education sciences

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Systematic Review

Teacher–AI Collaboration and the Professionalization of Teachers in the Age of Automation: A Systematic Review

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Abstract

Teacher–AI collaboration is increasingly present in educational settings, yet little is known about how it is conceptualized in empirical research and what this implies for teacher preparation. This review synthesizes 39 empirical studies on teacher professionalization published between 2015 and 2025 to examine how responsibilities for detecting, diagnosing, and acting on educational data are distributed between teachers and AI systems. Results indicate a predominant focus on learning analytics and natural language processing tools, largely operating at intermediate to high levels of automation. In these configurations, teachers are primarily positioned as interpreters or monitors of AI outputs. In addition, our analysis identifies a consistent pattern: as AI systems assume greater pedagogical autonomy, teacher training described in the literature remains brief, procedural, and largely limited to technical familiarization. These findings suggest that different automation configurations entail distinct competence demands, and that teacher preparation must move beyond technical training to conceptualize teacher–AI collaboration as ongoing professional sensemaking within hybrid intelligent systems grounded in educational values.

Keywords: artificial intelligence; teacher training; teacher professional development; AIED

1. Introduction

Artificial intelligence (AI) systems are increasingly embedded in teaching and learning in ways that extend beyond conventional educational technologies. Contemporary AI systems can detect patterns in learner data (e.g., Chen et al., 2020), diagnose learning needs (e.g., Macarini et al., 2019), and generate recommendations or automated pedagogical actions (e.g., S. Zhang & Chen, 2022). This raises a fundamental challenge: as AI systems take on a more active role in educational decision-making, they reshape what it means for teachers to exercise professional judgement and responsibility in practice.

This raises the question of what responsible teacher–AI collaboration entails, and how teacher professionalization can support it. Teacher professionalization entails the capacity for professional judgment, the ability to contextualize knowledge, weigh competing values, and take responsibility for decisions in complex and uncertain situations (Biesta, 2009). Here, it is important to note that collaboration typically implies mutual accountability and the capacity for negotiation between parties (Holstein et al., 2020). AI systems, however, lack moral agency, cannot be held accountable for outcomes, and do not possess the ethical understanding that underpins professional responsibility (Cukurova, 2025). We therefore

Academic Editors: Guilhermina Miranda and António Faria

Received: 9 April 2026
Revised: 29 May 2026
Accepted: 8 June 2026
Published: 13 June 2026

 https://doi.org/10.3390/educsci16060938

use "teacher–AI collaboration" to describe arrangements in which tasks and decisions are dynamically distributed between teachers and AI systems, while recognizing that ethical responsibility remains with the teacher.

This perspective aligns with the augmentation and hybrid intelligence frameworks, which conceptualize AI not as a replacement for human expertise but as a system designed to complement and extend human cognition and professional practice (Cukurova, 2025; Ley et al., 2026). From this perspective, the educational value of AI depends not only on what technology can do, but on how responsibilities, control, and agency are distributed between teachers and AI systems. Throughout this review, we use the term teacher–AI collaboration as an umbrella concept to capture these different forms of interaction.

Understanding teacher–AI collaboration requires attention to the kinds of AI systems that teachers are asked to work with. Much of the established research tradition in Artificial Intelligence in Education (AIED) has focused on the design and evaluation of systems intended to support teaching and learning through adaptive feedback, learner modelling, and instructional guidance (McCalla, 2023). These systems detect learner behavior, diagnose learning needs, and provide informational or adaptive support that teachers can interpret and act upon (Mavrikis et al., 2021). In this sense, AIED systems directly shape how teachers notice, reason about, and respond to students' learning.

Recently, the emergence of generative AI (GenAI) has introduced a different class of systems into educational discourse (Giannakos et al., 2025). In this review, we use the term GenAI to refer to general-purpose systems designed for open-ended content generation across contexts (e.g., ChatGPT), where pedagogical goals and constraints are defined primarily by the user rather than embedded in the system (European Commission, 2022). In such interactions, teacher agency typically lies in prompting, evaluating, and adapting generated outputs (Alfarwan, 2025).

By contrast, our review focuses on AI systems that are purpose-built for educational contexts (AIED), where AI functionality is embedded within instructional processes such as diagnosing learning needs, generating feedback, or guiding learning activities (Molenaar et al., 2025). These systems are particularly relevant because they directly structure how teachers interpret, decide, and act within instructional processes, thereby making visible how professional responsibilities are redistributed in practice. While some of them may incorporate techniques such as large language models (LLMs), they are analytically distinct from general-purpose GenAI tools because they are designed around specific educational theory (Molenaar et al., 2025).

Previous reviews have addressed aspects of AI in teacher professionalization from different perspectives. Some have focused on teachers' AI literacy and conceptual understanding (Salas-Pilco et al., 2022; Sperling et al., 2024), others on specific pedagogical domains such as language education (Bahari et al., 2022) or assessment and instructional support (Celik et al., 2022), and more recent work has examined the implications of generative AI for teacher education (Brandão et al., 2024). Tan et al. (2025) further showed that relatively little research on AI has focused explicitly on teacher professional development. While these studies provide valuable insights, they do not systematically examine how different configurations of AI systems reshape teacher roles and how teacher preparation aligns with these changes.

From a professionalization perspective, this omission is significant. In conceptualizing teacher professionalization, we draw on Clarke and Hollingsworth's (2002) Interconnected Model of Professional Growth (IMPG), which frames teacher learning as a dynamic, cyclical process across four interconnected domains: the *external domain* (sources of information, stimulus, or support), the *personal domain* (teachers' knowledge, beliefs, and attitudes), the *domain of practice* (professional experimentation), and the *domain of consequence* (professional agency). Change is mediated through two processes of *reflection* and *enactment* that operate in an ongoing cycle rather than as a linear sequence. This model is particularly suited to the present review because it treats professional growth not as a discrete training event but as an iterative process in which experience and reflection continuously inform one another, a dynamic that becomes especially complex when AI systems are introduced into the professional environment. As AI systems take on greater roles in detecting, diagnosing, and acting within instructional processes, they redistribute professional responsibilities in ways that are not merely technical but pedagogical and ethical. Teachers are required to interpret AI outputs, calibrate trust, make context-sensitive decisions, and remain accountable for instructional outcomes in increasingly complex human–AI systems (Kim, 2024; Molenaar, 2022). Understanding these shifts is essential for designing teacher education that prepares teachers not only to use AI, but to engage with it as part of their professional practice.

To conceptualize teacher–AI collaboration, we draw on two complementary frameworks: The Detect–Diagnose–Act (DDA) framework (Molenaar et al., 2021; Ninaus & Sailer, 2022; Tabuenca et al. (2021) and the six levels of automation model (Molenaar, 2022). DDA conceptualizes AIED-systems functioning through three interdependent operations: detection (identifying patterns in the data), diagnosis (interpreting those patterns into pedagogically meaningful states), and action (initiating or supporting pedagogical responses). In human-only teaching, all three functions are performed by the teacher. In AI-supported settings, one or more of these functions may be partially or fully delegated to an AI system, reshaping what teachers are expected to notice, reason about, and act upon.

The six levels of the automation model are inspired by similar models used in the automobile industry (Parasuraman et al., 2000) and was proposed by Molenaar (2022) to describe how much of each DDA function is delegated to AI and how much remains under human control (Figure 1). At the low end (Level 1), teachers perform all functions manually with no AI support. At the high end (Level 6), AI performs all three functions autonomously. Intermediate levels represent different configurations of shared control: for example, AI may support detection while teachers retain responsibility for diagnosis and action, or AI may both detect and diagnose while teachers decide how to respond. These levels are analytically important because they imply qualitatively different professional roles and competence demands for teachers.

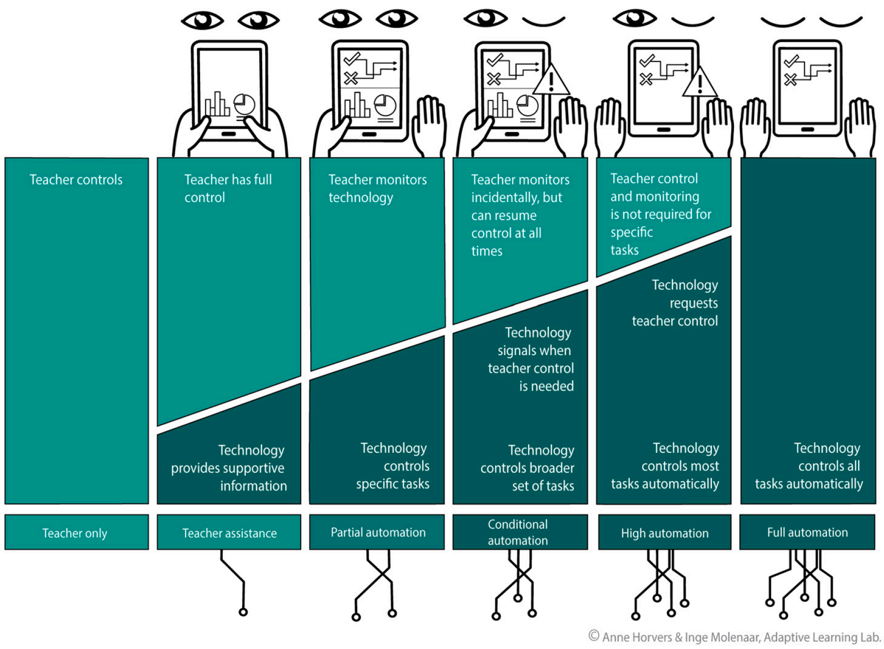

Figure 1. The Six Levels of the Automation Model (Molenaar, 2022).

Together, these two frameworks can help map how that judgment is distributed across human–AI systems and are particularly well-suited to analyzing what teacher preparation for AI collaboration requires.

Accordingly, the review addresses the following research questions:

RQ1: What AI technologies and pedagogical goals are addressed in studies on teacher professionalization, and how are they connected?

RQ2: How is teacher–AI collaboration conceptualized across studies, in terms of functional AI roles (Detect–Diagnose–Act) and levels of automation?

RQ3: What training do teachers receive, and how does this align with the demands of different automation configurations?

2. Materials and Methods

To answer the research questions, we conducted a systematic review (Petticrew & Roberts, 2006). In retrieving the documents, we adopted the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) procedure (Moher et al., 2009).

2.1. Data Sources and Retrieval

The search was performed in September 2025 and limited to the past 10 years to capture the current research landscape and ensure sufficient sample size (Barrot, 2021). We used Web of Science and Scopus to implement search strings using key concepts of AI in education derived from previous studies and literature reviews (Celik et al., 2022; Salas-Pilco et al., 2022; Sperling et al., 2024). We chose not to include specialized terms, such as 'intelligent computer-assisted language learning', and did not restrict the search to specific conceptual labels such as "collaboration," as our primary aim was to capture a broad range of studies in which teachers work with AI tools. To ensure that relevant instances of teacher–AI collaboration were still identified, we applied a two-stage screening process in which full texts were examined to identify studies where teachers actively engaged with AI outputs to inform or adapt their pedagogical decisions. As a result, we used the following query: ["artificial intelligence" OR AI OR "machine learning" OR "natural language processing" OR "nlp" OR "learning analytics"] AND ["teacher training" OR "teacher professional development" OR "teacher education" OR "teacher professionalization" OR "teacher professionalization" OR "teacher preparation" OR "teacher education program*" OR "pre-service" OR preservice OR "in-service teacher*" OR inservice]. When the database allowed it, we refined the search to include only the paper title, abstract, and keywords, resulting in a total of 2034 publications.

2.2. Data Extraction and Synthesis

All search records were imported into Rayyan, a web-based application designed to support systematic reviews. In this process, we removed duplicates and records that did not fall under the category of journal papers. We then conducted a two-stage screening process to identify publications meeting our inclusion criteria. The first author and a co-author did the initial screening of the abstracts. The following inclusion criteria were applied: (a) articles published from 2015 to 2025; (b) articles published in English; (c) articles reporting empirical, primary research, defined as studies involving original data collection through experimental, quasi-experimental, or qualitative designs; (d) articles involving pre-service teachers, in-service teachers or teacher educators; (e) articles focused exclusively on AI in teacher education or professional development; (f) articles involving AIED, specifically designed or configured for an educational purpose; and (g) articles describing how teachers interact with AI. Teacher–AI collaboration was operationalized as an interaction in which teachers engaged with AI systems and used their output to inform, adapt, or reflect on pedagogical decisions or professional practice. For example, studies in which teachers were provided with automated teaching reports or analytics but did not engage with these outputs as part of their learning or decision-making process were not considered to involve teacher–AI collaboration and were therefore excluded.

Following the initial screening, 189 titles were identified for second-stage screening (see Figure 2), where we manually checked the full texts to ensure that enough information was provided on how teachers interacted with AI. Ultimately, 39 publications were selected for inclusion in the review.

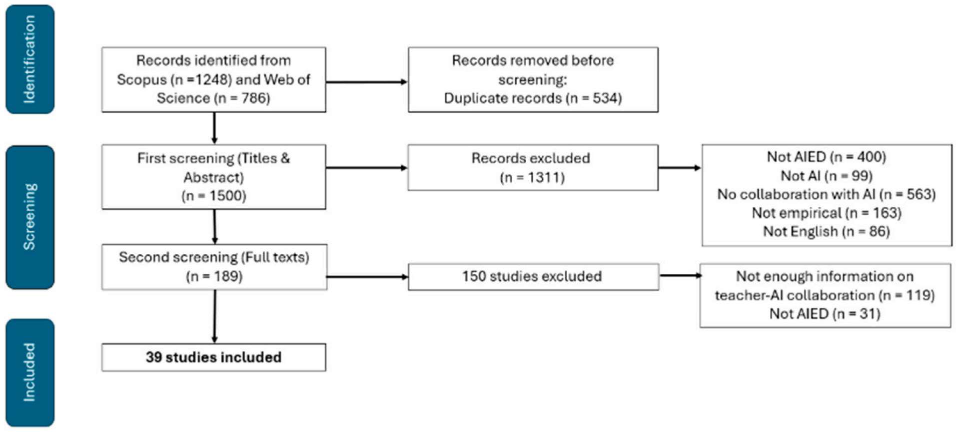

Figure 2. Process Chart of Literature Selection Following the Principles of PRISMA (Moher et al., 2009).

We then conducted content analysis using predetermined categories established prior to data analysis (Given, 2008). For RQ1, we analyzed the type of AI technology and pedagogical goals mentioned and whether participants were given the opportunity to reflect. Guided by the IMPG (Clarke & Hollingsworth, 2002), reflection opportunities and long-term follow-up were coded as indicators of whether studies created conditions for the cyclical professional learning as described in the model, rather than treating teacher–AI collaboration as a one-off event. Specifically, the IMPG identifies reflection and enactment as the mediating processes through which experience in the external domain connects to the personal domain and domain of practice, and ultimately generates lasting change in teachers' professional knowledge and behavior. For RQ2, we identified which DDA functions were supported by AI and then assessed the level of automation for each function in practice. To address RQ3, we synthesized the duration and the content of the training teachers received, drawing on Kennedy's (2014) typology of professional development orientations to characterize the degree to which training approaches supported teacher agency and sustained professional growth beyond procedural tool uptake.

Several measures were taken to ensure the trustworthiness of the review process. First, the coding scheme was developed deductively, grounded in two established analytical frameworks: The Detect–Diagnose–Act model (Molenaar, 2022) and the Six-Level Automation Model (Molenaar, 2022), which provided a theoretically justified basis for categorizing teacher and AI roles rather than relying on ad hoc interpretation. Second, a training phase was conducted in which the first and third author independently coded 10 studies (26% of the corpus), covering the full range of AI technologies and automation levels represented in the sample. Discrepancies were resolved through structured discussion until consensus was reached, and the decision rules emerging from that discussion were documented and applied consistently to the remaining studies. One example illustrates this process: for the Diagnose dimension, initial disagreement arose in cases where an AI system surfaced data patterns, but the teacher was responsible for interpreting them pedagogically. After discussion, these cases were reconciled as AI+Human, reflecting the principle that when AI pre-processes and presents interpreted information, it contributes to the diagnostic function even if the teacher makes the final interpretive judgment. Decision rules from the training phase were documented and applied consistently by the first author to the remaining 29 studies.

Inter-rater reliability for the training set was calculated using percentage agreement (PA), yielding PA = 100% for Detect (10/10), PA = 80% for Automation level and Act (8/10), and PA = 60% for Diagnose (6/10), with an overall PA of 80% (32/40 coding decisions). According to McHugh (2012), a score of 80% or higher is considered acceptable. The lower initial agreement on the Diagnose dimension reflected conceptual ambiguity in distinguishing AI-supported from teacher-led diagnosis when a system surfaces patterns but the teacher interprets them, a distinction that was explicitly addressed during the structured discussion.

We acknowledge that as researchers working in the field of AI in education, with experience in the design and study of AI-supported educational practices, our background may have shaped our analytical sensitivity toward teacher–AI collaboration as a redistribution of professional responsibility. To support transparency, we made our analytical framework explicit and documented decision rules emerging from the inter-rater training phase to ensure that interpretations were systematically grounded in the reviewed studies rather than in our own prior positions.

2.3. Sample Background and Demographics

The distribution of publications over the years indicates an uneven growth in scholarly interest in AI in teacher professionalization between 2017 and 2024 (Figure 3). During this period, the number of studies remains relatively low, with small fluctuations across years rather than a steady upward trend. In contrast, 2025 shows a pronounced surge in publications, suggesting a recent acceleration of research activity in this area. This likely reflects the growing visibility of AI in educational practice, as well as a heightened interest in the implications of AI for teachers' professional development.

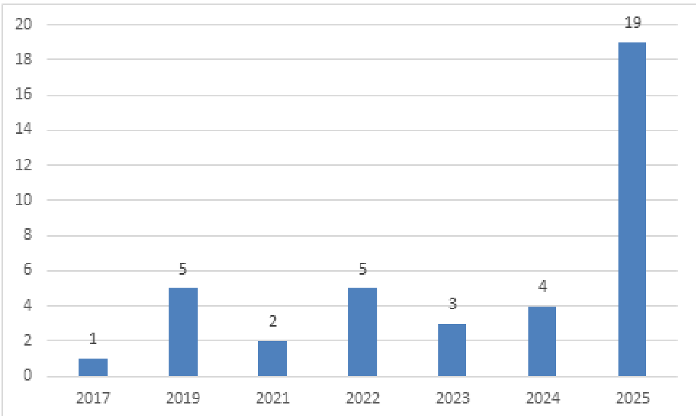

Figure 3. Number of studies per year.

The geographical distribution of the included studies indicates that research on AI and teacher professionalization is concentrated in a small number of countries. Most publications originate from the United States (N = 10) and China (N = 8), followed by South Korea (N = 5) and Turkey (N = 4). Germany and Estonia each contribute three studies, while Poland, the Netherlands, Indonesia, the United Kingdom, Sweden, and Spain are each represented by a single publication.

Regarding participants' educational levels, most studies focused on primary (N = 12) and secondary education (N = 11), followed by studies spanning multiple levels (K-12;

N = 7). Notably, a substantial number of studies (N = 9) did not specify participants' educational level, reflecting limited reporting of contextual details in the literature.

With respect to school subjects, STEM domains (science, technology, engineering, and mathematics) were most frequently studied (N = 20). Mixed-subject contexts appeared in seven studies, language subjects in four, and arts in only one study. Additionally, seven studies did not specify a school subject, underscoring a lack of clarity about instructional context in part of the literature.

Most reviewed studies focused on pre-service teachers (N = 30), with fewer examining in-service teachers (N = 8), and only one including both groups. This distribution suggests that research on AI and teacher professionalization predominantly conceptualizes AI-related learning as a preparatory activity rather than ongoing professional development. This pattern aligns with Tan et al. (2025), who similarly noted that only a minority of studies on AI in education explicitly address teacher professional development.

3. Results

This section describes the findings, analyzing them in relation to each research question, which is discussed in its own subsection. Table A1 (Appendix A) presents an overview of the analyzed studies.

3.1. AI Technologies and Pedagogical Goal (RQ1)

First, we identified the types of AI technologies employed, drawing on the classification frameworks from Mukhamediev et al. (2022) and Zafari et al. (2022). We also examined each tool's stage of development and its pedagogical purpose.

3.1.1. Type of AI Technology

Across the 39 included studies, the most frequently used AI technologies were learning analytics and natural language processing (NLP). Learning analytics tools appeared in 11 studies, typically in the form of teacher-facing dashboards or analytics reports that visualized learner activity or classroom interaction (e.g., Hunt et al., 2021). NLP-based systems were similarly prominent (10 studies), often analyzing teacher-generated text (e.g., explanations, diagnoses, responses) to provide adaptive feedback or recommendations.

Beyond these dominant categories, NLP combined with machine learning featured in five studies, and LLM approaches also appeared in five studies, frequently embedded in simulation-based environments or tutoring-style systems (e.g., Yılmaz et al., 2025). Fewer studies employed machine learning without an explicit NLP component (3 studies), speech recognition (2 studies), or hybrid configurations such as NLP plus speech recognition (2 studies) and speech recognition plus an LLM (1 study).

3.1.2. Developmental Stage of the AI Tools

Most tools were still in relatively early stages of development. Specifically, 26 studies investigated prototype systems, whereas 13 examined finalized tools. Prototypes were especially common among dashboard-based learning analytics tools (e.g., teacher assistance dashboards for collaborative learning) and NLP-driven feedback systems (e.g., adaptive feedback in simulations), suggesting that the field remains oriented toward design iteration, refinement, and proof-of-concept evaluation, rather than large-scale implementation.

3.1.3. Pedagogical Goal of AI

Regarding pedagogical purposes, most studies (n = 26) positioned AI as assisting teachers' learning or professional practice. For example, several studies used teacher-facing dashboards to make visible patterns in student collaboration, participation, or knowledge building, thereby scaffolding teachers' diagnostic reasoning and classroom orchestration (Bao et al., 2021; Kasepalu et al., 2022; Li et al., 2022; Yang et al., 2022, 2023). These dashboard-based studies largely involved pre-service teachers, often within university-based teacher education courses. Similarly, NLP-based tools, including the Teacher Responding Tool (Bywater et al., 2019), SAAI (Yoo et al., 2024), and explainable talk-move classifiers (Wang et al., 2024) provided automated analyses or feedback intended to inform teachers' interpretation of student work or classroom interaction. Other assistance-oriented studies targeted reflection or well-being through tools such as AI voice journaling (Demir & Özdemir, 2025) and AI-enhanced video-based reflection dashboards (Cai et al., 2025), again largely focusing on pre-service teachers during their training or the practicum.

A second set of studies (n = 7) framed AI as supporting teachers in designing instructional materials, assessments, or learning activities. Here, AI functions as a co-design resource. For example, GeoGebra Discovery supported pre-service teachers in designing and exploring mathematical tasks and outdoor math trails through automated reasoning (Martínez-Zarzuelo et al., 2025). Cahyono et al. (2025) similarly had pre-service teachers use AI-MoCap to design creative STEAM tasks in virtual environments. Oh (2025) employed MATH41 to help pre-service teachers generate and refine mathematical problems and visuals as part of lesson design. Uzumcu and Acilmis (2024) similarly examined how pre-service teachers integrated AI-powered creative tools (e.g., Blob Opera) into lesson planning. Liu et al. (2025) and Saar et al. (2022) involved in-service teachers, using analytics tools to inform and adapt instructional planning and classroom activity design in authentic contexts.

Few studies (n = 6) framed AI as a tool for practicing teaching in interactive environments. Conducted with pre-service teachers, these studies used AI-based simulations and chatbots as rehearsal spaces to develop instructional and relational skills before full-time classroom practice. Examples include virtual student environments such as EVETeach (N. Zhang et al., 2025) and LLM-enhanced classroom simulations (Zheng et al., 2025), as well as chatbot-based practice systems like Jiwoo or Eli that enabled iterative rehearsal of responsive questioning or non-violent communication (D. Lee et al., 2025; D. Lee & Yeo, 2022; G.-G. Lee et al., 2025; Schussler et al., 2017). Case-based simulations such as CASUS (Bauer et al., 2025; Sailer et al., 2023) similarly placed pre-service teachers in diagnostic scenarios with AI generating feedback in response to their written reasoning.

3.1.4. Opportunities for Reflection and Long-Term Follow-Up

Drawing on the IMPG, we coded for the presence of reflection opportunities and long-term follow-up as indicators of whether studies created conditions for the kind of cyclical, sustained professional learning the IMPG describes (Clarke & Hollingsworth, 2002). Reflection was coded when studies reported structured opportunities for teachers to articulate, evaluate, or build on their experience with the AI system. Long-term follow-up was coded when studies included data collection or structured activities beyond the immediate intervention period. Both indicators were coded at study level as binary variables (present/absent). Across the included studies, explicit opportunities for participant reflection were relatively uncommon. Only 10 studies reported a clear reflection component (e.g., structured prompts, reflective writing, retrospective verbal reports, or post-activity reflection tasks), whereas 29 studies did not report any dedicated space for reflection.

Where reflection was integrated, it typically took one of four forms. First, some studies supported retrospective sensemaking after interacting with AI outputs. For example, Bao et al. (2021) asked participants to reflect on their teaching process through retrospective verbal reports about how the dashboard supported diagnosis and intervention decisions. Similarly, Gerard et al. (2019) documented teacher reflection on both automated guidance and their own guidance strategies across multiple days of classroom implementation.

Second, reflection was sometimes operationalized as structured written reflection, aimed at consolidating learning. For instance, Schussler et al. (2017) included reflective essays comparing virtual and in-person role-play experiences, and Oh (2025) used reflection journals as a key data source to capture teachers' reasoning about lesson design and tool use.

Third, several studies incorporated brief post-activity reflection tasks or reflection-oriented prompts linked to AI-supported practice. D. Lee and Yeo (2022) included a voluntary reflection survey after chatbot interaction, while Yu et al. (2025) explicitly prompted participants to complete reflective writing tasks (from two perspectives) and compare experiences across different feedback conditions.

Finally, a small number of studies used reflection to elicit perceptions, concerns, and professional meaning-making around AI-supported learning experiences. For example, Demir and Özdemir (2025) captured participants' reflective accounts of benefits and concerns (including privacy and emotional disconnect) in AI voice journaling, and N. Zhang et al. (2025) reported reflective interview statements about challenges in building relationships and making instruction personally meaningful when teaching AI-powered virtual students.

Overall, these findings suggest that teacher–AI collaboration is typically operationalized through exposure to AI outputs (e.g., dashboards, automated feedback, recommendations, or interactive tools) rather than through structured cycles that support teachers in interpreting AI outputs, articulating their reasoning, and connecting insights to pedagogical decision-making.

Long-term follow-up was also almost entirely absent. Only Saar et al. (2022) conducted post-intervention interviews 8–10 months after tool use, examining teachers' perceived usefulness of learning analytics, ease of use, and intentions for future adoption. Teachers initially found the tools useful, but time constraints eventually hindered their sustained use. All other studies assessed outcomes only during or immediately after the training (e.g., post-tests, surveys, interaction logs, or short reflection tasks). From a professionalization perspective, this limits understanding about how teachers recalibrate trust, redistribute responsibility, and integrate AI into their professional identity over time.

3.2. Teacher–AI Collaboration Patterns

To address RQ2, we analyzed how teacher–AI collaboration is conceptualized across the reviewed studies along two dimensions (a) the functional role of AI in the pedagogical process and (b) the degree of automation and human control. To code DDA roles and automation levels, each study was read in full and the description of the AI system's functioning was mapped onto the three DDA operations, before an overall automation level (1–6) was assigned based on the degree to which each function was delegated to the AI system. Table A1 (Appendix A) presents an overview of the studies mapped onto the automation levels. Across the 39 studies, collaboration clustered at intermediate levels: 3 studies were classified at level 2, followed by 20 at Level 3, 5 at Level 4 and 11 at Level 5. Overall, this distribution indicates that current research predominantly investigates teacher–AI collaboration in contexts of partial to high automation, rather than in fully automated instructional settings.

3.2.1. Teacher Assistance (Level 2): AI Extends What Teachers Can Notice

Across the three studies classified at this level, AI supported detection by identifying patterns in student activity or artefacts and presented these patterns through visualizations or generative outputs. Interpretation and pedagogical decision-making remained entirely with the teacher. Two studies, for example, used dashboards to surface patterns in collaborative learning (Bao et al., 2021; Li et al., 2022). In both cases, the system detected and visualized patterns across groups, while teachers were responsible for interpreting the information and deciding whether and how to intervene. The third study (Uzumcu & Acilmis, 2024) examined AI-powered creative tools in lesson design. Here, AI generated musical artefacts, but teachers retained full control over task design, pedagogical goals, and classroom use. AI supported creative production, but not pedagogical interpretation or instructional decision-making.

Overall, teacher–AI collaboration at level 2 is characterized by AI functioning as a perceptual or generative aid, with teachers positioned as the primary sense makers and pedagogical decision-makers.

3.2.2. Partial Automation (Level 3): AI Supports Teachers' Pedagogical Reasoning

Across the 20 studies classified at this level, the dominant configuration was consistent: AI supported detection and (partial) diagnosis and sometimes proposed an action, while teachers remained responsible for validating relevance, contextualizing outputs, and enacting (or rejecting) responses.

A first pattern framed AI as a real-time pedagogical recommender that proposes instructional moves while leaving final judgment with the teacher. In the Teacher Responding Tool (Bywater et al., 2019), NLP analyzed students' written explanations and offered multiple responding options; teachers could adopt, adapt, or ignore them. Similarly, in Van Leeuwen et al. (2019), "advising" dashboards moved beyond data display by flagging and interpreting potential issues, while teachers retained authority to decide whether the interpretation fit the local context and what action was warranted. Mavrikis et al. (2019) showed the same logic in orchestration tools that identify learners who appear stuck or disengaged; teachers decide whether this calls for clarification, regrouping, or task adjustment.

A second cluster used AI to support teacher reflection by turning complex practice data (video, audio, transcripts) into structured indicators that teachers can examine and learn from. For example, Sert (2025) reported how QBot automatically detects and isolates "questioning moments" from recorded micro-teaching; AI structures the video for review but meaning-making and intended changes remain teacher-driven. Wang et al. (2024) adds an important nuance: AI not only classifies talk moves but also provides explanations (XAI) that help teachers understand why a classification was produced. In DDA terms AI strengthens the Diagnose function (it does not just label; it justifies), while teachers remain responsible for interpreting patterns and translating insights into practice.

A third pattern positioned AI as a tutor-like facilitator that adapts prompts and feedback based on teachers' responses. For example, Copur-Gencturk et al. (2024a, 2024b) used a virtual avatar that elicited responses, matched them to expected ideas or misconceptions, and generated hints and follow-up prompts until learning goals were met. In this arrangement, AI drives much of Detect–Diagnose and initiates candidate actions (feedback/hints), while the teacher advances learning primarily through responsive uptake rather than instructional control.

Other studies operationalized level 3 through AI-generated diagnostic feedback artifacts (scores, reports, warnings) that teachers must interpret and use. For instance, in Yoo et al. (2024), an automated scoring assistant generated reference scores and feedback for student responses; teachers' work centered on comparing, recalibrating rubrics, and adjusting scoring practices. The AI performs core detection/diagnosis (text processing and scoring), while the teacher enacts the professional action (revising judgment criteria and applying them).

Finally, some Level 3 studies place AI within design activity, where the system produced resources or representations, but teachers had to translate these into pedagogically meaningful tasks. In Cahyono et al. (2025), AI converted teacher-created movements into avatar dances; however, the pedagogical "diagnosis" of what the output could mean mathematically- and the action of designing tasks-remained teacher-led.

Taken together, Level 3 studies portray teachers primarily as pedagogical interpreters and editors of AI outputs. AI is no longer a passive display; it increasingly provides interpretations, classifications, feedback, and suggests next steps. Yet it remains advisory rather than autonomous: teachers are expected to validate, contextualize, and enact decisions. This makes Level 3 the central "human-in-the-loop" space, where professionalization depends less on operating tools and more on evaluative judgment, calibration, and principled uptake of AI recommendations.

3.2.3. Conditional Automation (Levels 4): AI Detects, Diagnoses, and Initiates Action Under Human Oversight

At Level 4, teacher–AI collaboration shifts from predominantly advisory support toward AI-initiated pedagogical action. Teachers remain actively involved through oversight, mediation, and correction. In Bauer et al. (2024) and Bauer et al. (2025), an AI system analyzed pre-service teachers' written diagnostic explanations and automatically delivered adaptive feedback. In both studies, AI performed detection (processing written explanations), diagnosis (classifying entities/activities), and action (issuing tailored feedback). Teacher agency resided in interpreting the feedback and regulating their own learning strategies.

Gerard et al. (2019) described this type of collaboration in an authentic classroom context. Automated knowledge-integration scoring generated adaptive guidance for students' science explanations. Importantly, the teacher was displaced: she monitored students' work and supported them in interpreting and applying the computer-generated hints during revision. Here, the teacher's role shifted toward ensuring that AI-generated guidance is understood, pedagogically appropriate, and productively enacted.

A further Level 4 configuration involves AI-initiated prompts within simulated teaching environments. In Pitura et al. (2025), a VR-AI-assisted simulation generated student questions during a teaching scenario, creating instructional contingencies that participants had to address. The AI tracked contextual features of the session and acted by producing questions that functioned as pedagogical triggers for applying content knowledge.

Taken together, Level 4 studies illustrate collaboration patterns in which AI becomes an active pedagogical agent rather than a tool that merely informs teacher judgment. Teachers remain in the instructional loop, but their agency is reconfigured: they less often make first-order instructional moves and more often respond to, mediate, or correct AI-initiated actions.

3.2.4. High Automation (Level 5): AI Manages the Loop; Humans Participate Within It

At Level 5, the reviewed studies depict teacher–AI collaboration in which AI systems run the instructional loop with substantial autonomy: they detect inputs, diagnose states, and act by sequencing tasks, generating responses, or delivering feedback in real time. Teachers (often positioned as learners) collaborate primarily by participating within AI-managed interactions, intervening mainly when breakdowns occur or when human judgment is required.

A first cluster includes systems that function as intelligent tutoring environments for teacher learning, where AI controls sequencing until mastery criteria are met. For example, in chatbot and simulation studies (D. Lee et al., 2025; D. Lee & Yeo, 2022; Schussler et al., 2017; Son, 2025; N. Zhang et al., 2025; Zheng et al., 2025), AI sustains the pedagogical scenario by generating virtual student talk and behavior, diagnosing teacher prompts or dialogue moves, and responding adaptively. Collaboration is "practice inside automation":

teachers rehearse teaching, but the AI controls timing, turn-taking and the boundaries of what counts as an appropriate move.

Other Level 5 studies position AI as an interactional actor in collaborative learning (G.-G. Lee et al., 2025), for example by responding to spoken queries and helping regulate group dialogue, or as an automated reflective partner (Demir & Özdemir, 2025), where AI processes journal entries and generates prompts and reminders.

Across Level 5 studies, the defining pattern is that AI runs the pedagogical interaction loop (tutoring, simulating, generating feedback) while teachers participate and adapt within this automation. Consequently, the focus of collaboration shifts from "interpreting AI outputs" toward monitoring interaction quality, handling breakdowns, calibrating trust, and maintaining pedagogical and ethical responsibility despite reduced direct control.

3.3. Training Duration and Content Across Automation Levels

Beyond the technological configuration of teacher–AI collaboration, the reviewed studies also varied substantially in the duration and content of the training provided to teachers.

In this section, 'training' refers specifically to tool-specific instruction provided to teachers regarding the AIED system such as orientation sessions, demonstration videos, or technical onboarding. To bring conceptual coherence to the varied terminology used across studies, we draw on Kennedy's (2014) typology, which classifies professional development along a spectrum from transmissive (knowledge delivery with limited teacher agency), through malleable (context-dependent, with some scope for adaptation), to transformative (collaborative inquiry that supports critical professional autonomy). Analyzing training approaches through this lens reveals systematic differences across automation levels in how teacher learning is conceptualized and supported.

3.3.1. Teacher Assistance (Level 2): Transmissive and Tool-Focused Preparation

At Level 2, where AI primarily supports detection and information provision, training was predominantly transmissive in character: brief, tool-centered, and focused on conveying system functionality rather than fostering pedagogical reasoning or professional autonomy. For example, Bao et al. (2021) introduced pre-service teachers to the Knowledge-Behavior-Social Dashboard through a 15 min video briefing, followed by tool use in a single session. The briefing emphasized what the dashboard displayed (knowledge elaboration, behavioral patterns, and social interaction indicators) rather than how teachers should adjust pedagogy in response to the analytics.

Similarly, Li et al. (2022) provided participants with an instruction manual (PDF and video) explaining the meaning of each KBSD indicator, along with a one-week self-paced familiarization period in which pre-service teachers could explore the dashboard independently. Training emphasized navigation and comprehension of visualizations, leaving pedagogical interpretation to the teachers. In Uzumcu and Acilmis (2024), training was minimal and largely procedural: Participants were introduced to three AI-powered music tools (Assisted Melody, Paint with Music, and Blob Opera) and were asked to integrate them into lesson plans, and structure their lessons using the 3E or 5E instructional models. However, no additional guidance was provided on how AI use should support learning goals within these models. Pre-service teachers were therefore expected to independently determine how to align the tools with instructional phases.

3.3.2. Partial Automation (Level 3): Predominantly Transmissive, with Isolated Malleable Features

At Level 3, training provision was uneven across the 20 studies, but remained predominantly transmissive, with only isolated examples approaching a more malleable orientation.

Many interventions relied on brief orientations focused on tool uptake: Cai et al. (2025) provided a 10 min introduction to a video-based professional learning platform, while Mavrikis et al. (2019) offered a 30 min demonstration of dashboard indicators. Somewhat longer but still tool-centered sessions included a 90 min introduction to GeoGebra Discovery (Martínez-Zarzuelo et al., 2025) and a 3 h workshop on AI in education and MagicSchool functionalities (Erdem Coşgun, 2025). Where tools were embedded in school practice, training tended to be longer and began to approach a malleable orientation: Liu et al. (2025) implemented a full-day onsite training for in-service teachers to use CPSLens and its associated game-based assessment environment, and Cabı and Türkoğlu (2025) provided 3 h of preparation on Moodle and the flipped learning model before weekly analytics reports were used. Some studies deliberately withheld training to observe naturalistic engagement (Van Leeuwen et al., 2019; Wang et al., 2024). Fewer studies involved more extended engagement—such as a three-week course-integrated intervention with MATH41 (Oh, 2025) or two weeks of classroom data collection following brief instruction (Saar et al., 2022).

3.3.3. Conditional and High Automation (Levels 4–5): Transmissive Onboarding into AI-Managed Environments

At higher levels of automation, training was more consistently transmissive, framed primarily as onboarding into an AI-managed environment with emphasis on role adoption, system navigation, and procedural readiness. Across Level 4 studies, preparation was typically brief: participants received a briefing introducing the case environment (Bauer et al., 2024), a short navigation video (Bauer et al., 2025), or self-paced preparation covering VR procedures (Pitura et al., 2025). An exception is Gerard et al. (2019), where preparation moved closer to a malleable orientation: over two hours, the teacher tested automated scoring by generating anticipated student explanations, learned to use the grading and commenting tools, and co-customized automated guidance with researchers.

At Level 5, training was often limited or not reported despite systems running more autonomous instructional sequences (e.g., Copur-Gencturk et al., 2024b; D. Lee & Yeo, 2022; D. Lee et al., 2025). Where training was described, it typically remained transmissive, consisting of guided familiarization: an instructor-led introduction to collaborating with an AI speaker (G.-G. Lee et al., 2025), a multi-module orientation plus trial interaction with a sample virtual student (N. Zhang et al., 2025), or short pre-session technical practice with on-site support in LLM-enhanced simulations (Zheng et al., 2025).

4. Discussion

This section summarizes key findings from the reviewed literature on AI in teacher education and professional development, identifies areas for future research and outlines theoretical and practical implications.

Empirical research on AI in teacher professionalization expanded unevenly between 2017 and 2024, followed by a sharp increase in 2025. This suggests that the field is still in a formative phase, yet it remains shaped by early-stage experimentation and rapid tool innovation. China and the United States are the most prolific countries, with fewer studies from Europe and other regions. As teacher professionalization is institutionally and culturally situated (Bulle, 2020), this concentration matters: many AI tools studied (e.g., conversational agents and feedback systems) implicitly encode assumptions about pedagogical reasoning, questioning practices, and instructional norms. Such assumptions are not neutral, especially when tools are not explicitly designed for educational contexts.

Some studies already address this issue. For instance, Son et al. (2024) adapted their AI chatbot to the Korean context based on prior research showing that U.S. and Korean pre-service teachers tend to ask different types of questions. This illustrates a broader point echoed in recent OECD analyses: general-purpose AI tools, while flexible, are often insufficiently grounded in curricular goals, pedagogical theories, and local instructional practices (OECD, 2026). When introduced into teacher professionalization, tools may therefore require not only linguistic adaptation, but pedagogical alignment with local patterns of professional reasoning. Future research should move beyond a narrow set of countries and include comparative designs examining how, for instance, classroom interaction norms or data governance shape teachers' engagement with AI in professional learning.

4.1. Type of AI Technology, Pedagogical Goals, and Reflection Opportunities

Learning analytics and NLP were the most frequently employed. This distribution suggests that AI use in teacher professionalization remains largely focused on data-driven insights and text-based applications, with limited exploration of multimodal AI. Robotics was notably absent in the studies reviewed. Studying teacher collaboration with robots may be valuable, especially given indications of teachers' reluctance toward adopting educational robots (Papadakis et al., 2021).

Teachers mainly collaborated with pre-selected AI tools, with limited opportunities to choose, adapt, or configure them. This aligns with the early stage of AI integration in teacher professionalization, where the emphasis remains on foundational AI competencies rather than advanced, personalized use. Yet the ability to critically evaluate, select, and adapt AI tools is itself a core dimension of AI literacy and professional competence (Miao & Cukurova, 2024). Greater teacher involvement in tool selection, design and adaptation can strengthen not only knowledge about AI, but also teachers' capacities to make well-informed pedagogical and ethical decisions in a continuously changing technological landscape (Leoste et al., 2019; Sillaots et al., 2024).

Regarding pedagogical goals, most studies framed AI as assistance for teacher learning and reflection ($n = 26$), primarily through dashboards, automated feedback, and reflective tools. Fewer studies positioned AI as supporting design ($n = 7$) or practice in interactive environments ($n = 6$). This indicates a prioritization of analytic and interpretive forms of teacher–AI collaboration over generative or rehearsal-oriented uses, consistent with the long-standing focus of the AIED field on supporting analysis, diagnosis, and feedback. At the same time, the recent emergence of LLMs that can be constrained and designed around educational goals suggests potential shifts in this landscape (see Topali et al., 2026).

Another key finding was the limited prevalence of structured reflection. While reflection was present in 10 of 39 studies, where it did occur, it tended to focus on retrospective sensemaking and professional meaning-making rather than on forward-looking, iterative engagement with AI outputs across multiple cycles of enactment. From the perspective of the IMPG, this limits the potential for sustained professional growth, as single or isolated reflection moments are unlikely to generate the cumulative change in teachers' professional knowledge, values, and practice (Clarke & Hollingsworth, 2002). Future research should therefore integrate reflection more consistently and explicitly address how AI reshapes responsibility, trust, and accountability in pedagogical decision-making across repeated cycles of practice.

4.2. Teacher–AI Collaboration Patterns

Teacher–AI collaboration was predominantly configured as teachers responding to AI-driven processes rather than shaping them. At intermediate automation (Level 3), AI typically detected and partially diagnosed learning or teaching processes, while teachers retained responsibility for interpretation and action. This "human-in-the-loop" configuration positions professional judgment as central. At higher automation (Levels 4–5), AI systems increasingly initiated pedagogical actions such as delivering feedback, generating questions, managing dialogue, or orchestrating simulated classrooms, while teachers primarily oversaw these processes, responded to system prompts, or intervened during breakdowns. Notably, no studies examined how teachers negotiate pedagogical responsibility within hybrid intelligent systems, particularly when AI outputs conflict with teachers' professional intuitions or knowledge of learners. Future research should therefore focus on teachers' sensemaking, resistance, and decision-making under conditions of higher automation, including how they calibrate trust and justify interventions or overrides.

4.3. Training Duration and Content Across Automation Levels

Across automation levels, training approaches were predominantly transmissive in orientation (Kennedy, 2014) and appeared systematically misaligned with both the complexity of teacher–AI collaboration and the depth of professional preparation required. Viewed through the IMPG, this misalignment has a structural character: when training is limited to procedural onboarding, it operates exclusively at the level of the external domain, equipping teachers with tool-specific knowledge without creating the conditions for reflection and enactment through which professional growth can occur (Clarke & Hollingsworth, 2002).

At lower automation (Level 2), training was brief and primarily transmissive, focusing on reading dashboards or navigating tools rather than integrating AI into pedagogical reasoning (Bao et al., 2021). Professional learning was framed as technical familiarization rather than professional transformation, reinforcing the view of AI as an add-on tool rather than a change in teaching practice.

At intermediate automation (Level 3), training was uneven and often still transmissive in character, despite teachers being expected to exercise substantial pedagogical judgment (e.g., Cai et al., 2025; Mavrikis et al., 2019). Even in more intensive cases (Liu et al., 2025), where in-service teachers received a full day of training, the focus remained on operational use rather than critical engagement with AI outputs. A small number of studies began to approach a more malleable orientation, embedding tool use within ongoing instructional practice but structured reflection remained largely absent, limiting the potential for sustained professional growth.

At higher automation (Levels 4–5), training mainly took the form of short transmissive onboarding into AI-managed environments (e.g., Bauer et al., 2024; Zheng et al., 2025), with limited attention to what it means for teachers to work under conditions where AI initiates actions. Here, professional learning was framed as adaptation to automation rather than preparation for new forms of professional responsibility. No studies at these levels approached a transformative orientation-one that would engage teachers in collaborative inquiry, critical reflection on AI-driven decision-making, or active negotiation of human–AI task distribution.

Overall, current approaches to teacher professionalization tend to prioritize immediate usability over deeper engagement with how AI reshapes pedagogical work. As AI increasingly shapes pedagogical processes, teacher professionalization would benefit from more pedagogically grounded preparation for human–AI collaboration, explicitly addressing when teachers should intervene or override AI, how to evaluate AI-driven actions against pedagogical values, and how to maintain professional agency in increasingly automated environments.

5. Implications

The findings underscore the need to refine how teacher–AI collaboration is theorized in teacher professionalization research. The clustering of studies at intermediate and high levels of automation (Levels 3 and 5) indicates that current work conceptualizes teachers as participants in hybrid intelligent systems (Ley et al., 2026). However, collaboration is predominantly treated as a moment-to-moment interaction with tools rather than as an evolving process of professional sensemaking (Cukurova, 2025). Methodologically, combining the DDA framework with the automation model proved valuable for distinguishing qualitatively different configurations of teacher–AI collaboration. Together, these frameworks clarify that such collaboration is not a single phenomenon but varies with the tool(s) teachers engage with. For example, at Level 3, where AI typically detects and partially diagnoses while teachers retain responsibility for action, collaboration positions teachers primarily as pedagogical interpreters of AI. This implies a competence profile centered on critical data literacy, evaluative judgment, and ethical calibration: teachers must understand what AI outputs represent, assess their reliability, and translate recommendations into contextually appropriate pedagogical decisions. Teacher–AI collaboration at this level is therefore better understood as distributed professional reasoning, where human judgment remains decisive.

At Level 5, AI systems often manage the instructional loops (e.g., sequencing tasks, generating responses, or simulating students) while teachers participate with and oversee these processes. Here, collaboration repositions teachers as supervisors of automated systems, requiring competencies related to system oversight, trust calibration, and ethical governance. The DDA framework and automation continuum thus provide a promising foundation for articulating how AI reshapes professional teacher roles in hybrid intelligent educational contexts, and for guiding future empirical work linking specific forms of automation to corresponding competence requirements.

For teacher preparation, the findings imply that rather than treating AI integration as a matter of technical onboarding, programs should create structured learning sequences that move teachers progressively through the full IMPG cycle. This means not only introducing AI tools but designing explicit opportunities for reflection on how AI outputs engage teachers' professional knowledge and values (personal domain), for enactment in authentic instructional settings (domain of practice), and for examination of consequences for professional agency (domain of consequence). In Kennedy's (2014) terms, this implies moving away from predominantly transmissive training toward malleable and ultimately transformative orientations that build teachers' capacity to critically evaluate, adapt, and contest AI-driven processes rather than simply learn to operate them. The finding that only 10 of 39 studies incorporated structured reflection on AI use suggests that current approaches largely leave this dimension unaddressed: without sustained cycles of enactment and reflection, teachers are unlikely to develop the professional intuition and ethical judgment needed to recognize when AI outputs should be questioned, contested, or overridden. Such capacities become increasingly critical as automation levels rise.

The findings also raise a deeper question about the nature of teacher agency in hybrid intelligent systems. Across the reviewed studies, teachers are largely positioned as responders to AI-structured interactions, a pattern that mirrors the transmissive orientation of training more broadly. A more robust theorization of teacher–AI collaboration would foreground teachers as active sense makers who also shape the conditions under which AI operates: selecting tools, configuring parameters, contesting outputs, and anchoring AI action in professional values. Engaging teachers in design or customization of AI tools, rather than positioning them solely as end-users, can strengthen agency and deepen understanding of how AI systems work, what assumptions they embed, and how they shape pedagogical possibilities (Holstein et al., 2019). Co-design also provides concrete contexts for developing competencies in evaluating automation choices, negotiating task distribution between humans and AI, and aligning system outputs with curricular and pedagogical goals (Sillaots et al., 2024).

Finally, as AI systems operate at higher levels of automation, the distribution of ethical responsibility becomes increasingly complex. However, few of the reviewed studied engage with questions of explainability, error, or override. Future research on AI in teacher professionalization should therefore explicitly address ethical governance: how to recognize when AI outputs are unreliable, biased, or pedagogically inappropriate, how to justify overriding AI-driven decisions, and how to maintain accountability in systems where there is a partial shift to automated processes.

6. Future Research Directions

Future research directions may address some of the key gaps identified in the current evidence base. These may include the following:

First, empirical studies need to explore the cognitive and ethical processes teachers engage in when they contest or adapt AI-driven decisions at higher automation levels (Levels 4–5). Second, longitudinal design-based research could test scaffolded professionalization sequences that progressively introduce teachers to increasing automation levels. This would clarify how evaluative judgment and trust calibration evolve as the AI-system takes on more complex diagnostic and instructional tasks. Finally, future work could focus on participatory co-design methodologies that involve teachers in configuring the parameters of AI tools. Investigating these contexts could help understand how teachers anchor automated actions in pedagogical values, thereby ensuring that human agency remains the decisive force in increasingly automated instructional loops.

Author Contributions: Conceptualization, O.C., R.P.V., and P.G.; methodology, O.C. and P.G.; formal analysis, O.C. and P.G.; data curation, O.C.; writing—original draft preparation, O.C., and R.P.V.; writing—review and editing, O.C., R.P.V., and P.G.; visualization, O.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Dutch National Growth Fund through NOLAI, the National Education Lab Artificial Intelligence.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AIED	Artificial Intelligence in Education
IMPG	Interconnected Model of Professional Growth
DDA	Detect-Diagnose-Act
LLM	Large Language Model
NLP	Natural Language Processing
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-analyses

Appendix A

Table A1. Overview of Studies Included in the Review.

Paper	Year	Country	Participants	School Level	School Subject	Sample Size	AI Technology	Degree of Development AI Tool	Training Duration	Content	Reflection	Follow-Up	Automation Level	Detect	Diagnose	Act
Bao et al. (2021)	2021	USA	PST	Secondary education	STEM	35	Learning analytics	Prototype	15 min	Video briefing on the KBSD	Yes	No	2	AI	Human	Human
Bauer et al. (2024)	2024	Germany	PST	N/A	N/A	60	NLP	Prototype	N/A	Briefing + orientation to simulation and teacher role	No	No	4	AI	AI	AI
Bauer et al. (2025)	2024	Germany	PST	K-12	Mixed	332	NLP	Prototype	N/A	Short video about navigating in CASUS	No	No	4	AI	AI	AI
Bywater et al. (2019)	2019	USA	PST	Secondary education	STEM	4	NLP	Prototype	N/A	N/A	No	No	3	AI	AI	AI + Human
Cabı and Türkoğlu (2025)	2025	Turkey	PST	N/A	N/A	127	Learning analytics	Finalized	3 h	Training on how to use the LMS (Moodle) and the Flipped Learning model	No	No	3	AI	AI	Human
Cahyono et al. (2025)	2025	Indonesia	PST	N/A	STEM	25	Machine learning	Finalized	N/A	N/A	No	No	3	AI	AI + Human	Human
Cai et al. (2025)	2025	China	PST	N/A	N/A	48	NLP and machine learning	Finalized	10 min	Orientation to the video-based PD platform + login procedures	No	No	3	AI	AI + Human	Human
Copur-Gencturk et al. (2024a)	2024	USA	PST	Secondary education	STEM	70	NLP	Prototype	N/A	N/A	No	No	3	AI	AI	AI + Human
Copur-Gencturk et al. (2024b)	2024	USA	PST	Secondary education	STEM	29	NLP	Prototype	N/A	N/A	No	No	5	AI	AI	AI
Demir and Özdemir (2025)	2025	Turkey	PST	Secondary education	Languages	8	Speech recognition	Finalized	N/A	Demonstration of Audio Diary app (features and procedures)	Yes	No	5	AI	AI	AI
Erdem Coşgun (2025)	2025	Turkey	PST	Secondary education	Languages	27	Large language model	Finalized	3 h	Introductory session on AI in education + MagicSchool tools	Yes	No	3	AI	AI	AI + Human
Gerard et al. (2019)	2019	USA	PST	Primary education	STEM	1	NLP	Prototype	2 h	Collaborative customization of automated scoring tool	Yes	No	4	AI	AI	AI + Human

Table A1. *Cont.*

Paper	Year	Country	Participants	School Level	School Subject	Sample Size	AI Technology	Degree of Development AI Tool	Training Duration	Content	Reflection	Follow-Up	Automation Level	Detect	Diagnose	Act
Hunt et al. (2021)	2021	Estonia	PST	Primary education	N/A	135	Learning Analytics	Prototype	1 seminar	Manuals and videos on using e-portfolio and LA tools	No	No	3	AI	AI	Human + AI
Kasepalu et al. (2022)	2022	Estonia	PST	Secondary education	STEM	21	Learning analytics	Prototype	N/A	N/A	No	No	3	AI	AI	Human
D. Lee and Yeo (2022)	2022	USA	PST	Primary education	STEM	23	NLP and machine learning	Prototype	N/A	N/A	Yes	No	5	AI	AI	AI
D. Lee et al. (2025)	2025	USA	PST	Primary education	STEM	23	NLP and machine learning	Prototype	N/A	N/A	No	No	5	AI	AI	AI
G.-G. Lee et al. (2025)	2025	South Korea	PST	Primary education	STEM	20	NLP and speech recognition	Prototype	N/A	Introduction to CLAIS system and group use with AI speaker	No	No	5	AI	AI	AI
Li et al. (2022)	2022	China	PST	N/A	STEM	19	Learning analytics	Prototype	1 week	Self-paced manuals (PDF + video) on dashboard indicators	No	No	2	AI	Human	Human
Liu et al. (2025)	2025	China	PST	K-12	Mixed	300	Learning analytics	Prototype	1 day	Multimedia materials + full-day hands-on training on CPSLens/D-City Fighter	No	No	3	AI	AI	Human
Martínez-Zarzuelo et al. (2025)	2025	Spain	PST	K-12	STEM	140	Machine learning	Finalized	90 min	Introduction to GeoGebra Discovery and automated reasoning tool	No	No	3	AI	AI	Human
Mavrikis et al. (2019)	2019	UK	PST	N/A	STEM	24	Learning analytics	Prototype	30 min	Demonstration of Teacher Assistance (TA) tools using real classroom data	No	No	3	AI	AI	Human
Oh (2025)	2025	South Korea	PST	Secondary education	STEM	24	Large language model	Finalized	3 weeks	Week 1: AI orientation; Weeks 2–4: hands-on MATH41 training	Yes	No	3	AI	AI	Human
Pitura et al. (2025)	2025	Poland	PST	Secondary education	Languages	17	Speech recognition	Finalized	N/A	Self-paced orientation to VR procedure	No	No	4	AI	AI	AI
Saar et al. (2022)	2022	Estonia	PST	K-12	Mixed	15	Learning analytics	Prototype	N/A	Brief tool instruction	No	Interviews 8–10 months later	3	AI	AI	Human

Table A1. *Cont.*

Paper	Year	Country	Participants	School Level	School Subject	Sample Size	AI Technology	Degree of Development AI Tool	Training Duration	Content	Reflection	Follow-Up	Automation Level	Detect	Diagnose	Act
Sailer et al. (2023)	2023	Germany	PST	K-12	N/A	176	NLP	Prototype	N/A	Short introductory video to CASUS platform	No	No	5	AI	AI	AI
Schussler et al. (2017)	2017	USA	PST	Primary education	Mixed	23	NLP	Prototype	N/A	N/A	Yes	No	5	AI	AI	AI
Sert (2025)	2025	Sweden	PST	Secondary education	Languages	6	NLP and speech recognition	Finalized	N/A	Instructions on using QBot for lesson reflection	No	No	3	AI	AI	Human
Son (2025)	2025	South Korea	PST	Primary education	STEM	138	NLP and machine learning	Prototype	N/A	N/A	No	No	5	AI	AI	AI
Son et al. (2024)	2025	South Korea	PST	Primary education	STEM	131	NLP and machine learning	Prototype	N/A	N/A	No	No	5	AI	AI	AI
Uzumcu and Acilmis (2024)	2024	Turkey	PST	Primary education	Arts	32	Machine learning	Finalized	N/A	N/A	No	No	2	Human	Human	Human
Van Leeuwen et al. (2019)	2019	Netherlands	PST	Primary education	N/A	53	Learning analytics	Prototype	Not applicable	Not applicable	No	No	3	AI	AI	Human
Wang et al. (2024)	2019	China	PST	N/A	Mixed	59	NLP	Prototype	Not applicable	Not applicable	No	No	3	AI	AI	Human
Yang et al. (2022)	2022	China	PST	K-12	Mixed	68	Learning analytics	Finalized	1.5 h	Guided introduction to KBDeX visualizations and key SNA concepts	No	No	3	AI	AI interprets, humans refine the diagnosis	Human
Yang et al. (2023)	2023	China	PST	N/A	N/A	80	Learning analytics	Finalized	1.5 h	Guided reflective assessment using KBDeX + prompt sheets	No	No	3	AI	AI interprets, humans refine the diagnosis	Human
Yılmaz et al. (2025)	2025	USA	PST	Primary education	STEM	26	Large language model	Finalized	5 sessions of 75 min	Scaffolded course on mathematics with gradual AI integration	No	No	4	AI	AI	AI
Yoo et al. (2024)	2025	South Korea	PST	Secondary education	STEM	4	NLP	Prototype	N/A	N/A	No	No	3	AI	AI	AI + Human

Table A1. *Cont.*

Paper	Year	Country	Participants	School Level	School Subject	Sample Size	AI Technology	Degree of Development AI Tool	Training Duration	Content	Reflection	Follow-Up	Automation Level	Detect	Diagnose	Act
Yu et al. (2025)	2025	China	PST	Primary education	STEM	58	Speech recognition and large language model	Prototype	N/A	N/A	Yes	No	3	AI	AI	AI + Human
N. Zhang et al. (2025)	2025	USA	PST	N/A	STEM	24	Large language model	Prototype	N/A	Orientation modules on teaching virtual students + practice session	Yes	No	5	AI	AI	AI
Zheng et al. (2025)	2025	China	PST	K-12	Mixed	12	Large language model	Prototype	5–10 min	Technical support + 5–10 min practice before simulation	Yes	No	5	AI	AI	AI

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https://doi.org/10.3390/educsci16060938