

Understanding Teachers' Adoption of AI-Based Tools in Special and Inclusive Education: A Systematic Review and UTAUT-Based Integrative Framework

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ABSTRACT:

Artificial intelligence is increasingly used in special and inclusive education, yet teachers do not adopt these tools in the same way or under the same conditions. This systematic literature review examines the factors shaping teachers' adoption of AI-based educational tools through the Unified Theory of Acceptance and Use of Technology (UTAUT). Following PRISMA 2020, 120 Scopus records were screened, 36 full-text studies were assessed, and 28 studies published between 2024 and 2026 were included in the final synthesis. Findings were mapped against performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy emerged as the clearest adoption driver, particularly where AI supported personalization, accessibility, planning, and learner support. Facilitating conditions were also prominent, especially training, infrastructure, technical support, and institutional readiness. Evidence for effort expectancy was mixed, while social influence appeared mainly through leadership, professional norms, and organizational expectations. Three factors repeatedly extended the original UTAUT structure: AI literacy and self-efficacy, trust and ethical assurance, and pedagogical compatibility with professional agency. The review proposes a parsimonious UTAUT-based integrative framework for studying AI adoption in special and inclusive education. The findings suggest that teachers' adoption depends not only on expected benefits and available resources, but also on whether they can understand, trust, and meaningfully control AI within their professional practice.

Keywords: AI literacy, inclusive education, special education, technology acceptance, UTAUT.

1. Introduction

Artificial intelligence is entering special and inclusive education through generative tools, adaptive systems, learning analytics, assistive technologies, and teacher-facing decision support. The possible benefits are easy to see. AI

can reduce preparation time, adapt materials, widen access, and help teachers respond to varied learner needs. Still, adoption remains uneven. Studies repeatedly report positive attitudes alongside limited classroom use, especially where training, infrastructure, policy, or confidence are

weak (Almarzouq et al., 2025; Fteiha et al., 2025; Goldman et al., 2025).

This gap matters more in special education than in many ordinary technology settings. Teachers work with individualized plans, sensitive learner data, and decisions that often require professional judgement. A tool may be useful but still feel unsafe. It may be easy to operate yet poorly matched to a learner. Recent qualitative work shows that teachers often negotiate AI use rather than simply accept or reject it. Fairness, privacy, individualization, and control remain part of the decision (Kim et al., 2026; Marras & Pasqualotto, 2026).

Technology acceptance theory offers a useful way to organize this growing literature. The Unified Theory of Acceptance and Use of Technology (UTAUT) explains adoption through performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). These constructs fit much of the emerging evidence. Teachers ask whether AI improves their work, how difficult it is to use, what others expect, and whether the school provides enough support. Yet AI also raises issues that the original model did not address directly. AI literacy, trust, ethical assurance, and professional control appear repeatedly in special and inclusive education.

Existing reviews of teachers' AI adoption are broader and usually treat educators as one group (Taheri et al., 2025; Tan et al., 2025). The special and inclusive education literature is newer, scattered across different methods, and not consistently grounded in one theory. Some studies use UTAUT or TAM, while others examine readiness, perceptions, barriers, or actual use without a formal acceptance model (Amouri et al., 2025; Fteiha et al., 2025; Zraydi et al., 2026). A focused synthesis is therefore useful.

This review has three objectives. First, it identifies how the four core UTAUT factors appear in research on teachers' adoption of AI in special and inclusive education. Second, it examines recurring influences that cannot be represented well by the original model. Third, it develops a parsimonious UTAUT-based

framework for future empirical testing. The review gives priority to adoption, intention, readiness, use, acceptability, and implementation evidence rather than the technical performance of AI systems alone.

2. Methodology

2.1 Design

A systematic literature review design was used. PRISMA 2020 guided the reporting of identification, screening, retrieval, and inclusion (Page et al., 2021). The synthesis was qualitative and theory guided. A meta-analysis was not attempted because the studies used different populations, technologies, outcomes, and research designs.

2.2 Participants/Sample

The review sample consisted of empirical studies concerning teachers, educators, or pre-service teachers in special or inclusive education. Studies had to examine identifiable AI-based technology and provide evidence on adoption, behavioral intention, readiness, actual use, acceptability, perceptions, or implementation conditions. Studies focused only on students, general educational technology without AI, or technical effectiveness without meaningful teacher-related adoption evidence were excluded.

The refined Scopus search produced 225 records. After limiting results to English-language final journal articles and conference papers, 120 records remained. Title and abstract screening retained 47 reports for retrieval. Thirty-six full texts were obtained and assessed. Eight were excluded at full-text stage, leaving 28 studies in the primary synthesis. Eleven reports could not be retrieved. One detailed research brief was used only as supplementary context and was not counted among the 28 studies.

2.3 Instruments

Three review tools were used: a predefined screening form, a structured extraction matrix, and a design-sensitive appraisal checklist informed by the Mixed Methods Appraisal Tool principles (Hong et al., 2018). The extraction matrix recorded study context, sample, design, AI

technology, theoretical model, adoption outcome, main findings, barriers, and enabling conditions.

2.4 Procedure

Scopus was searched on 18 July 2026. A preliminary broad query returned 558 records and was used to remove obvious search noise. The final query combined four concept blocks: AI technologies, special or inclusive education, teachers or educators, and adoption-related terms. UTAUT and TAM were not required search terms because doing so would have excluded relevant studies that examined adoption without naming a theory. No year restriction was applied.

The final search logic was: TITLE-ABS-KEY(("artificial intelligence" OR "generative AI" OR "AI-based tool*" OR ChatGPT OR "large language model*" OR "intelligent tutoring system*") AND ("special education" OR "special educational need*" OR "inclusive education" OR "learning disabilit*" OR "intellectual disabilit*" OR "developmental disabilit*" OR autis* OR neurodivers*) AND (teacher* OR educator* OR instructor*) AND (adopt* OR accept* OR "behavioral intention" OR readiness OR willingness OR attitude* OR perception* OR "intention to use" OR "technology acceptance"))).

Records were screened against the eligibility rules. Borderline studies were retained for full-text review rather than excluded early. Full texts were sought through publisher pages, repositories, and legally available author copies. The full-text exclusions were: no direct adoption focus (3), population or context mismatch (2), AI not central to the study (2), and intervention-only evidence without meaningful adoption evidence (1).

2.5 Data Analysis

Findings were coded in two stages. First, adoption drivers and barriers were retained in the language used by each study. The second stage mapped those codes to performance expectancy, effort expectancy, social influence, and facilitating conditions. Recurrent factors that did not fit the four constructs cleanly were then compared across studies. The final framework retained only extensions that appeared repeatedly and added clear meaning beyond core UTAUT. Thematic synthesis followed the general logic of Thomas & Harden, (2008).

3. Results

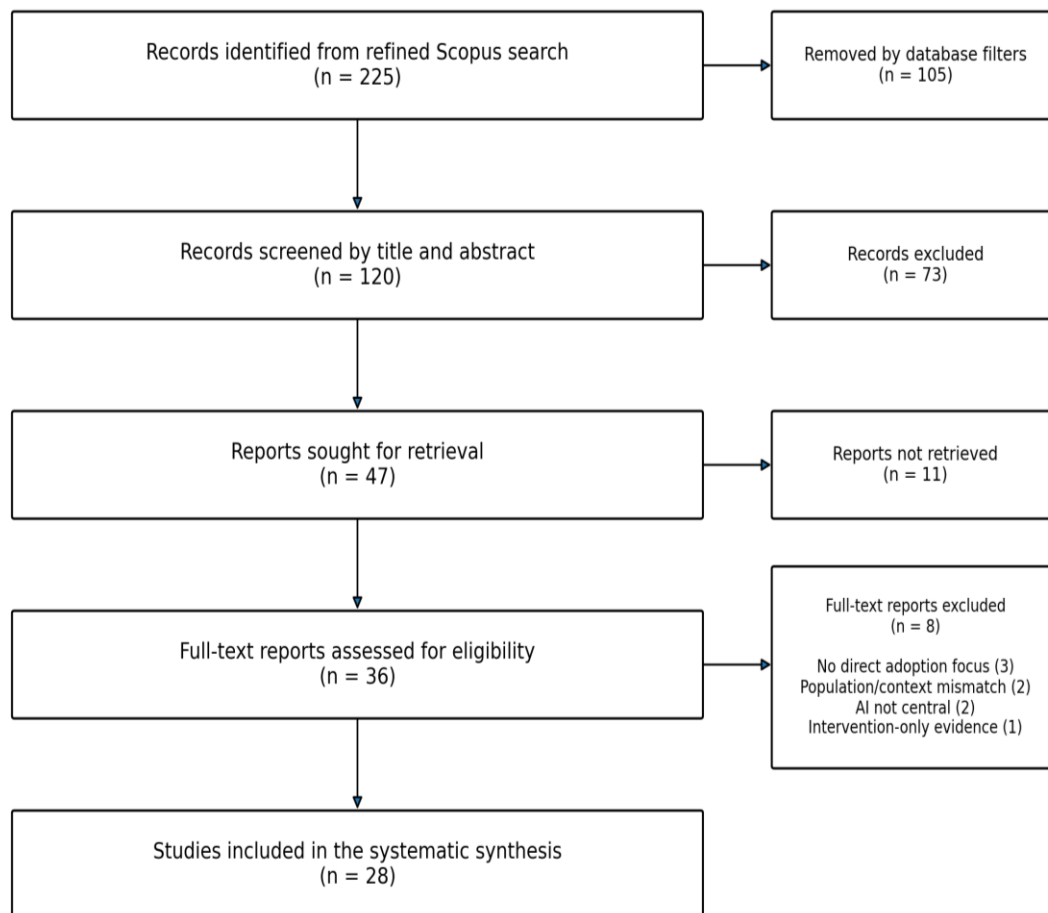
3.1 Study selection and profile

The final synthesis included 28 studies published between 2024 and 2026: two from 2024, eleven from 2025, and fifteen from 2026. Quantitative surveys and model-testing studies were most common. Mixed-method and qualitative studies added evidence on classroom fit, ethics, professional judgement, and institutional conditions. Only a small part of the corpus examined sustained use through experimental or longitudinal designs.

The evidence was geographically diverse but concentrated in the Middle East and Asia. Saudi Arabia, the United Arab Emirates, Kuwait, Jordan, Pakistan, Malaysia, Morocco, Turkey, Nigeria, several European settings, the United States, and online teacher communities were represented. The technologies ranged from general AI applications and generative AI to adaptive platforms, AI-supported learning management systems, learning analytics, and assistive tools.

PRISMA 2020 flow diagram

A preliminary scoping query returned 558 records; the formal refined search returned 225.



One inaccessible journal article had a detailed research brief. It was used only as supplementary context and was not counted in the synthesis.

Figure 1. PRISMA 2020 flow diagram for study identification and selection.

3.2 Direct evidence from acceptance models

The studies that tested acceptance models did not produce one uniform pattern. UTAUT remained useful, but the strength and direction of

individual paths varied by setting. This variation is important because the literature is still at an early stage and many teachers have limited experience with the systems being evaluated.

Study and context	Model	Main adoption finding
Zraydi et al. (2026), UAE teachers supporting students with learning disabilities	UTAUT	Effort expectancy was significant but negative ($\beta = -.29$); social influence was positive ($\beta = .31$). Performance expectancy and facilitating conditions were not significant direct predictors.
Adigun et al. (2025), Nigerian pre-service teachers in inclusive education	UTAUT + technological self-efficacy	Effort expectancy had the strongest positive direct effect ($\beta = .67$). Performance expectancy, social influence, and facilitating conditions also had significant direct paths, but their negative signs reflected low perceived conditions. Self-efficacy has indirect effects for performance expectancy and social influence.

Amouri et al. (2025), Moroccan pre-service teachers	TAM2	Perceived usefulness was the strongest predictor of acceptability, followed by perceived ease of use, voluntariness, and subjective norms.
Gadzhimusieva et al. (2026), special education teachers using an AI-driven LMS	Extended TAM	Perceived usefulness ($\beta = .65$) and perceived ease of use ($\beta = .51$) positively predicted behavioral intention. Ease of use also increased perceived usefulness.
Fteiha et al. (2025), general and special education teachers in the UAE	Readiness model / SEM	Attitudes predicted AI-related practice. Prior AI training strongly strengthened the relationship between knowledge and practice.
Altaikhaineh et al. (2026), Jordan and UAE	UTAUT2 + socio-cognitive perspective	Higher readiness was linked with stronger training, policy support, and institutional conditions. Privacy and insufficient training remained recurring barriers.

Table 1. Direct evidence from UTAUT and related acceptance models.

3.3 UTAUT synthesis across the 28 studies

Performance expectancy was the clearest theme across the wider evidence base. Teachers valued AI when it improved personalization, accessibility, planning efficiency, student engagement, or decision support (Basaruddin & Mustafa, 2026; Li et al., 2024; Wong et al., 2025). In special education, usefulness was rarely only about speed. It was tied to whether the tool helped an individual learner. Studies of ChatGPT-assisted task analysis and AI-supported teacher coaching also showed concrete efficiency and implementation gains (Balikci, 2026; Balikci et al., 2026).

Effort expectancy was important but less stable. Ease of use supported intention in TAM-based work and in the Nigerian UTAUT study, yet the UAE UTAUT study reported a significant negative path. The finding does not mean difficulty causes adoption. It is more likely shows that teachers who seriously consider AI may also recognize the effort required to verify outputs and fit them to learner needs. Across descriptive studies, interface simplicity and usability still mattered (Costescu et al., 2026; Gadzhimusieva et al., 2026).

Social influence was tested directly less often. It was positive in the UAE UTAUT study and appeared through subjective norms in TAM2. Outside formal models, the social environment

was usually described through school leadership, professional communities, and policy expectations. Leadership effects were not always positive, however. Almaki et al. (2025) found negative moderation in several relationships, suggesting that organizational influence depends on how support is experienced rather than its mere presence.

Facilitating conditions were the most persistent implementation issue. Training, infrastructure, technical support, access to approved tools, and clear school policy appeared repeatedly. In Kuwait, lack of infrastructure and insufficient AI training were the highest-rated barriers (Almarzouq et al., 2025). Fteiha et al. (2025) found that prior AI training strongly changed whether knowledge translated into practice. Goldman et al. (2025) also showed that formal technology preparation predicted AI use, while device access alone did not. These findings separate having technology from being ready to use it.

Factor	Synthesis from the review	Role in final framework
Performance expectancy	Strong and consistent. Benefits centered on personalization, accessibility, engagement, efficiency, and instructional support.	Retained as a core UTAUT construct. Accessibility and inclusion value are treated as part of its domain-specific meaning.
Effort expectancy	Relevant but context sensitive. Ease of use usually helped adoption, although one UTAUT study found a negative path.	Retained as a core construct; future studies should distinguish initial learning effort from routine ease of use.
Social influence	Direct evidence was limited. Subjective norms, colleagues, leaders, and policy expectations still shaped adoption.	Retained as a core construct. Leadership influence partly sits here but also overlaps with facilitating conditions.
Facilitating conditions	Very prominent. Training, infrastructure, technical support, resources, and policy clarity repeatedly enabled or blocked use.	Retained as a core construct with a direct enabling role in actual use.
AI literacy and self-efficacy	Knowledge, confidence, preparation, and AI anxiety affected attitudes, readiness, and use.	Added as an extension because internal capability is not the same as external support.
Trust and ethical assurance	Privacy, bias, reliability, safety, and data governance were recurring concerns.	Added as an extension because teachers may reject useful systems they do not trust.
Pedagogical compatibility and professional agency	Teachers wanted AI to fit learner needs and preserve human judgement.	Added as an extension because fit and professional control are central in special and inclusive education.

Table 2. UTAUT-based synthesis of adoption factors.

3.4 Context-specific extensions and final framework

Three extensions were retained after the cross-study synthesis. First, AI literacy and self-efficacy captured the teacher's ability to understand, evaluate, and use AI. Sümer-Dodur (2025) found that AI literacy and AI anxiety shaped pre-service special education teachers' attitudes. Alqarni, (2026) similarly identified confidence as a key influence on willingness to adopt generative AI. These findings are related to facilitating conditions, but they describe an internal capability rather than the external environment.

Second, trust and ethical assurance covered privacy, algorithmic bias, safety, reliability, and data governance. These concerns appeared in mixed-method and qualitative studies across different settings (Altakhaineh et al., 2026; Li et al., 2024). Trust therefore sits beside usefulness. A tool can appear beneficial and still be rejected

when teachers cannot judge its reliability or responsibility is unclear.

Third, pedagogical compatibility and professional agency captured the need for AI to fit the learner, the instructional goal, and the teacher's professional role. Marras & Pasqualotto (2026) found that teachers accepted technology when professional oversight and contextual alignment were preserved. The EMPOWER platform used a similar human-in-the-loop logic, allowing teachers to adapt AI recommendations rather than follow them automatically (Costescu et al., 2026).

Two other recurring themes were absorbed into the core model to keep the framework parsimonious. Accessibility and inclusion value are treated as the special-education meaning of performance expectancy. Leadership and organizational support are treated mainly through facilitating conditions and, where social

expectations are involved, social influence. This avoids expanding UTAUT with factors that substantially duplicate its original constructs.

UTAUT-based integrative framework for teachers' AI adoption

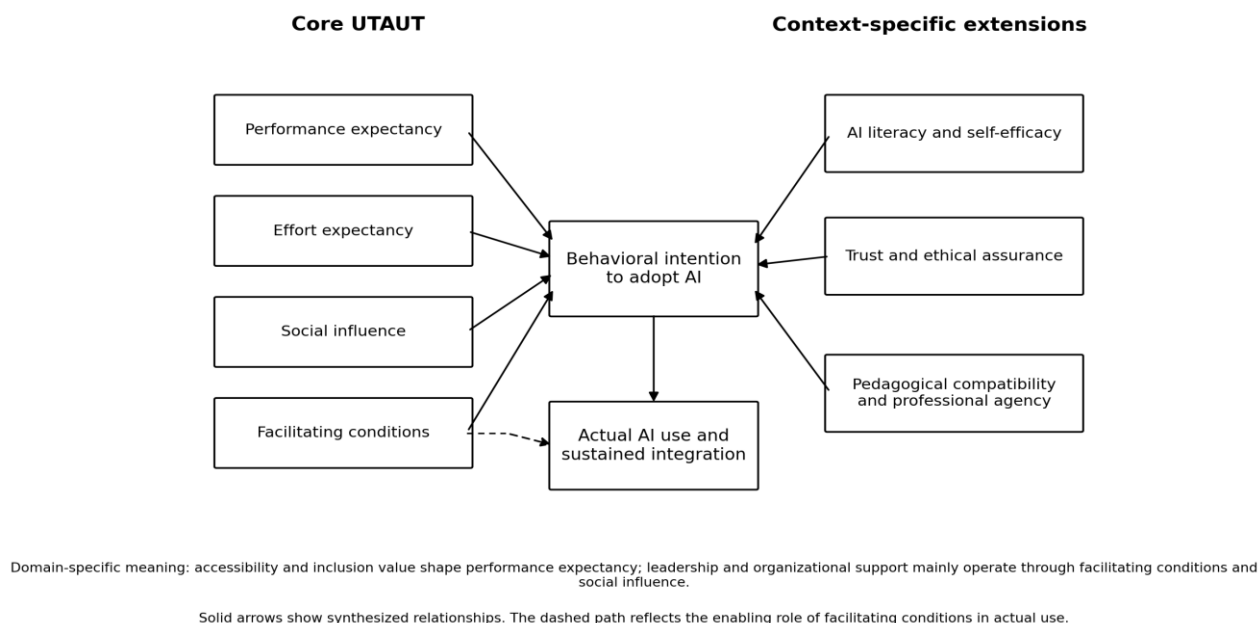


Figure 2. UTAUT-based integrative framework for teachers' adoption of AI in special and inclusive education.

4. Discussion

The review shows that UTAUT still provides a useful backbone for understanding teachers' AI adoption. Performance expectancy and facilitating conditions were especially visible. Teachers need to see a real educational benefit, and schools need to make use possible. This sounds straightforward, but the studies show a repeated gap between the two. Positive attitudes were common, while actual use often remained moderate or low (Almarzouq et al., 2025; Alnaim & Al-Otaibi, 2025; Goldman et al., 2025).

The meaning of performance expectancy is also different in this context. Teachers do not judge AI only by productivity. They ask whether it helps a learner participate, communicate, write, access content, or receive a more individualized response. For that reason, accessibility and inclusion value should be measured explicitly within performance expectancy when UTAUT is applied to special education. A generic usefulness scale may miss this part.

Effort expectancy needs more careful treatment. The mixed findings suggest that early adoption can involve substantial hidden work. Teachers may need to learn prompting, verify generated content, protect student information, and adjust outputs for individual plans. Future studies should separate initial learning effort from routine ease of use. The same AI tool can score differently on those two ideas.

Facilitating conditions look broader than infrastructure alone. Training repeatedly mattered, and in some studies, it changed whether knowledge became actual practice. Clear policy and technical support were also important. Schools therefore should not measure readiness by counting devices. Access without preparation may do little. The evidence from Goldman et al. (2025) is useful here: technology coursework predicted AI use, while one-to-one device access alone did not.

The proposed extensions keep the framework close to UTAUT rather than replacing it. AI

literacy and self-efficacy explain whether teachers can use AI critically. Trust and ethical assurance explain whether they are willing to rely on it. Pedagogical compatibility and professional agency explain whether AI fits professional practice. These factors are especially relevant when teachers work with sensitive data and learners who require individualized support.

For practice, the main implication is simple. Schools should treat AI adoption as a professional development and governance issue, not only software purchase. Teachers need protected time to test tools, realistic training, clear privacy rules, and a way to challenge or override AI outputs. Leadership can help, but support should not become pressure. The mixed leadership evidence suggests that teachers respond better to practical help and autonomy than to adoption targets alone (Almaki et al., 2025).

Policy should also remain cautious about one-size-fits-all AI programs. The evidence base is highly contextual. Readiness differed across countries, school locations, training histories, and professional groups (Altakhaineh et al., 2026; Fteiha et al., 2025; Zraydi et al., 2026). A staged approach is more defensible: pilot the tool, train teachers, examine actual use, and then decide whether wider implementation is justified.

Several limitations should be considered. Scopus was the only formal database, so relevant work indexed elsewhere may have been missed. Eleven reports could not be retrieved in full. Screening and coding were not independently duplicated by

a second reviewer, which increases the possibility of judgement bias. The evidence included is also very recent: all 28 studies were published from 2024 onward, and most relied on cross-sectional or self-report data. The final framework is therefore a synthesis framework, not a validated causal model. Longitudinal studies, usage logs, and multi-country tests are needed before the proposed relationships can be treated as stable.

5. Conclusion

Teachers' adoption of AI in special and inclusive education can be explained largely through UTAUT, but the original model needs some adjustment for this setting. Performance expectancy, effort expectancy, social influence, and facilitating conditions remain relevant. The strongest practical message is that perceived benefit does not guarantee use. Training, infrastructure, policy, and technical support often decide whether intention becomes classroom practice.

Three additions make the model more suitable for AI: AI literacy and self-efficacy, trust and ethical assurance, and pedagogical compatibility and professional agency. Accessibility should be built into the meaning of performance expectancy, while leadership and organizational support can mostly be represented through facilitating conditions and social influence. Future research should test this smaller framework with practicing special education teachers, measure actual AI use rather than intention alone, and compare settings with different levels of institutional support.

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