.00	75	25
WoS	Zhang Z	8	19	1.33	382	24
WoS	Sharifi A	16	22	2.67	857	22
WoS	Li J	9	18	1.50	335	22
WoS	Wang H	7	19	1.17	387	21
WoS	Wang X	7	12	1.75	168	19
WoS	Li M	7	11	1.75	138	18
WoS	Fu Y	5	6	2.50	46	7
WoS	Wan Z	5	6	2.50	46	7
WoS	Bergmann P	2	2	0.33	555	2
WoS	Sattlegger D	2	2	0.33	555	2
WoS	Carsten C	1	1	0.17	518	1
Scopus	Liu J	6	10	1.20	183	10
Scopus	Sanusi It	6	6	2.00	207	6
Scopus	Zhang Y	5	6	0.83	53	16
Scopus	Chen Y	5	11	1.00	121	12
Scopus	Wang J	5	8	0.83	71	11
Scopus	Ayanwale Ma	5	7	1.67	122	7
Scopus	Chiu Tkf	5	5	0.83	748	5
Scopus	Wang Y	4	6	1.33	39	18
Scopus	Zhang W	4	10	0.80	166	10
Scopus	Wang L	4	9	0.80	506	9
Scopus	Moorhouse Bl	4	5	2.00	129	5
Scopus	Li X	3	12	0.50	163	22
Scopus	Zhang X	3	9	0.75	166	9
Scopus	Kohnke L	3	8	1.50	85	8
Scopus	Gu Mm	3	3	1.50	23	3
Scopus	Li Y	2	5	0.40	26	13
Scopus	Tan S	2	2	0.67	1962	2
Scopus	Bergmann P	2	2	0.33	670	2
Scopus	Sattlegger D	2	2	0.33	670	2
Scopus	Rudolph J	1	1	0.33	981	1
WoS	Carsten C	1	1	0.17	518	1

(up to 2.50), showing that citations accrue quickly once papers appear. The lone CVPR contribution illustrates another path to visibility: a single, method-heavy study can attract more than 500 citations even inside a discipline-specific conference.

Scopus perspective

Here conference series are more dominant. LNCS, CVPR proceedings, and the ACM/IEEE collections raise average citation counts and push EIT to a g-index of 30 and an m-index of 3.00 — the strongest performance across both databases. Computers and Education: Artificial Intelligence and Education Sciences provide balanced, journal-level stability, while the Journal of Applied Learning and Teaching shows that just two highly cited conceptual pieces can yield exceptional total-citation values.

Journals covered by both sources (EIT, Education Sciences, Sustainability, ILE) consistently register higher h, g, and total-citation figures in Scopus, even when WoS lists more items. The differential—typically 20–40 %—stems from Scopus's broader conference coverage and quicker citation harvesting. WoS, by contrast, supplies a wider but flatter citation landscape, favouring steady, collaborative scholarship over sharply rising "hit" papers.

Contribution of the Authors

Web of Science profile. Influence in WoS is concentrated among a compact cluster of predominantly Chinese-affiliated authors (**Table 3**). Sharifi A is the clear outlier: An h-index of 16, an m-index of 2.67, and 857 total citations from just 22 papers suggest sustained, high-velocity impact over the 2020–2025 window. A second tier — Li Y, Zhang Y, Wang Y, Chen Z, and Zhang Z — combine h-indices of 7-9 with 24-37 publications, indicating steady productivity and citation uptake. At the opposite extreme stand authors such as Bergmann P and Sattlegger D, whose two co-authored studies each exceed 500 citations; their low h- and m-indices (2 and 0.33) reveal dependence on single landmark papers rather than a broad oeuvre.

Scopus profile. Scopus displays a flatter, more eclectic landscape. No one surpasses an h-index of 6, but several names reach high m-indices — Sanusi It and Moorhouse BL both at 2.00—implying rapid early citation accrual. The presence of Chiu TKF (748 citations from five papers) and Tan S (1962 citations from two papers) again underline the role of blockbuster studies, many arising in AI or computer-vision venues that Scopus captures more comprehensively than WoS. Authors who write a lot, like Zhang Y (16

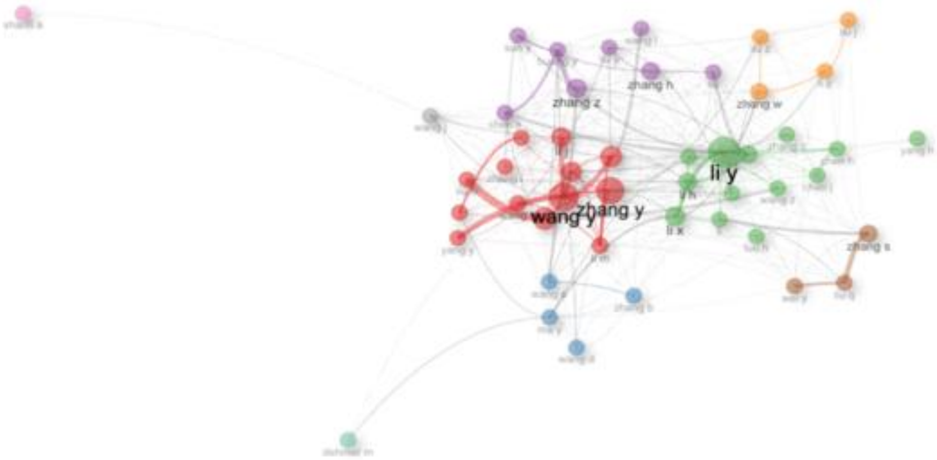

Figure 2. Network graph for authors in WoS (Source: Authors' own elaboration)

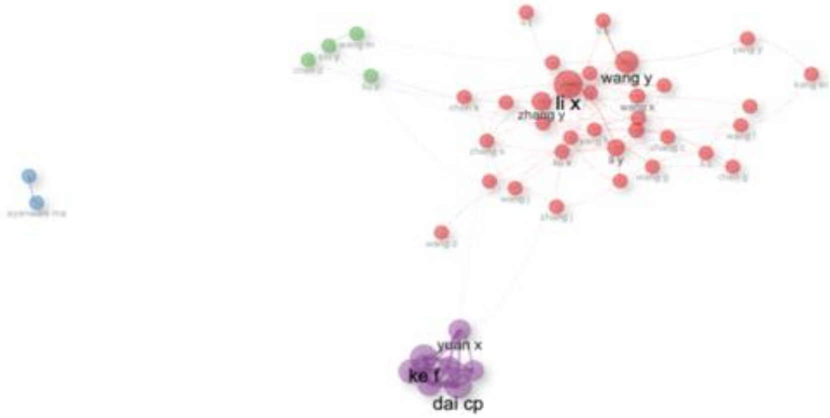

Figure 3. Network graph for authors in Scopus (Source: Authors' own elaboration)

Scopus pieces) and Li X (22 papers), have low citation densities, which suggests that their work is more incremental than groundbreaking.

There are only a few last names—Li, Zhang, Wang, and Chen—that show up on both lists, but their performance scores are typically very different: Zhang Y has an h-index of 9 in WoS but only 5 in Scopus. This shows that her work is only available on certain databases. On the other hand, writers with a lot of citations for a single paper (like Bergmann P and Sattlegger D) do a little better in Scopus since conference proceedings help them reach more people.

The WoS map (**Figure 3**) is organized around three tightly knit hubs that interlock through a handful of bridge actors. Cluster 1 (red) groups the familiar triad Zhang Y – Wang Y – Chen Z. They exhibit the highest PageRank scores and betweenness values after Li Y, which confirms their dual role as citation magnets and conduits for information flow inside the field. Cluster 3(green) centers on Li Y; his betweenness (118) and the longest closeness distance (0.0156) mark him as the principal broker linking the red and purple regions. Several satellites illustrate the unequal reach of individual authors: Sharifi A appears in a separate pink node, signaling thematic specialization with no co-authorship ties, while Dehmer M forms a light-blue dyad that connects back to the main graph only through weak edges. Overall, WoS shows a moderately decentralized structure—dense cores surrounded by peripheral single-topic researchers—favoring a small set of Chinese authors who coordinate multiple sub-groups.

The Scopus diagram (**Figure 3**) is more centralized. Nearly all productive authors fall into a single giant component (red), commanded by Li X and Wang Y. Li X tops every centrality index (betweenness $\approx$ 145; PageRank $\approx$ 0.058), indicating that most collaboration paths still route through him even in a much larger graph. Large betweenness values for Wang S (178) and Zhang W (116) hint at a second layer of gatekeepers who manage entry to specialized niches. Three small, color-coded enclaves remain outside this core: a Nigerian dyad (Ayanwale MA – Sanusi IT), a green triad led by Liu Z, and a purple cluster around Dai CP and Ke F. Their isolation suggests that Scopus captures pockets of regional or methodological expertise that have not yet merged with the dominant Sino-centric network.

WoS collaboration is multi-polar; Scopus is star shaped. In WoS, redundancy among hubs (red vs. green vs. purple) may buffer the field against information silos, whereas Scopus relies heavily on a single path via Li X. Brokerage roles also shift: Li Y is the key broker in WoS but is only a mid-level node in Scopus, where Li X and Wang S assume that task. Finally, isolates differ in origin: WoS isolates are senior, high-impact outsiders (Sharifi A, Dehmer M), while Scopus isolates tend to be emerging groups from under-represented regions.

Table 4. Most influential institutions in AI for preservice teachers' education

Databases	Institutions	Articles
Wos	Shahid Rajaee Teacher Training University	236
Wos	Central China Normal University	216
Wos	King Mongkuts University Technol North Bangkok	68
Wos	University of Yaoundé I	63
Wos	University Bamenda	46
Wos	Henan University of Technology	44
Wos	The Chinese University Of Hong Kong	42
Wos	South China Normal University	38
Wos	The Education University Of Hong Kong	36
Wos	Zhejiang Normal University	35
Scopus	The Education University Of Hong Kong	36
Scopus	Central China Normal University	27
Scopus	The Chinese University Of Hong Kong	17
Scopus	South China Normal University	16
Scopus	University Of Johannesburg	16
Scopus	University Of Virginia	16
Scopus	Beijing Normal University	14
Scopus	National Taiwan Normal University	14
Scopus	University Of Eastern Finland	14
Scopus	Arizona State University	12

Contribution of Institutions

Web of science

Institutional output is highly skewed (**Table 4**). Shahid Rajaee Teacher Training University leads by a wide margin (236 papers), nearly matching the combined production of the next two institutions. Central China Normal University (216) cements China's centrality, while a long tail of teacher-training or regionally focused universities—from Thailand (King Mongkut's UTNB) to Cameroon (Yaoundé I, Bamenda)—contributes modest but visible streams. The dominance of specialty teacher-education campuses suggests that WoS indexes numerous national or regional journals where these universities publish extensively.

Scopus

The hierarchy flattens considerably (**Table 4**). No institution exceeds 36 articles, and the top tier is led by The Education University of Hong Kong, followed by Central China Normal (27) and a mix of Asian, African, European, and U.S. universities. Scopus's broader disciplinary coverage appears to dilute any single university's share, reflecting its preference for selective journals and major conferences over high-volume local outlets.

Central China Normal's WoS count is eight times higher than its Scopus total, indicating that many of its outputs appear in domestic Chinese journals or series absent from Scopus. A similar inflation applies to Shahid Rajaee University, which disappears entirely from the Scopus top list—underscoring database-specific visibility. WoS privileges institutions in Iran, mainland China, and Africa, whereas Scopus brings in global research universities (Arizona State, Virginia, Eastern Finland). This difference likely stems from Scopus's stronger coverage of high-impact, English-language journals where Western institutions traditionally publish. Only four affiliations—The Education University of Hong Kong, Central China Normal, The Chinese University of Hong Kong, and South China Normal—appear in both tables, yet with smaller numerical gaps (e.g., 42 vs 17 papers for CUHK). Their dual presence signals balanced publication strategies that target both regional and international venues.

Contribution of the Countries

In Web of Science landscape, output is dominated by China (2693 papers) and the United States (584), yet their citation density is modest—about 2.2 and 1.8 citations per article, respectively (**Figure 4**). Germany publishes far less (226 papers) but secures five citations per paper, the highest efficiency in the WoS list. Finland, Portugal, and Iran also convert small-to-medium portfolios into above-average impact ($\approx$ 3 - 2.7 citations per paper). In contrast, Cameroon, Ukraine, and Indonesia show large volumes with weak citation traction, indicating that their work circulates mainly within domestic or regional outlets.

In the Scopus landscape (**Figure 4**), the volume hierarchy remains — China first, the United States second — but citation performance shifts. Smaller research economies rise sharply: Finland averages more than 12 citations per paper, South Korea over nine, and Spain above six. Saudi Arabia, South Africa, and Germany also exceed five citations per article. These numbers point to a concentration of highly cited studies—often conference papers or English-language journal articles—that Scopus indexes more comprehensively than WoS. Large producers such as India, Indonesia, and the United Kingdom sit at the opposite end of the efficiency scale ($\approx$ 1 - 2 citations per paper).

China's articles count in WoS is four times its Scopus figure, confirming that a substantial share of its teacher-education research appears in national journals absent from Scopus. The same pattern holds for Iran and Cameroon. By contrast, Western and Nordic countries gain visibility in Scopus, where their work earns proportionally more citations. Germany illustrates the point: almost identical citation efficiency in both databases (~5 citations per paper) but a larger share of its articles surface in Scopus. The divergent profiles warn evaluators that database choice can inflate either productivity (WoS) or impact (Scopus) for the same

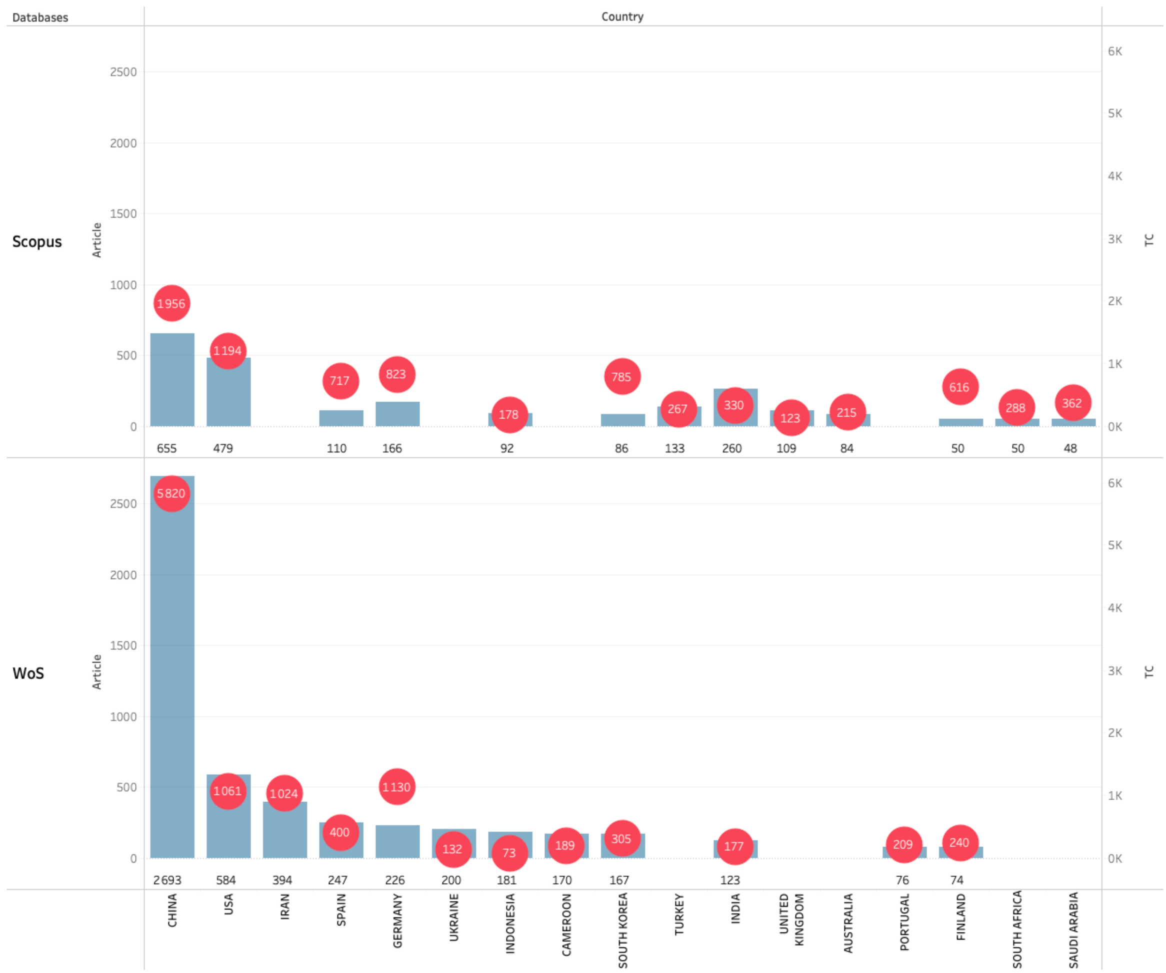

Figure 4. Total citation and article based on countries (Source: Authors' own elaboration)

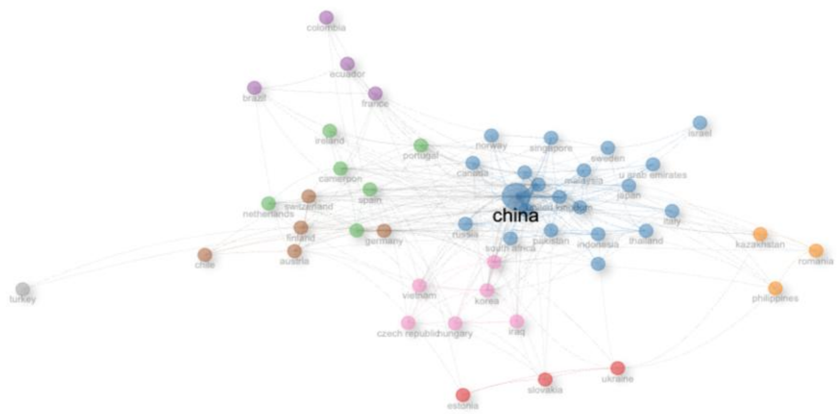

Figure 5. Network graph for countries in WoS (Source: Authors' own elaboration)

country. Germany and Finland rank near the top in both sources. South Korea and Saudi Arabia look average in WoS but excel in Scopus because their highest-impact outputs appear in international AI venues. China, India, and Indonesia rely on sheer publication numbers; their citation rates remain below the global mean.

Figure 5 is strongly Sino-centric: China dominates every central-ity metric (betweenness $\approx$ 248; closeness $\approx$ 0.017; PageRank $\approx$ 0.124), with the USA (betweenness $\approx$ 100) and Iran ($\approx$ 200) forming the two main secondary gateways. Most highly connected nations—e.g., the United Kingdom, Germany, Spain, Finland—are embedded in China-led collaboration paths, giving the graph a "hub-and-spoke" structure. Peripheral blocs are small and weakly integrated: Eastern-European dyads (Ukraine–Slovakia–

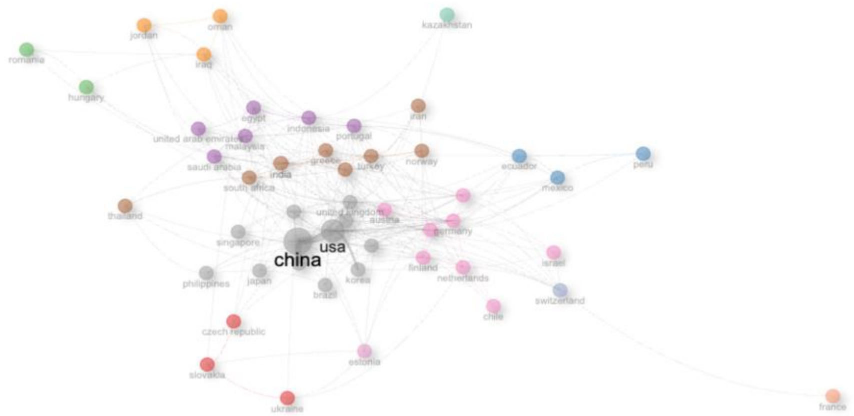

Figure 6. Network graph for countries in Scopus (Source: Authors' own elaboration)

Estonia), South-East Asian triads (Thailand, Philippines, UAE), and a single Turkish isolate. In short, WoS portrays a dense Asian core radiating outward through a handful of strategic bridges, while many medium-output countries remain one or two steps removed from that core.

In Scopus network (**Figure 6**), here the core expands into a tri-polar cluster centered on the USA (betweenness ≈ 208; PageRank ≈ 0.095), China (≈ 148; 0.083), and the United Kingdom (≈ 111; 0.060). Their triadic cohesion shortens mean path lengths, explaining why the USA now outranks China in closeness (0.015 vs 0.014) and functions as the primary broker of cross-regional ties. A second ring of European and Asian connectors—Spain, India, Germany, Finland, Austria—exhibits sizeable betweenness (20-90) and feeds multiple thematic sub-communities (clusters 4–7). The periphery is more populated than in WoS but also more porous: France is almost isolated, while Latin-American nodes (Ecuador, Mexico, Peru) and Central-Asian Kazakhstan attach through single chains to the core.

WoS emphasizes depth within an Asia-dominated collaboration system; Scopus depicts breadth, revealing stronger trans-Atlantic and pan-European brokerage. The shift in brokerage from China (WoS) to the USA (Scopus) suggests that many US-led, English-language projects reach visibility sooner in Scopus, whereas regionally focused Chinese partnerships accumulate in WoS-indexed domestic journals. Countries such as Spain, Finland, and India are consistently effective brokers, but their strategic value (betweenness share) nearly doubles in Scopus, signaling that their most internationally oriented work is preferentially captured there.

Contribution of the Articles

Both data sets confirm that generative AI—especially ChatGPT—has become the decisive conversation driver in pre-service teacher education (**Table 5**). Chiu's (2023) essay on ChatGPT and Midjourney tops WoS (103 citations yr) and ranks second in Scopus (126 citations yr). Rudolph et al.'s (2023) provocative "bull-shit spewer" paper, absent from WoS, is the runaway leader in Scopus (327 citations yr), showing how conference-style or practitioner outlets can outpace traditional journals when a disruptive technology appears.

WoS still privileges studies that blend psychological or curricular theory with technology integration. Celik (2023) (Intelligent-TPACK), Lucas et al. (2021) (digital competence), and Wang et al. (2021) (TAM-based adoption factors) illustrate a pattern: strong conceptual framing + survey or SEM methods = rapid citation uptake. Sustainability and ethics are rising fast — Abulibdeh et al. (2024) link AI to the UN SDGs (31 normalised TC), while Chiu and Chai's (2020) curriculum piece retains long-tail influence.

Scopus amplifies policy, ethics and large-scale reviews. Nguyen et al.'s (2023) ethical principles (145 citations yr) and González-Calatayud's (2021) systematic review on AI for assessment (44 citations yr) sit alongside classic horizon-scanning pieces (Luan et al., 2020). The database also captures specialised angles—trust (Nazaretsky et al., 2022), writing assistance (Imran & Almusharraf, 2023), TPACK in the ChatGPT era (Mishra et al., 2023)—suggesting a broader thematic net than WoS.

Four titles — Chiu (2023), Celik (2023), Chiu and Chai (2020), Lee et al. (2024) — appear in both lists: Each mixes classroom application with an explicit ethical or motivational lens. WoS leans toward theory-driven adoption studies; Scopus rewards debates and reviews that stake out policy or future-research ground. Scopus features more 2023-2024 work, confirming its quicker indexing cycle; WoS still draws sizable citations from 2020-2021 staples.

Keyword Network Analysis

The WoS network splits almost cleanly into two thematic zones (**Figure 7**). Cluster 2 (blue) is pedagogical: The heart - node "education" dominates every centrality index (betweenness 165; PageRank ≈ 0.082). Around it orbits "artificial intelligence", "technology" and teacher-specific terms such as "teacher education", "preservice teachers", and "ChatGPT". Paths between these nodes are dense and short, signaling an integrated discussion of how AI applications, perceptions, and acceptance feed directly

Table 5. Most influential paper in AI for preservice teachers' education

Databases	Citations	Total Citations	TC per Year	Normalized TC
WoS	Chiu, 2023	206	103.0	53.2
WoS	Celik, 2023	187	62.3	21.0
WoS	Lucas et al., 2021	140	28.0	10.1
WoS	Wang et al., 2021	129	25.8	9.3
WoS	Chiu & Chai, 2020	129	21.5	7.8
WoS	Abulibdeh et al., 2024	120	60.0	31.0
WoS	Van den Berg & du Plessis, 2023	91	30.3	10.2
WoS	Wang et al., 2024a	55	55.0	77.5
WoS	Lee et al., 2024	15	15.0	21.1
WoS	Darmawansah et al., 2024	9	9.0	12.7
Scopus	Rudolph et al., 2023	981	327.0	56.2
Scopus	Nguyen et al., 2023	437	145.7	25.0
Scopus	Luan et al., 2020	349	58.2	12.6
Scopus	Celik, 2023	300	100.0	17.2
Scopus	Chiu, 2023	252	126.0	55.7
Scopus	González-Calatayud et al., 2021	223	44.6	13.7
Scopus	Chiu & Chai, 2020	223	37.2	8.1
Scopus	Nazaretsky et al., 2022	219	54.8	11.2
Scopus	Imran & Almusharraf, 2023	184	61.3	10.5
Scopus	Mishra et al., 2023	158	52.7	9.0
Scopus	Ayanwale et al., 2024b	17	17.0	26.0
Scopus	Lee et al., 2024	17	17.0	26.0
Scopus	Derakhshan, 2025	15	15.0	22.9

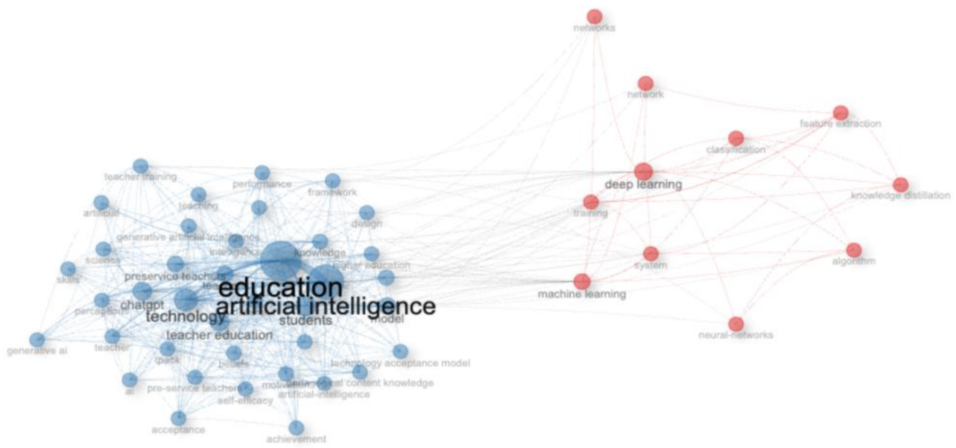

Figure 7. Network graph for keywords in WoS (Source: Authors' own elaboration)

into teacher preparation. Cluster 1 (red) is technical: "deep learning," "machine learning," and their companions ("feature extraction", "knowledge distillation", "neural networks") form a tight but comparatively self-contained sub-graph. Betweenness scores are high for "deep learning" (56) yet near-zero for most other algorithmic terms, showing that educational papers pull selected methods—principally deep learning—into the pedagogical discourse while leaving much of the algorithmic vocabulary isolated. Thin grey ties connecting the clusters confirm that only a handful of bridging papers explicitly combine classroom concerns with advanced architecture.

Scopus reveals a broader, five-cluster system in which pedagogical concepts occupy the core and technical ideas radiate outward (**Figure 8**). The purple hub (Cluster 4) centres on "students," "teaching," and "teachers'," each with very high betweenness (102, 58, 46) and closeness ($\approx$ 0.020). Adjacent green nodes (Cluster 3) add "deep learning", "learning systems", and "student teachers", illustrating that educational research now embeds sophisticated ML vocabulary more seamlessly than in WoS. A red enclave (Cluster 1) houses cutting-edge AI topics – "adversarial machine learning", "contrastive learning", "federated learning" - whose betweenness is relatively modest but closeness is the highest in the map ($\approx$ 0.018). Their position suggests emerging but still peripheral conversations that could migrate toward the core as pedagogical use cases mature. Finally, orange and blue clusters cover computer-vision terms ("image segmentation", "knowledge distillation") and practical deployment tags ("professional development", "generative AI"), respectively, illustrating a more diversified landscape than WoS.

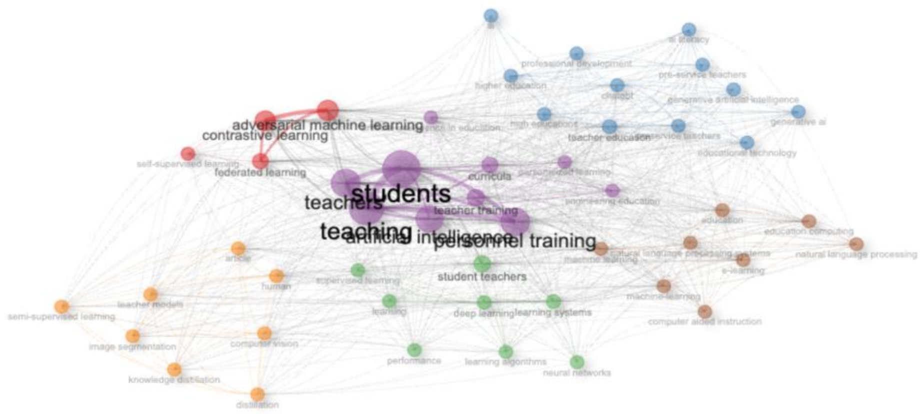

Figure 8. Network graph for keywords in Scopus (Source: Authors' own elaboration)

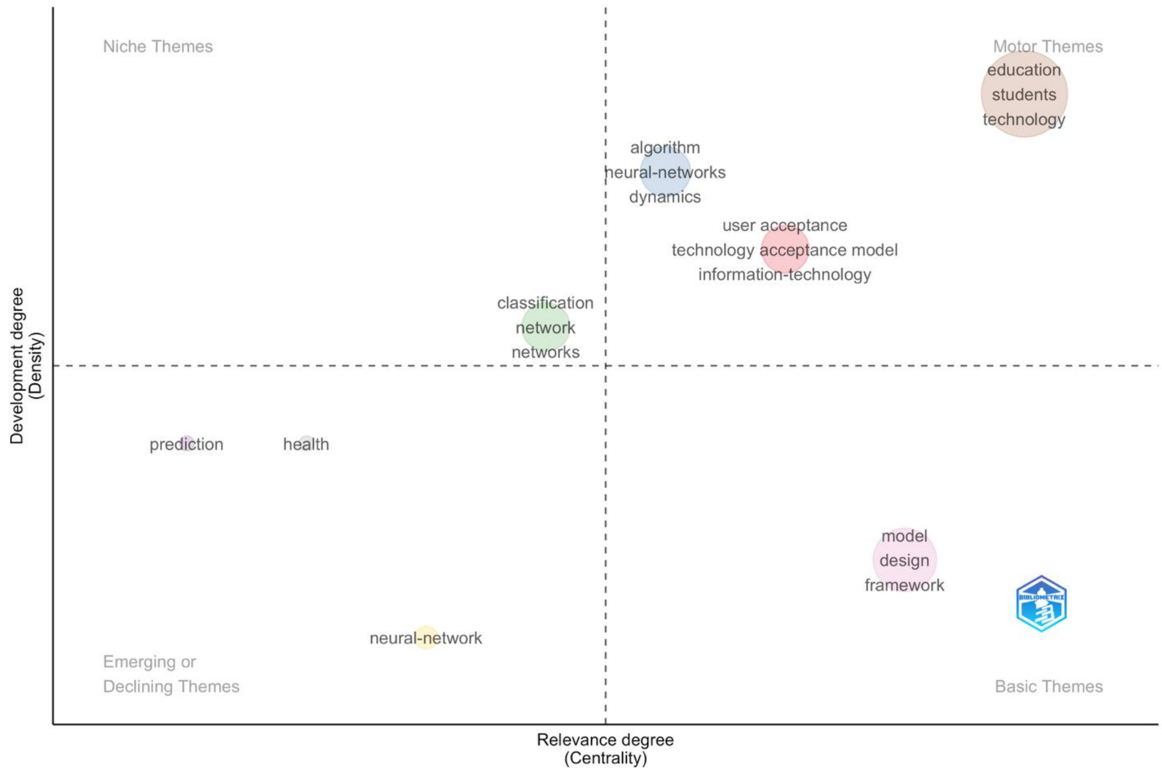

Figure 9. Thematic analysis for keywords in WoS (Source: Authors' own elaboration)

Thematic Analysis

In Web of Science (as shown in **Figure 9**), a mature and pedagogy-first landscape are output. The motor-theme quadrant is dominated by a single, wide "education – students – technology" cluster. Its high centrality (e.g., education betweenness ≈ 165) and above-average density show that instructional questions drive—and interconnect—most other topics. Immediately beneath, a model–design–framework set of basic themes supports this core, indicating that conceptual scaffolds rather than raw algorithms organize much of the debate. Two additional zones are visible: a medium-density user-acceptance cluster (TAM, intention, perspective) sitting on the mid-right border, which acts as a methodological bridge between technical work and classroom research, and a low-density neural-network/prediction/health patch in the lower half of the map—evidence that certain data-science niches are losing visibility within pre-service teacher studies.

In Scopus (as shown in **Figure 10**), technical niches and pedagogical basics are output but no clear motor yet is output. In contrast, Scopus places the large students–teachers–personnel training grouping in the basic-theme quadrant: it is central to crosstalk (high betweenness for students ≈ 102) but still sparse internally, suggesting an early stage of theoretical consolidation.

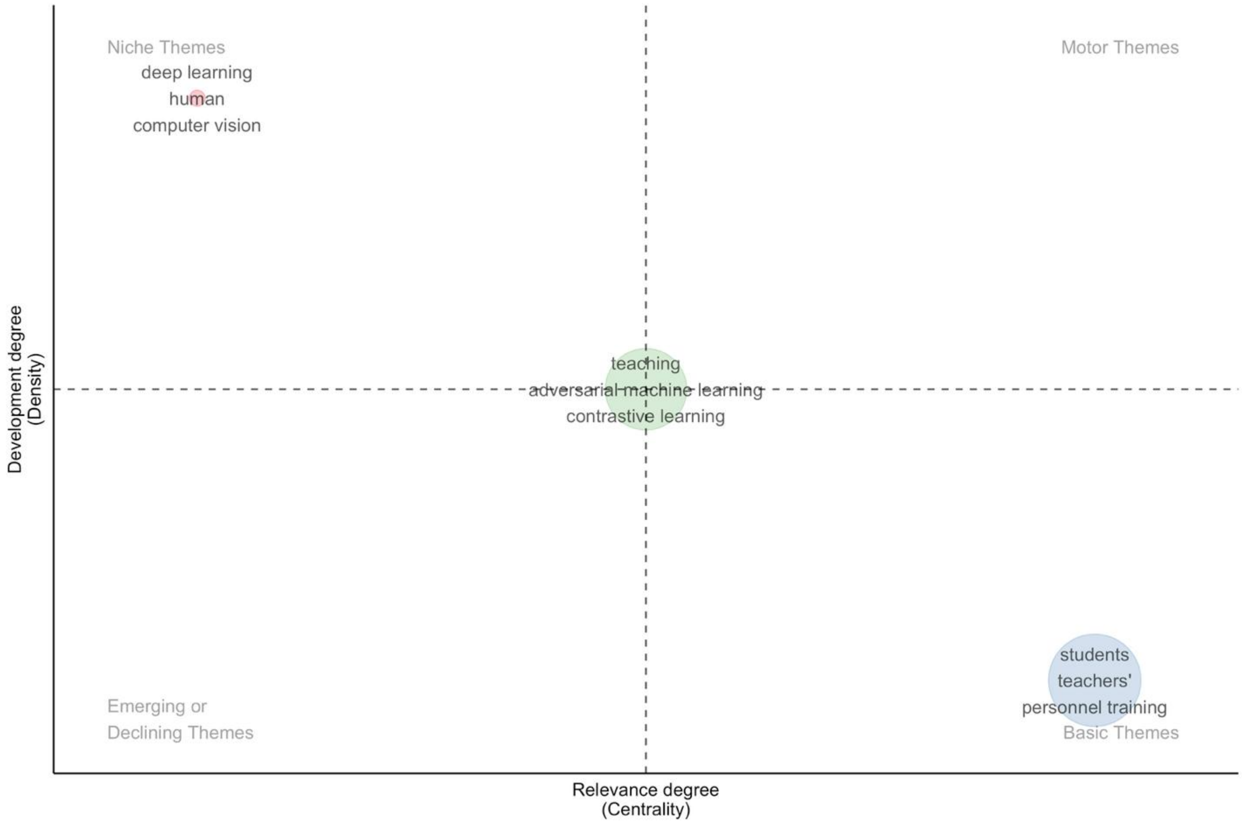

Figure 10. Thematic analysis for keywords in Scopus (Source: Authors' own elaboration)

The only high-density area is the deep-learning/computer-vision niche in the upper-left quadrant; its tight internal links (e.g., deep learning density indicators > 0.002) show vigorous method¬ological refinement, yet limited outreach to the wider educational agenda. A centrally located but medium-density teaching + adversarial/contrastive/federated learning cluster hints at an emerging bridge between pedagogy and cutting-edge AI, but its position on the axes (density $\approx$ centrality threshold) means it has not matured into a motor theme.

WoS therefore depicts a field whose pedagogical concerns are both well developed and structurally pivotal; sophisticated AI methods sit at the periphery and feed in only when framed through user-oriented constructs such as acceptance or performance. Scopus reverses this emphasis: advanced machine-learning paradigms dominate the high-density space, while foundational educational constructs remain basic, still accumulating the internal coherence needed to become self-sustaining research streams. The absence of a clear motor theme in Scopus suggests that the AI-in-teacher-education conversation there is still coalescing, pulled between technical experimentation and nascent pedagogical application.

DISCUSSION

This analysis reveals that Web of Science and Scopus databases capture AI teacher education literature through distinct lenses. Scopus' significantly higher annual growth rate (41.38% vs. 18.83%) and younger article profile (1.46 vs. 1.87 years) can be explained by the fact that this database captures rapidly developing and emerging research areas earlier (Aria & Cuccurullo, 2017). Similarly, the higher average citation values observed in Scopus (8.823 vs 7.235) are due to the platform's wider citation network resulting from its more comprehensive indexing of conference proceedings and gray literature. However, WoS's higher international collaboration rates (23.31% vs. 21.78%) and wider total document coverage can be attributed to the database's preference for well-established academic journals and indexing policies that support a collaborative research culture (Donthu et al., 2021). These differences emphasize the critical importance of the triangulation approach in bibliometric studies and show the limitations of generalizations that researchers can make based on a single database. Especially in rapidly developing technology-oriented research areas, it becomes imperative to utilize the complementary strengths of both databases to obtain a more holistic picture of the literature.

The findings suggest that there are significant asymmetries in the global distribution of AI teacher education research, reflecting the dynamics of geopolitical science. China's dominance in both databases, especially in WoS with 2693 articles, is remarkable and reflects the country's strategic investments in AI and educational technologies in academic outputs. However, a different picture emerges when this quantitative superiority is evaluated in terms of citation productivity; countries such as Germany and Finland prove the success of their quality-oriented publishing strategies with high impact values ranging from five to twelve citations per article. This reflects the fundamental difference between the quantitative growth-oriented academic policies of developing countries and the quality and impact-oriented strategies of developed countries, as emphasized by Mongeon and Paul-Hus (2015) and Pranckutė (2021).

The results of the network analysis reveal striking differences in the geographical structuring of academic collaboration. The transformation of the China-centered "hub-and-spoke" structure observed in WoS into a tripolar (China-US-UK) system in Scopus shows that different databases reflect different dimensions of academic diplomacy. This transformation, especially the stronger mediating role of the United States in Scopus (betweenness $\approx$ 208), emphasizes the influence of English-language publishing and international conferences on global scholarly discourse. However, the peripheral positions and isolated clusters of African and Latin American countries in both databases raise structural inequalities in the global scientific system and the debate on "scientific colonization" (Alatas, 2003; Ruckstuhl & Amoamo, 2022). This situation brings with it the risk that the voices of developing countries are not sufficiently heard in strategically important research areas such as AI teacher education and reveals the necessity of a multipolar academic world order.

The analysis shows that the release of ChatGPT in November 2022 caused a major change in the way AI teacher education research is done. Almost all the top cited publications are about generative AI and were published after 2023. This shows how quickly this change in technology has changed the way people talk about it in academia. Rudolph et al. (2023) controversial article "ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?" was the most cited in Scopus, with 981 citations. This shows how disruptive technologies have changed the way scientists think about knowledge, to the point where even controversial topics are seen as legitimate in the academic world. Chiu's (2023) study was also about ChatGPT and Midjourney, which were both highly ranked in both databases (103 citations in WoS and 126 citations each year in Scopus). This marked the start of a new age of generative AI in educational research. As Kasneci et al. (2023) point out, this situation shows that the "pre-ChatGPT" and "post-ChatGPT" times in educational technology are now a part of history.

The keyword networks study demonstrates that this change in thinking has caused huge changes in both research topics and the way ideas are organized. The use of new names like "generative AI," "ChatGPT," and "prompt engineering" instead of the old ones "machine learning" and "artificial intelligence" shows that the field's theoretical framework is changing quickly. Mishra et al. (2023) rethinking of the TPACK framework for the "ChatGPT era" and Celik (2023) AI-TPACK model are examples of systematic attempts to adapt old educational theories to this new way of doing things. Wang et al. (2024a) say that this fast transition could make researchers pay too much attention to the short-term effects of technology and not enough to the long-term effects on teaching. So, it's important to look at where generative AI fits into educational research from the point of view of pedagogical requirements and educational values, not technological determinism.

The results of the study show that the theoretical frameworks used in AI teacher education research have changed a lot, and that previous notions about educational technology have been changed to fit the needs of the AI era. The biggest change is the rethinking of the TPACK (Technological Pedagogical Content Knowledge) model that Celik (2023) came up with and calling it AI-TPACK (Artificial Intelligence-TPACK). This development highlights the need to extend traditional theories of technology integration to encompass the unique characteristics of AI (autonomous decision-making, learning capacity, ethical issues). Similarly, Mishra et al.'s (2023) "TPACK in the era of ChatGPT" approach highlights the depth of the paradigmatic shift in theoretical frameworks by systematically addressing how generative AI is transforming every dimension of teacher knowledge (technological, pedagogical, content knowledge). This evolution is also reflected in theories of technology acceptance; the TAM/UTAUT-based studies of Sun et al. (2025) and Zhang et al. (2023) prove the need to integrate AI-specific factors (trust, transparency, ethical concerns) into the traditional dimensions of "perceived usefulness" and "ease of use". Cross-cultural comparisons have shown that there can be meaningful differences in the direction and magnitude of model relationships; however, the PEU→PU, PU→ Attitude, and Attitude→Intention pathways remained consistent in both contexts. Therefore, regional strategies (e.g. designs aimed at reducing anxiety and increasing experience) should be developed in teacher education (Konca et al., 2025).

The thematic analysis results reveal that the theoretical maturation process proceeds at different speeds across databases. In WoS, the cluster "education-students-technology" is the motor theme, indicating that pedagogy-oriented theoretical frameworks are forming a stronger conceptual structure on this platform, whereas in Scopus, no clear motor theme has yet emerged, indicating that the field is still in the process of theoretical consolidation. This is in line with the development cycle of technology integration theories as emphasized by Koehler et al. (2017), confirming the emergence of fragmented theoretical approaches followed by synthesized frameworks during the integration of new technologies into educational systems. The increase of hybrid models, such as Wang et al.'s (2024a) approach integrating Planned Behavior Theory and AI literacy, can be considered as an indication of methodological diversification in the field, as well as a search for theoretical unity. This process emphasizes the need for a systematic synthesis of theoretical contributions from the fields of educational sciences, computer science and psychology because of the interdisciplinary nature of AI teacher education research.

The results of the thematic analysis make it clear that the AI teacher education research field has not yet reached conceptual maturity and suffers from disciplinary fragmentation. Although the cluster "education-students-technology" is the motor theme in WoS, the fact that a clear motor theme has not yet emerged in Scopus shows the lack of theoretical consolidation in the field. The keyword network analysis reveals that the connections between technical concepts ("deep learning", "neural networks") and pedagogical concepts ("education", "teaching") are weak and that conceptual structures to bridge these two fields have not yet developed. This situation shows that the "technical-pedagogical divide" problem emphasized by Zawacki-Richter et al. (2019) in educational technology research continues in the AI context. In particular, the isolated position of the high-density "deep learning/computer vision" cluster observed in Scopus from the pedagogical field indicates that the epistemological and methodological differences between AI researchers and educational researchers have not yet been resolved. This conceptual immaturity, as (Tsai & Gasevic, 2017) note, is typical of emerging technology-education research fields, but emphasizes that interdisciplinary theoretical synthesis has become an urgent need for AI's potential impact on education to be fully realized.

GenAI designs embedded in classroom applications (e.g., AI-supported digital storytelling) enhance learners' reflective thinking and metacognition. Therefore, it is recommended that GenAI be approached in teacher education not merely as a tool but as an activity design grounded in learning sciences (Wei et al., 2025). Aligned and short-cycle micro-learning modules enhance teacher candidates' AI-TPACK development and self-regulation skills, thereby increasing GenAI confidence and usage. Program design should include small but intensive application packages and 'quick win' activities (Liu et al., 2025).

CONCLUSION

This comprehensive bibliometric analysis reveals that pre-service teachers' AI education research between 2020 and 2025 is a rapidly evolving field and is experiencing paradigmatic shifts, especially after the emergence of generative AI technologies. The comparative analysis of Web of Science and Scopus databases highlights the importance of triangulation in bibliometric studies; WoS highlights pedagogy-centered research, while Scopus captures more diverse and technically oriented contributions. The fact that Chinese institutions are in charge while European countries have a lot of citations shows how AI research is funded and published around the world.

The shift from standard technology acceptance models to AI-specific frameworks like AI-TPACK shows that theories are getting more mature. But there is still a lot of conceptual fragmentation between technical AI ideas and their use in teaching. After the ChatGPT paradigm change, researchers have shifted their focus to generative AI applications, ethical issues, and inclusive educational approaches. This has led to a huge rise in the number of times that studies about ChatGPT were cited in 2023.

RECOMMENDATIONS

To close the gap between technological and pedagogical knowledge and progress from acceptance studies to long-term classroom practice, future research should focus on working together across disciplines. Teacher education programs should provide whole AI literacy courses that include both technical skills and ethical and teaching practices. Policy makers should promote research networks that work together to fix geographic gaps in AI education research and encourage AI development that includes everyone.

LIMITATIONS

This study only looks at English-language publications from 2020 to 2025, which could mean that it doesn't show enough non-Western research and historical events. The fast-changing language of AI may have left out recent work that used new frameworks, and bibliometric methods don't show the qualitative differences between individual contributions. Network analyses depend on co-authorship patterns that might not show informal collaborations, and finding new themes depends on publishing patterns that might not be able to accurately anticipate where things are going in the future because AI technologies change so quickly. Even if there are some problems with this analysis, it gives us useful information about current trends and future directions in AI pre-service teacher education research. It also helps us grasp the theory and how to use it in real life in this important and quickly changing subject.

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APPENDIX

A-Search query

((“artificial intelligence” OR AI OR “machine learning” OR “deep learning” OR “neural network*” OR “natural language processing” OR “computer vision” OR “automated system*” OR “intelligent system*” OR “smart system*”) AND (“pre-service teacher*” OR “preservice teacher*” OR “student teacher*” OR “teacher candidate*” OR “prospective teacher*” OR “future teacher*” OR “teacher preparation” OR “teacher training” OR “teacher education” OR “initial teacher education” OR “teacher development”))