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AI Integration in Mathematics Education: Comparison of Teacher Perceptions, Professional Development, Curricular Frameworks, and Challenges

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ABSTRACT

Implementation of AI in teaching mathematics depends on the willingness of teachers and the SES. This review (2015-2025) shows that teachers do not deny the possibility of AI differentiation and administrative workload, but they are very worried about the issues of pedagogy and morality, as well as their occupational status. The effective adoption relies upon gaps in technological-pedagogical-content knowledge (TPACK) and systemic obstacles such as infrastructure and misalignment of policy between teachers. The results highlight the importance of specific professional growth and effective institutional reinforcement to negotiate the AI revolution in the mathematics classroom in a fair and meaningful way, which can be of significant note to policymakers and educational administrators.

Keywords: Artificial intelligence, Teaching and Learning Mathematics, Attitudes, Professional development, Educational technology, Barriers to implementation.

Introduction

It is becoming true that the fast development of artificial intelligence (AI) has already started reshaping educational environments and providing new opportunities in personalized learning, automated evaluation, and intelligent tutoring systems. [1]. AI technology has no doubt the potential to improve student engagement and conceptual knowledge in a particular school subject: mathematics, as individualized instruction and instant feedback turn out to be especially promising in this area [2]. Nevertheless, integration of AI in the classrooms can only succeed depending on the teachers themselves, who must apply it. Attitudes of teachers towards the use of AI, their preparedness, and acceptance of the technology are determining factors in whether such innovations provide effective changes to their teaching and learning process [3, 4].

Although a wide variety of AI-enhanced educational tools are becoming increasingly accessible, it has been found that there are a lot of mathematics teachers who are not ready or do not want to integrate such products into their teaching [5]. Such reluctance is provoked by several factors, such as low exposure to the applications of AI, ethical considerations, and a lack of understanding of how the tools would fit into the objectives of the curriculum [6]. Also, it is not rare to say that professional development programs do not offer the proper training on how to integrate AI, which means that educators will not be skilled or confident enough to take advantage of these technologies [7, 8]. These barriers, without their elimination, can never attain the potential that AI can bring to mathematics education.

However, the world environment of AI usage in studying mathematics is not balanced. Although most of the studies are based on the technologically advanced systems, small but significant studies based on the Middle East and North Africa (MENA), Sub-Saharan Africa, and refugee education settings highlight the existence of specific implementation challenges. As an illustration, device scarcity, lack of trust in the AI platform, and the absence of PD infrastructure are mentioned in the studies of the refugee-hosting population in such areas, as Jordan and Lebanon. These contexts support the possibility of developing context-sensitive models of AI integration [9, 10]**.**

This paper explores the attitude of mathematics teachers toward the use of AI in their classrooms, their preparedness, and difficulties with this idea. The understanding of crucial factors that can either positively or negatively impact the successful integration of AI tools in mathematics instruction will be provided by analyzing the attitudes towards it, the areas to undergo training, and the obstacles to successful implementation among educators. These results will help to provide a better idea of ways to help schools, policymakers, and educators assist mathematics teachers in migrating to this technological transformation. Finally, this study aims to inform approaches that the teachers can use to take out the power of AI in mathematics education without the fear of taking advantage or, in other words, to ensure that these new technologies develop rather than disrupt effective teaching and learning in mathematics.

To comprehend more about the behaviors of teachers adapting to AI within math classrooms, this overview looks at the Unified Theory of Acceptance and Use of Technology (UTAUT), Technology Acceptance Model (TAM), and the Substitution, Augmentation, Modification, and Refinement (SAMR) model. These models can be used to contextualize the critical concerns, namely, perceived usefulness, expectation of effort, and pedagogical transformation phases influencing the readiness/ability of the teachers in the field of AI integration. They also supplement the TPACK (Technological Pedagogical Content Knowledge) framework, providing psychological and behavioral aspects of technology acceptance. This review takes an evaluative and analytical approach to understanding the intersection of AI integration, curriculum alignment, and educator preparedness in mathematics education. It critically assesses teacher experiences, PD strategies, and systemic barriers based on empirical studies from diverse regions.

Methodology

Search Strategy and Data Sources

In this review, a systematic narrative synthesis approach has been used to discuss the available literature around the preparedness of mathematics teachers to embrace the use of AI. A systematic search involving a maximum of five research databases (ERIC, Web of Science, Scopus, IEEE Xplore, and PsycINFO) with the help of controlled vocabulary and Boolean expressions of keywords in the three domains (that is, AI, mathematics education, and teachers' perceptions) was employed. Only peer-reviewed studies published between 2015-2024 were considered.

Inclusion and Exclusion Criteria

Studies were included with the following inclusion criteria: (1) have an empirical nature (qualitative, quantitative, or mixed approaches), (2) focus on the tasks of mathematics educator perception, professional development, or the use of AI tools in mathematics directly, and (3) are published in journal articles that follow peer review.
Studies were excluded based on the following grounds: (1) They added no math-specific discussion to their general education discussion, (2) They used hypothetical rather than real-world situations to discuss AI, or (3) They were reviews, opinion pieces, and editorials.

Screening and Quality Assessment

They passed through strict three-stage screening (title/abstract review, full-text assessment, and quality assessment) to find high-quality papers that managed to remove systematic errors and achieved geographical coverage within the final corpus.

Study Distribution and Contextual Considerations

The resulting corpus of 52 works had a very wide geographic scope: 34% in East Asia (China, Japan, South Korea), 29% in North America (mainly the U.S.), 21% in Europe (e.g., Finland, U.K.), 9% in South Asia and MENA, and 7% Sub-Saharan

Africa and Latin America. The draw of cultural context played a key role in the interpretations, e.g., the East Asian studies were hinged on studying readiness, whereas the Nordic included well-being and equity of a student. Due attention was paid to these patterns during the synthesis procedure so that prejudicial cultural generalization does not occur.

Data Analysis and Synthesis Approach

Use of an inductive-deductive approach was used in the analysis to derive similar themes along three conceptual areas, which included teacher attitudes, professional development needs, and implementation challenges. Quantitative results were synthesized via descriptive statistics, and effect sizes were calculated, whereas qualitative data were subject to thematic analysis through NVivo by coding of emergent patterns.

The study did not collect primary data (e.g., surveys or interviews) because it is a systematic narrative review. Rather, teacher perceptions, professional development requirements, and implementation difficulties were integrated into the results of 52 carefully selected empirical studies. These researchers employed different procedures, such as conventional scales and instruments referring to frameworks such as TAM and AI-TPACK, semi-structured interviews, and classroom observations of AI-integration.

The synthesis was completed through thematic coding of reported data that is categorized in three conceptual categories: (1) teacher attitudes toward AI, 2) professional development needs and readiness, and 3) systemic and contextual barriers. A third of the studies were coded separately by two individuals, to confirm reliability (inter-rate agreement $\kappa= 0.82$); differences in coding were discussed. Triangulation of comparable results strengthened patterns, whereas with outliers, certain contextual diversity is highlighted (e.g., rural, urban, inexperienced, or experienced teachers).

Justification for Narrative Synthesis

Narrative synthesis was chosen because the studies were heterogeneous when it came to study designs, outcome measures, and data types. Although quantitative data were extracted and summarized, there was too much variability in operational definitions (e.g., AI readiness, pedagogical alignment), and the set of effect sizes was not similar enough to do reliable statistical aggregation. Narrative synthesis enabled improving contextual interpretation, particularly on the qualitative insights and cultural nuances that could be missed through the meta-analytic approach.

Table 1: Overview of Included Studies (n = 52) by Region, Method, and Focus Area.

Region	Number of Studies	Methodological Type	Primary Focus
East Asia	18	Mixed / Quantitative	AI adoption readiness, test prep orientation

North America	15	Qualitative / Mixed	Teacher perception, equity issues
Europe	11	Quantitative	PD models, integration strategies
South Asia & MENA	5	Qualitative	Access barriers, curriculum fit
Sub-Saharan Africa	2	Mixed	Infrastructure gaps, teacher beliefs
Latin America	1	Quantitative	Student engagement with AI tools

Results

The review is an in-depth synthesis of findings on 52 empirical studies with the aim of giving a precise impression of the ways in which mathematics teachers perceive, prepare, and struggle with AI when incorporated into the classroom. AI-supported ways of instruction were coded to align with (a) the NCTM Principles and Standards and related process strands (problem solving, reasoning, representation, communication and connections); (b) the NRC strands of mathematical proficiency (conceptual understanding, procedural fluency, strategic competence, adaptive reasoning and productive disposition); and (c) country-based emphases in national curriculum as revealed in policy or research summaries in Jordan, Saudi Arabia, Japan, Singapore, China, the United States, and Finland.

The findings expose intricate three-dimensional interactions that differ widely in educational settings, grades, and teacher demographics. In the following text, we provide a richer analysis that is organized based on three underlying themes using abundant qualitative evidence and quantitative findings of analyzed articles.

The Teacher Perspectives on AI: The Optimism and Worry Spectrum

AI Benefits in Mathematics Education

In numerous studies, mathematics teachers acknowledged that AI could revolutionize the teaching and learning of mathematics in several ways:

In 78 percent (n=41) of the research, teachers appreciated the potential of AI to offer adaptive student pathways depending on their needs [11]. To take an example, AI-based learning solutions such as DreamBox and Khan Academy have been described as having the ability to provide real-time changes in the difficulty levels of problems according to the performance of students [12].

In 62 percent of the studies (n=32), teachers cited that AI was potentially useful to mitigate valuation loads, especially when grading standardized algorithms and step-by-step fluency challenges [13]. As one of the teachers pointed out, it saved her hours in marking the worksheets, and she could concentrate instead on the misconceptions [14]. An application of AI in the form of gamified tools (e.g., Prodigy Math) was pointed out as a way to improve student motivation, particularly those experiencing difficulties [15].

Old Problems and Oppositions

Though there are these benefits, the teachers showed a lot of reservations, which were in the following four categories:

A lot of secondary teachers (especially the ones teaching higher-level math) did not believe in the ability of AI to promote higher-order thinking [16]. Studies mentioned the possibility that AI will oversimplify the definition of complex problems or that it will not be able to model messy mathematical reasoning [17, 18].

Existential fears were found in qualitative studies, and veteran teachers asked themselves whether they still had a place in an AI-augmented classroom. Participants wondered, what is then left to do, when AI can be used to explain algebra in a better way [19].

Issues of data privacy became a priority [20], as over half of the studies mentioned the fear of students being watched and by algorithmic bias [21]. Rural educators, especially, were concerned about inequity issues in the case of AI tools and access to high-speed internet [22].

On the contrary, a small percentage of the teachers were confident that AI would lessen their workload [23]. Many of them predicted more work to be done learning new systems, checking the outputs of the AI, and balancing AI guidance with sensible judgment of their own [24].

Demographic Difference in Attitudes

Teachers with low experience were more likely to adopt AI, but they could not develop pedagogical integration abilities. Veterans demonstrated more skepticism, but were much more able to apply AI to their own philosophies of teaching [25].

Teachers working in East Asian systems (e.g., South Korea, China) prioritized the contribution of AI in preparation to competitive tests, whereas Nordic teachers paid more attention to equity and student well-being [26].

There are a number of studies that used UTAUT directly to understand the AI adoption behavior. These research works had a focus on such constructs as performance expectancy, effort expectancy, social influence, and facilitating conditions. Teachers who had the attitude that perceived AI tools as something favoring student outcomes, and at the same time easy to use adopted AI tools more. Nevertheless, the absence of institutional support and peer support minimized adoption rates especially in the low-resource settings [27-29].

Meanwhile, the SAMR model assisted in classifying the method of AI tools execution among instructors. At the level of substitution, teachers manipulated AI to take the form of automated assessment and drill practice. At the level of augmentation, adaptive learning systems produced feedback [30, 31]. Far fewer cases went to the levels of modification and redefinition- when AI was used to change fundamental practices of instruction or enable new modalities of student interaction- which were often caused by deficient confidence or training. This evidence indicates a superficial application of AI that restrains its potential of transformation.

Table 2: Frequency of Reported Teacher Perceptions Across Studies.

Theme	Number of Studies (n=52)	Percentage
Belief in AI's potential to personalize learning	41	78%
Use of AI for reducing assessment workload	32	62%
Concern about AI promoting shallow thinking	29	56%
Ethical concerns (privacy, algorithmic bias)	27	52%
Anxiety about professional redundancy	19	37%
Expectation of increased workload	13	25%

Professional Development Needs and Readiness Gaps: A Multidimensional Challenge

Technological Pedagogical Content Knowledge (TPACK) Gaps: The AI-Math Pedagogical Gap

The review revealed that there were deep deficits in the capacity of the teachers to engage in effective synthesis of the AI technologies and the mathematics pedagogy in the framework of the TPACK model introduced [32]. Such shortcomings would be reflected in three essential domains:

Inefficacy of Tool Selection: In thirteen out of sixteen studies analyzed, educators could not use AI tools strategically, as they could not select them according to mathematical concepts and standards [33]. Indicatively, even though they knew that Desmos was useful to visualize functions, only few could use its AI-based adaptive feedback capabilities to learn more concepts. In the same vein, teachers often accessed GeoGebra as a static geometry program with little use of the AI dynamic proof features [34].

Difficulties with Data Interpretation: Bom and analytics that were created by AI (e.g., learning dashboards that predict misconception patterns in students) were underutilized. Most of the observed cases where teachers had access to real-time performance data, yet they lacked exposure to instruction on how to support the following: 1) algorithmic recommendations referring to the human ability to pedagogical judgment; 2) false positives concerning error detection; and 3) machine-generated insights into differentiated instructional techniques [35, 36].

Binary implementation patterns: A potential nightmare of binary implementation patterns was witnessed with teachers adhering to either low-level remedial purposes (automated drill practice) or high-ability enrichment (challenge problems) and overlooking the opportunity to make implementation considerations more holistic. That was especially evident in learning algebra, where the potential of AI to model the different strategies of trying to find a solution was seldom realized [37, 38].

These results support the significance of the TPACK framework not only as a reference but a diagnostic framework. The lack of matching of technological tools with content-specific pedagogy contributes to the necessity of special interventions aimed at building all three components of TPACK, namely technological, pedagogical, and content knowledge, at the same time, instead of addressing them separately [39].

Efficient Professional Development Models: What and Why is Effective

A review of effective training programs provided the identification of three evidence-based factors that significantly preconditioned change in AI adoption:

Discipline-Specific Design: Exclusive mathematics PD (e.g., "Using AI to Teach Fraction Operations") showed 40 percent implementation rates of generic PD training using digital tools [40]. The best programs: 1) Extraordinary sessions on mathematical standards (e.g., Common Core 7. RP.A.2 proportional reasoning), 2) Offered illustrative video cases of AI-aided math lessons, 3) Built in time to get teachers to align the AI functions to their curriculum pacing guides [41, 42].

Experiential Learning Cycles: Styles that use a model of Try-Analyze-Refine had a 2.1x higher retention rate in comparison to lecture-based types. In other words, in the AI-PD system teachers: 1) Co-taught trial lessons with AI tutors, 2) Analyzed the video recordings with the AI-reported interaction heatmaps, 3) Refined their implementation by repeating the micro-teaching sessions [43].

Continuous Coaching: Schools receiving biweekly instructional coaching (on the use of AI) had 2.3 times larger use rates after one year than participants of the single workshop. Successful coaches: 1) Modeled the use of AI think-aloud during lessons, 2) Co-planned AI- and non-AI-based units, and 3) Aided teacher to work out edge cases when AI recommendations disagreed with professional ones [44, 45].

Unmet Needs: The PD Paradox

Two glaring gaps existed between professional development initiatives:

Differentiation of Support Requirements: Early career teachers mainly require: 1) Basic tools of navigation in AI, 2) Protocols of data security, and 3) Classroom management in device-rich settings [46]. In contrast, experienced teachers (15+ years) needed assistance in the following areas: 1) The changeover of current teaching schemes by becoming AI-based, 2) the analysis of the bias in algorithms of the math material, and 3) coaching of the peer teachers into dealing with change resistance [47, 48].

Moreover, along with no direct mention of frameworks such as SAMR or models of technology use, such as UTAUT, a lot of professional development interventions were too focused too tool. Educators had a tough time finding the logic of how they could practically apply AI beyond utility-based functions. Including these models in PD design can support a more explicit flow of ideas and help teachers trace their individual development on the way to becoming transformative users of AI.

Time Poverty Crisis: Most of the teachers cited time as the major obstacle to PD. It took an average teacher 11-14 hours to become competent in basic use of AI, but most districts only spent 03 hours per year on training on tech [49]. Worsening this, most of the PD needed took place off the clock, which led to a measure of inequity to educators who have child-rearing obligations.

These are the dilemmas of implementation according to Systemic Barriers to Implementation: Beyond the Classroom

Institutional Problems: Institutional Infrastructure-Policy Misalignment

Three structural obstacles had always interfered with AI integration:

Resource Shortages: Across various studies, an average number of schools did not: 1) have reliable broadband (particularly in rural districts, 3.2 times more likely to be shortchanged), 2) provide device-to-student ratios of 1:3 or higher, and 3) employ a full-time technical support staff [50-52]. Another Appalachian educator explained how she planned whole lessons based on the classroom that had functioning tablets.

Assessment Misalignment: The formal requirements of standardized testing were at complete odds with AI in 1) Process-over-answer assessment (instead of answer-only tests), 2) Team-based problem-solving and 3) Existence of alternative solution paths. This placed a so-called double bind in which the teacher realized the benefit of AI in the pedagogical process, but they have the pressure to focus on the test-prep strategies [53, 54].

Bureaucratic Inertia: See Temporal Lag for results, but briefly, AI tools can be waiting in long queues, at the mercy of places such as 1) Legal departments (data privacy), 2) budget committees, and 3) alignment of curriculum bands. Another metropolitan subdivision spent 14 months to sanction an AI algebra tutor, at the same time it required it [55, 56].

As seen through the UTAUT lens, a key feature missing in most of the low-performing schools was the facilitating conditions, which were identified as a drastic but very important point [27-29]. In the absence of powerful IT assistance, access to the devices, and coordination at the policy levels, even initially willing teachers described the failure to integrate AI. This was the sharpest in the rural and under-financed schools, where the interest in AI was curbed by the logistical choke point.

Context is Important, and so are Cultural and Equity Concerns

Different problems with implementation were drastically different culturally and socioeconomically:

East vs. West Adoption Patterns: East Asian systems (e.g., Shanghai, Singapore) exhibited a course of philosophically rooted integration as: 1) 3-month pilot phases, 2) Intensive misalignment against national M (s), and 3) Implicit links to Confucian principles of learning. On the other hand, schools in the U.S. had comparatively quicker albeit superficial adoption, in which their tools were frequently employed independently of fundamental instructions [57, 58].

Moreover, comparative SAMR-based analysis implies a significant difference in implementation. Singaporean and Finnish teachers, who work in a well sustained and flexible curricular environment, are better placed to operate at modification or redefinition level whereas most U.S. and the schools in the MENA have to be content with remaining in the substitution level due to more inflexible curricula, insufficient training and limitations of infrastructural facilities. This trend is in accordance with what has been observed in a more general scope regarding the lack of advancement of SAMR usage in the ordinary practice [59].

The Poverty Disparity: Title I schools experienced an exacerbation of potential barriers: 1) 4.1 times increased probability of cost-related challenges, 2) 2.8 times fewer devices per student, 3) 5.6 times greater teacher turnover that inhibited the continuity of PD [60]. The schools also registered increased parental distrust of AI in the education process.

Such differences can be explained and correlated with the Digital Divide Theory that focuses on the unequal access to technology, infrastructure, and digital literacy in urban and rural or under-resourced environments. Moreover, according to the approach of Critical Pedagogy, the asymmetrical application of AI to education preserves the power status quo and can have an exclusionary effect on already disadvantaged students. The application of the theories will not only allow situating the access issues but also the ideological and cultural aspects of AI implementation in mathematics classrooms.

Best Practices in the Offing: Way Forward

Three models demonstrated the potential of sustainable implementation:

Staged Adoption Structures: Teachers who initially experience the therapeutic rather than pedagogical application of AI feel more confident in the field and can then use the technology as a teaching tool [61, 62]. This crawl-walk-run derived 37 percent less resistance as compared to a complete successful rollout.

Teacher-Guided AI Panels: Schools that had educator task forces to: 1) Curate the tools, 2) Create guidelines on how to use them, and 3) Advocate to secure required resources reported 52% satisfaction improvement. These committees were particularly useful as a way of dealing with ethical issues [63, 64].

Policy-Implementation Bridges: Districts that combined the use of AI with 1) Reform of assessment policy, 2) Investment in infrastructure, and 3) Parent education campaign experienced 50 percent less opt-outs and more consistent use. The most successful examples had dealt with AI inclusion as a multi-year systemic transformation instead of the purchase of technology [65].

The trend analysis of the studies considered in the time of 10 years indicates the changing attitude of mathematics teachers to the use of AI. In the previous research (2015-2018), skepticism and doubt dictated the field. The levels of perception showed a shift on optimism with experimental use in 2019-2021. From 2022-2025, there were increasing studies of more shades of opinion with less or more balance between pedagogical potential and structural anxiety.

Practical Implications for Low-Resource and Conflict-Affected Contexts

The results of this review have some unique implications as far as under-resourced and conflict-related environments like refugee camps or low-income areas (including those of Baqa and other sites) are concerned. In this regard, the AI integration plans should focus on low-bandwidth, offline-friendly AI mechanisms (e.g., pre-loaded

adaptive apps or tutoring systems based on SMS) that can bypass infrastructure inadequacy.

About coping with the constant turnover of teachers, which is characteristic of weak environments, micro-modular PD programs should be considered. As an example, 3-hour asynchronous video-based master-level units on AI-supported strategy on formative feedback in math or using AI dashboard to group learners in remedial settings can be flexible. There must be translation and contextualization linguistically and culturally of these, especially in multilingual people or displaced people. For example, teachers in a Jordanian school in the low-resource village of a camp used a simplified form of Quizalize (an off-line adaptation of the formative quiz tool powered by artificial intelligence). After only two coaching sessions and sharing among peers, more than 60 percent of math teachers used it once a week to diagnose misunderstandings of the students. The flexibility and the lack of heavy technologies needed, as well as the local teachers co-authoring it, made the program successful. (See Table 3 for more detail).

Table 3: To ensure sustainability, PD programs should include three adaptable tracks:

PD Track	Target Audience	Focus
Track A: Starter Kits	Early-career / tech-novice	Tool navigation, basic AI ethics, and device use
Track B: Curriculum Fit	Mid-career/curriculum leaders	Aligning AI features with math standards
Track C: Peer Leadership	Veteran / PD facilitators	Leading AI integration, mentoring peers

These modules exhibit a high rate of retention and implementation when incorporated in current school schedules, even in stressed contexts. Such efforts can also be extended in conflict-torn territories via alliances with NGOs and donor agencies such as open-source archives and locally rooted mentor systems.

Conclusion

Such a systematic review sheds light into the multifaceted relationships between the potential and practicalities of AI implementation into mathematics teaching. The results highlight the importance of the fact that successful adoption is not possible only with the availability of advanced tools, rather it also implies considering pedagogical issues of the teachers, clear professional development, and support systems of the system. Although the opportunities of utilizing AI to improve personalized instruction and alleviate the administrative overhead are unprecedented, even in live classes, the translation is dependent on the technological sophistication of educators as well as their philosophical compatibility with AI-powered learning and contextual limitations. The review indicates that the most effective methods include teachers as co-designers of the integration process, discipline-specific professional development with a long-term approach to supporting them and the policy frameworks oriented at aligning the assessment methods with innovative educational practices. Synthesis of the AI revolution in the education system, this synthesis proposes a balanced formulation of strategies, which considers both the usage of AI potential and the irreplicable human side of mathematics instruction, especially in terms of fostering deep conceptual learning, creative thinking, and quality teacher-learner relationships.

Moreover, when a lot of the current available literature focuses on technologically advanced settings, this review shows that there are distinct avenues through which the effective strategies of AI integration can be adopted in low-resource and conflict-afflicted settings. AI adoption can be made to fit fragile educational ecosystems through scaled professional development paths, culturally responsive resources, and implementation models led by the teachers. It requires more cooperation internationally and donor-driven infrastructural investments as well as context-sensitive AI policy regimes capable of safeguarding teachers as well as equity to students.

Limitations

Although this review can give thorough insights, a few limitations must be considered. To begin with, the saturation of the literature with research findings in high-income nations (especially the U.S., EU, and East Asia) can restrict the range of applicability of the research outcomes to low-resource learning environments in which infrastructure and culture are vastly distinct. Second, the fast development of AI technologies implies that already some of the considered studies (especially those conducted in the early 2010s) might represent dated tools or ways of real-life application. Third, it is possible that the guidelines contained in the grey literature or industry reports have not received enough attention in the library review because of a focus on peer-reviewed material. Fourth, the qualitative synthesis method, being the provider of maximum contextual insight, does not allow for concluding about the extent of noted effects. Lastly, the unpublished negative results (publication bias) could not be captured in their entirety in the review, and successful implementation cases may be overrepresented. In research, longitudinal research in various contexts should take the lead with the aim of monitoring the changes in perceptions and practices within the teaching profession that may be followed by the development of AI.

Statement and declaration

Conflict of interest

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The data used in this study are available with the manuscript.

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