

Mapping the research landscape of AI-supported professional development for special education teachers in science education: A bibliometric and content analysis

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Abstract

This study maps the global research landscape (2023-2026) regarding artificial intelligence (AI)-supported learning and teacher professional development (TPD) in inclusive science education. Records of any document type were retrieved from Scopus, Web of Science, and ERIC (N = 271) and screened in accordance with the PRISMA 2020 guidelines, resulting in 27 full-text studies that addressed AI, special education, and science/STEM contexts with implications for teacher practice. Descriptive bibliometric indicators (publication year and country) were combined with a thematic content analysis of a structured synthesis matrix covering AI technologies, target populations, and study designs. The results indicate a marked increase in publications (55.6% of the corpus in 2026, a partial year) with geographical contributions from the USA, Indonesia, and Greece. The thematic synthesis of literature has led to the following four themes: (1) teacher competence, AI literacy, and professional development, (2) accessibility, universal design for learning (UDL), and personalization, (3) immersive, multisensory, and robotic AI technologies, and (4) AI assessment, auto-scoring, and learning analytics. In terms of methodology, the corpus comprises systematic reviews and conceptual frameworks (37.0%), quantitative (25.9%), and qualitative research (25.9%), whereas experimental studies are scarce (11.1%). The synthesis suggests that one-off orientation sessions are unlikely to build sustainable classroom integration capacity, whereas experiential TPD models combining 'learner-first' prompt engineering, technological pedagogical content knowledge extended for AI, and UDL principles were associated with higher teaching self-efficacy and instructional adaptation. Multisensory AI environments such as virtual reality and educational robotics were reported to support conceptual learning among students with special educational needs (SEND), particularly those with autism spectrum disorder, although this evidence rests on few studies. Furthermore, the implementation of AI machine learning scoring showed substantial agreement with human scorers in one study (quadratic weighted kappa = 0.72) and may reduce teachers' workload. However, the issues associated with algorithmic bias, web content accessibility guidelines accessibility compliance, and data privacy necessitate that AI be viewed as pedagogical co-mediator not as a substitute for teachers.

Keywords: special education, inclusive science education, artificial intelligence, teacher professional development, bibliometric analysis

Contribution to the literature

- This study is among the first science-education-specific mappings of the literature at the intersection of artificial intelligence (AI), special education, and teacher professional development (TPD), and differs from earlier STEM-wide reviews by explicitly drawing out implications for TPD (27 studies, 2023-2026; Scopus, Web of Science (WoS), and ERIC; PRISMA 2020).
- Methodologically, it combines a descriptive bibliometric profile with a thematic content analysis of a structured synthesis matrix, revealing that the field is concentrated in a few research groups, that experimental evidence is scarce (11.1%), and that the literature falls into four thematic clusters, which are integrated into a framework linking TPD, teacher self-efficacy, student outcomes, and ethical guardrails.
- For practice and policy, it suggests that sustained, experience-based TPD (learner-first prompt engineering, TPACK-AI, and universal design for learning [UDL]) is likely to be more effective than one-off orientation sessions, and that AI should be positioned as a pedagogical co-mediator with teacher-in-the-loop validation, bias audits, and data privacy safeguards rather than as a substitute for teachers.

INTRODUCTION

Science learning inherently requires students to deal with abstract models, multistep processes of problem solving, and intricate visual-spatial models (Buzzi et al., 2025; Kotsari et al., 2026). Students who have disabilities such as autism spectrum disorder (ASD), specific learning disabilities (SLD), impaired vision or hearing, and physical disabilities face a number of challenges when trying to access mainstream science curricula. When working with such learners, an inclusive education system is supposed to apply different approaches that will address the needs of such learners (Florian, 2015). However, special education teachers and science educators find themselves facing a number of challenges. These include excessive paperwork, lack of time for lesson planning, and the shortage of specialized instructional materials (Howorth et al., 2025; Tazi et al., 2026). The rapid proliferation of AI applications, including generative AI (GenAI), large language models (LLMs), adaptive learning analytics, educational robotics, and virtual reality (VR)/augmented reality (AR) platforms, offers considerable potential for redesigning science education in more inclusive ways (Liyanage & Mallawatantri, 2025). These technologies can adjust texts to learners' comprehension levels (Fränkel et al., 2026; Wong et al., 2026), generate multimodal sensory supports (Kotsari et al., 2026; Li et al., 2025), automate formative assessment (Clark et al., 2025; Terrazas-Arellanes et al., 2025), and provide real-time instructional support aligned with students' individualized education programs (IEPs) (Howorth et al., 2025; Roski et al., 2024). In spite of the tremendous technological capabilities of the AI solutions available, their incorporation into special education science classes is very inconsistent (Buzzi et al., 2025; Campado et al., 2023; Tazi et al., 2026). The use of AI solutions in classroom settings still largely depends on the individual initiatives of teachers alone (Pleasant & Morris, 2026). One of the significant bottlenecks that limit effective implementation of AI technologies in special education is associated with TPD. Traditional

approaches to TPD involve orientation seminars or lecture-based seminars that do not consider the peculiarities of the application of educational technology in inclusive science instruction (Estrada Palencia et al., 2025; Sumandya et al., 2026a). They concentrate on the basic functionality of computer programs without addressing such important issues as pedagogical decision-making, which is essential for adaptation of scientific abstractions for special students' needs. Thus, teachers working with disabled children often suffer from high levels of technology-related anxiety, low teaching efficacy, and uncertainty of the way to apply AI technology appropriately. Additionally, although the academic literature on educational AI has grown very fast from 2023 to 2026, there has been no coherent methodology or conceptualization in this body of work. The past studies are mostly split between those involving classroom pilots of the technology, algorithm tests, and policy analyses of general nature. So far, there is a lack of systematic bibliometric and content analysis of the literature that deals with the way AI-enabled TPD is conceptualized, operationalized, and assessed for special education and science instruction. Although a few reviews have addressed AI and STEM education for students with disabilities (Buzzi et al., 2025; Liyanage & Mallawatantri, 2025; Pieriboni et al., 2026), they address STEM broadly and give limited attention to TPD; the present study differs in its science-education focus and its explicit synthesis of implications for TPD. In order to fill this significant gap in the current knowledge, the present research provides a systematic mapping and synthesis of all eligible records (journal articles, conference papers, a book chapter, and preprints) published between 2023 and 2026.

Theoretical Framework

TPACK-AI and universal design for learning inclusive science education

Effective technology integration in special education requires a conceptual framework that balances content

knowledge, pedagogical expertise, and technological capability. This study is grounded in technological pedagogical content knowledge extended for AI (TPACK-AI) (Estrada Palencia et al., 2025) and in Zabala's (2005) student, environment, tasks, and tools (SETT) framework. According to the TPACK-AI framework, in the inclusive science classroom, technology integration is more than just knowing how to work with technology; teachers should have the pedagogical skills to match AI technology with scientific method approaches and disability types (Demir et al., 2026). The SETT framework, on the other hand, helps reinforce this concept by making sure that AI technologies are chosen depending on the evaluation of learning needs of the students, classroom environment and task requirements. Alongside TPACK-AI, UDL is the key framework behind inclusive instructional design (Ay et al., 2015; CAST, 2018; Florian, 2015). According to UDL, there are three essential guidelines that include multiple means of representation (providing scientific content in different formats), multiple means of action and expression (providing different ways for students to prove their scientific knowledge), and multiple means of engagement (building interest, effort, and self-regulation). The emergence of AI technologies allows extending the possibilities of implementing UDL in science classrooms considerably. LLMs and generative tools allow teachers to quickly translate any scientific text into simple stories, diagrams, and images that are tailored specifically to students with ASD or dyslexia (Bilgen et al., 2026; Goyal & Chander, 2026b; Wong et al., 2026) as well as help with executive functions when doing complicated scientific research (Howorth et al., 2025).

In addition, immersive and assistive AI technologies help to implement UDL by breaking down the barriers related to physical, sensory, and communicative access. VR simulators, haptic feedback technologies, and educational robotics enable individuals with autism and motor disabilities to experience scientific concepts like light reflection, chemical reactions, or physical laws in a safe way and via interactive and multisensory channels (Cecil & Gupta, 2024; Kotsari et al., 2026). Meanwhile, screen-reading applications, real-time speech-to-text software, and automatic image descriptions correspond to the guidelines outlined in web content accessibility guidelines (WCAG) 2.1/2.2 and promote equal access of visually and hearing impaired students to educational material (Buzzi et al., 2025; Pieriboni et al., 2026). In this way, the combination of TPACK-AI and UDL makes it clear that AI is used in the context of instruction not as a replacement of special education practices, but as an active driver for universal science curriculum access. Through the combination of TPACK-AI, SETT, and UDL, instructional designers will be able to create flexible learning experiences which consider the learner

variability while ensuring the cognitive depth of science lessons.

Teacher self-efficacy and AI-supported teacher professional development models

In essence, the successful implementation of AI tools as effective inclusive science teaching is fundamentally dependent on teacher agency, efficacy, and competency. Through Bandura's (1997) self-efficacy theory and UNESCO's (2024) AI competency framework for Teachers, this research stresses the importance of teacher confidence in his/her ability to implement AI-enabled instruction as being essential in determining the level of its actual classroom implementation. According to structural equation modeling studies, mere knowledge about technology is not enough to make any significant impact; instead, it is the teaching self-efficacy and digital culture within the institution that act as significant drivers of teachers' use of AI for differentiated teaching (Sumandya et al., 2026c).

In order to develop strong self-efficacy, professional development frameworks need to move away from short and passive workshops to continuous and practical learning spaces (Estrada Palencia et al., 2025; Rizos et al., 2024). Modern TPD systems use partial least squares structural equation modeling (PLS-SEM), artificial neural networks (ANN), and unified theory of acceptance and use of technology to assess how practical training directly affects teachers' attitudes, usefulness, and overall satisfaction (Sumandya et al., 2026a, 2026d). Good TPD frameworks involve practice where teachers design science lessons with AI technology and assess the AI-generated content for its instructional value.

The key factor in modern TPD programs with the support of AI technology is building 'learner-first' prompt engineering skills of the special education teachers (Goyal & Chander, 2026a). Instead of using general AI questions, educators learn to create structured prompts with the explicit inclusion of goals from the IEP plan, principles of UDL, and 5Es (engage, explore, explain, elaborate, evaluate) instruction strategy. With the help of prompt engineering, educators are able to create differentiated science stories, adaptive quizzes, and individual visual prompts effectively. Besides, using AI machine learning scoring (AI-MLS) system for formative assessment decreases grading efforts and provides more opportunities for teachers to spend time with students (Terrazas-Arellanes et al., 2025). Sustainable TPD models need to include strict ethics literacy and data governance requirements (UNESCO, 2021). Teachers should be trained to detect algorithmic biases, protect students from content hallucination, guarantee their data privacy and human control over AI assessments (Islam et al., 2026; Tazi et al., 2026).

Purpose of the Study and Research Questions

The rationale of the current study is to systematically map the growing literature on the issue of integrating AI into science education for special education students and to assess how this literature helps reveal the TPD needs, competencies, and practices in this context. Instead of considering the issues of AI, special education, and STEM teaching as three unrelated topics of research, the focus will be made on the intersection of these three aspects, guided by the assumption that any useful pedagogical guidelines for special education science teachers can only be generated by means of analyzing literature addressing all three aspects at once. In this regard, the study will include bibliometric analysis of the selected literature (temporal and geographic distribution of studies, AI technologies used in studies) along with a qualitative analysis of the literature (thematic grouping of articles, methodology of the selected studies, and empirical findings).

Accordingly, the study is guided by one overarching research question (RQ) and five sub-questions: What does the existing empirical and conceptual literature reveal about how AI is integrated into science instruction for students who receive special education services, and how does this integration inform the professional development needs, competencies, and practices of special education teachers?

1. How is the identified literature distributed across publication years, and what temporal trends characterize the growth of this research area?
2. What is the geographical distribution of the reviewed studies, and how do national research contexts relate to the disability categories and educational levels addressed?
3. Which specific AI technologies are employed across the reviewed studies, and through which mechanisms are they integrated into special education science instruction?
4. Into which thematic clusters can the reviewed literature be organized, and what methodological paradigms characterize research within each cluster?
5. What do the reviewed studies report regarding teacher self-efficacy, student learning outcomes, and ethical or technical risks associated with AI use, and what implications do these findings carry for the design of TPD?

METHOD

Research Design

This research used a two-step approach, which entailed both descriptive bibliometric and qualitative content analysis of the whole corpus of literature (Donthu et al., 2021; Hsieh & Shannon, 2005), on the

PRISMA 2020 reporting guidelines (Page et al., 2021). Bibliometric analysis was used to address the issues of quantification of literature (RQ1 & RQ2) (Zupic & Čater, 2015), while content analysis was used to address issues related to the technological, thematic, methodological, and empirical aspects of the literature (RQ3, RQ4, and RQ5) (Mayring, 2014). The bibliometric component is descriptive (frequency distributions by publication year and country) and does not include co-citation, co-authorship, or keyword co-occurrence analyses.

Data Sources and Search Strategy

Systematic review of the literature was undertaken through a selection of three databases with complementary subject matter coverage such as Scopus, WoS, and ERIC. There were no restrictions on the year of publication or types of documents as it was essential to track the entire evolution of the field starting from its emergence; only works in English were considered. Although no year restriction was applied, all records meeting the eligibility criteria were published between 2023 and 2026.

The following Boolean search string was applied to the title, abstract, and keyword (subject/topic) index of each database: ("artificial intelligence" OR "generative AI" OR "machine learning" OR "large language model*" OR "chatbot*" OR "intelligent tutoring system*" OR "AI-based" OR "AI-powered" OR "AI-driven" OR "AI-enabled" OR "adaptive learning" OR ChatGPT) AND ("special education" OR "special needs" OR "students with disability*" OR "learners with disability*" OR "children with disability*" OR "inclusive education" OR "inclusive classroom*" OR "inclusive school*" OR "learning disability*" OR "intellectual disability*" OR "autism*" OR ADHD OR neurodiversity*" OR "special educational needs" OR SEN OR "exceptional learners" OR exceptionalism*) AND ("science education" OR "science teacher*" OR "science classroom*" OR "STEM education" OR "STEM teacher*" OR "STEM learning" OR "chemistry teacher*" OR "biology teacher*" OR "physics teacher*").

The following three-block design was created to capture, in tandem:

- (a) the existence of AI element, which, in turn, includes a broad spectrum of technologies such as GenAI, machine learning, adaptive systems, and intelligent tutoring systems,
- (b) the interaction with special education within the context of different disability types and inclusive education terminology, not just a specific diagnosis, and
- (c) the science/STEM educational framework, identified through both subject-specific language (science, chemistry, biology, physics) and the broader STEM framework.

The search resulted in 73 entries from Scopus, 68 from WoS, and 130 from ERIC, for a total of 271 entries.

Eligibility Criteria

A study was eligible for inclusion if it

- (a) included empirical, theoretical, or review level engagement with a specific AI technology,
- (b) considered at least one special education population, such as but not limited to ASDs, learning disabilities, intellectual disabilities, attention-deficit hyperactivity disorders, sensory visual or hearing impairment, or other students with special educational needs (SEND),
- (c) engaged with science education or a STEM context which maintained its association with a particular science discipline,
- (d) was published in English language, and
- (e) had direct or indirect implications for teacher practice, teacher competencies, or TPD in this context.

Reviews and conceptual/policy papers which summarized implications for TPD in the field were included regardless of whether any empirical findings were involved or not.

The exclusion criteria were

- (a) studies which focused on STEM education through only math, computer science, and engineering education without any association with a science discipline,
- (b) articles that covered educational technology and ICT integration without any AI component,
- (c) articles not addressing any issue related to special education, disabilities, and inclusive education,
- (d) those which had no relevance to teaching or TPD,
- (e) those which were not written in English, and
- (f) duplicates which were found in multiple databases.

Study Selection Process

The selection process of the studies involved following four steps according to PRISMA 2020 guidelines, identification, screening, eligibility, and inclusion. Out of the total number of 271 identified studies through the three databases, 26 duplicate studies were excluded at the beginning of the screening phase, which resulted in 245 unique records for the screening phase. From this set, 198 records were excluded as not being eligible (the most common reasons for exclusion were not including one of the components, AI, the special education, or the STEM science component), while 47 records were identified as requiring a full-text review. The full texts of 9 records could not be obtained, leaving 38 articles reviewed in their full texts based on the criteria of eligibility. After reviewing the full texts, 11 articles were further excluded, most often because they related to non-science STEM areas, lack of an AI

component, special education population not being targeted, or having no relevance to teachers' professional development. A few retained studies (Asanaka et al., 2025; Islam et al., 2026; Wang et al., 2023; Wong et al., 2026) were situated in engineering or computing contexts, which lie close to exclusion criterion (a). They were retained because they examine AI-supported accessibility and inclusion in broader STEM learning and carry explicit implications for teacher practice. Screening and coding were conducted by the author; to enhance consistency, the coding of the synthesis matrix was repeated after two weeks, and ambiguous cases were resolved through discussion with two. The absence of independent double coding is acknowledged as a limitation. There remain 27 studies which constitute the final corpus and are used in the analyses that follow (see **Figure 1**).

Data Extraction and Coding

For all 27 studies included in the review, the following data were extracted in a structured synthesis matrix: source (author and year), country/research context, research design and methodology, objective, category of disability of interest, AI technology/technologies used, how AI was incorporated into the teaching or assessment process, and the educational level targeted. The matrix is the main unit of analysis of the content analysis part of the study and serves as the basis of the classification in answer to **RQ3** and **RQ4**.

Data Analysis

Bibliometric descriptive statistics, namely frequencies and percentages in years of publication and country of origin, were performed to answer **RQ1** and **RQ2**. For **RQ3**, the AI technologies discussed in the 27 articles were categorized into recurring technology types via inductive methods. For **RQ4**, the studies were sorted into thematic groups based on the comparison of their stated purposes, target population, and methodology; moreover, each thematic group was described based on the dominant designs used therein. For **RQ5**, the empirical findings regarding teacher self-efficacy and professional development, learning outcomes of students, and potential risks associated with ethical and/or technological issues were integrated via a cross-case integrative synthesis approach, which resulted in a structural framework involving teacher, student, assessment, and policy aspects of AI-enabled special education science instruction.

RESULTS

The results are structured based on the five sub-RQs driving the analysis – from the descriptive bibliometric overview of the included 27 papers (**RQ1** & **RQ2**) through to the technological, thematic and

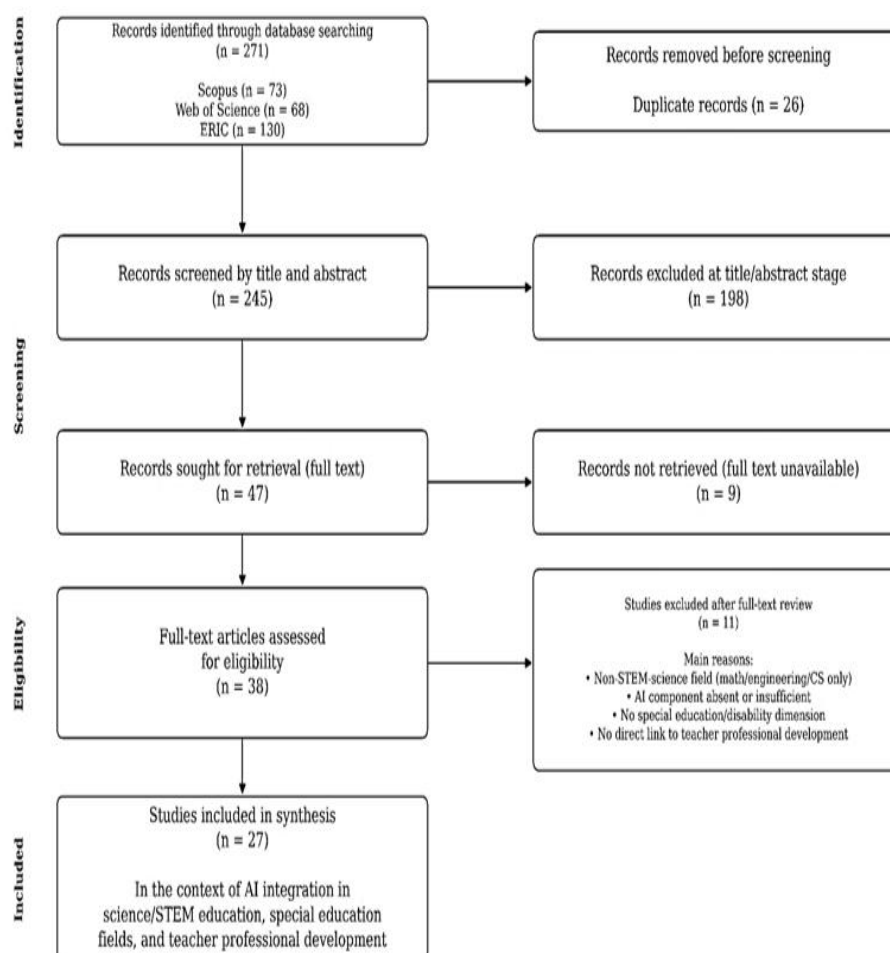


Figure 1. PRISMA 2020 flow diagram (created by the authors based on data)

Table 1. Distribution of reviewed studies by publication year

PY	n	P (%)	Representative sources
2023	1	3.7	Wang et al. (2023)
2024	3	11.1	Cecil and Gupta (2024); Kotsari and Smyrniou (2024); Roski et al. (2024)
2025	8	29.6	Asanaka et al. (2025); Begel et al. (2025); Clark et al. (2025); Estrada Palencia et al. (2025); Howorth et al. (2025); Li et al. (2025); Liyanage and Mallawatantri (2025); Terrazas-Arellanes et al. (2025)
2026	15	55.6	Fränkel et al. (2026); Goyal and Chander (2026a, 2026b); Islam et al. (2026); Kotsari et al. (2026); Milakis et al. (2026); Pieriboni et al. (2026); Pleasants and Morris (2026); Quan et al. (2026); Sumandya et al. (2026a, 2026b, 2026c, 2026d); Tazi et al. (2026); Wong et al. (2026)
Total	27	100	

Note. PY: Publication year; P: Percentage; Data for 2026 are incomplete (search conducted in August 2026); the 2026 share should therefore be interpreted with caution; Percentages are calculated relative to the total number of included studies (N = 27)

methodological features of the corpus (**RQ3 & RQ4**), to the empirical, ethical and professional development implications derived from the corpus (**RQ5**).

Temporal Distribution of the Reviewed Literature

An analysis of the distribution of the publication years shows that there is an unmistakable trend towards increasingly active scientific exploration of the field of intersection between AI and special education science/STEM instruction.

As illustrated in **Table 1**, just one paper (3.7%) was found for the year 2023, while three papers (11.1%) were published in 2024, eight papers (29.6%) in 2025 and

fifteen papers (55.6%) in 2026 (a partial year at the time of the search), which constitutes the majority of the corpus (see **Table 1** and **Figure 2**).

Bibliometric and Geographical Profile

Geographical spread of the analyzed literature reveals a clear predominance of scientific work in the USA, which is represented by 11 out of 27 articles (40.7%). The work carried out in the USA is especially focused on assessment algorithms of AI, VR systems, haptic reality systems, accessibility standards, and neurodiversity support in higher education institutions.

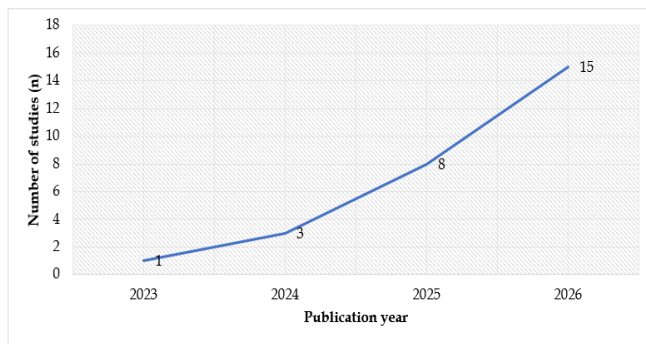


Figure 2. Temporal trend of reviewed publications (2023-2026) (created by the authors based on data)

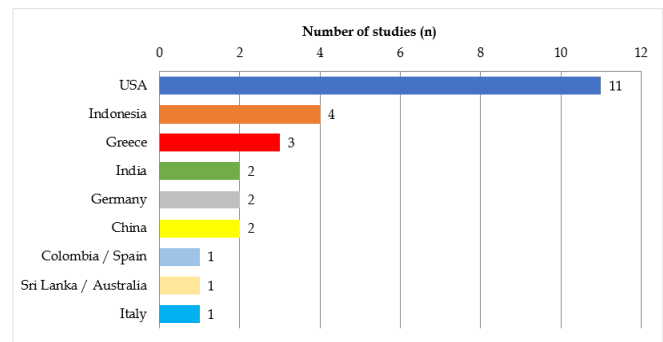


Figure 3. Geographical distribution of reviewed research studies by country (created by the authors based on data)

Table 2. Geographical distribution of reviewed studies

Country/region	n	P (%)	Core research focus and representative authors
USA	11	40.7	AI assessment algorithms, VR/haptic systems, accessibility standards, and higher-education neurodiversity support (Asanaka, Begel, Cecil, Clark, Howorth, Islam, Pleasants, Tazi, Terrazas-Arellanes, Wang, Wong)
Indonesia	4	14.8	PLS-SEM structural modeling of teacher AI competencies, self-efficacy, and digital culture (Sumandya)
Greece	3	11.1	Educational robotics and VR simulations for autistic learners in STEAM contexts (Kotsari, Smyrniou, Milakis)
India	2	7.4	GenAI prompt engineering, UDL lesson planning, and inclusive science storytelling (Goyal, Chander)
Germany	2	7.4	AIIE framework, machine-learning learning analytics, and systematic science-education reviews (Fränkel, Roski)
China	2	7.4	AI museum accessibility services and virtual science laboratories (Li, Quan)
Colombia/Spain	1	3.7	Systematic review of TPACK and AI in inclusive chemistry teaching (Estrada Palencia)
Sri Lanka/Australia	1	3.7	Unified multimodal AI/LLM framework for SEND STEM education (Liyanage, Mallawatantri)
Italy	1	3.7	ICT and AI accessibility tools for sensory and motor disabilities (Pieriboni)
Total	27	100	

Note. P: Percentage; Studies with multiple national affiliations are listed under the lead author's primary institutional country; percentages are calculated relative to N = 27;

Second largest number of scientific papers is provided by Indonesia, where there are four (14.8%) papers representing a well-grounded methodological approach based on structural models of PLS-SEM of teacher AI competencies, digital culture, and self-efficacy in inclusive schools. Because these four studies appear to originate from the same research group, possible sample overlap cannot be ruled out, and they should not be treated as fully independent evidence where cited as mutually supporting. There are three papers (11.1%) related to educational robotics and VR simulations for autistic people in STEM from Greece. Two papers (7.4%) are provided by India, Germany, and China (see [Table 2](#) and [Figure 3](#)).

In that regard, the field may now be characterized by a handful of research groups working on their ongoing programs, the Indonesian PLS-SEM approach and the Greek robotics/VR approach, for example, rather than by many different independently conducted researches scattered all across the globe. What is more important is the fact that, while the foci of national researches tend to correlate with the disabilities categories and the

education levels that are locally important, American researchers' attention focuses more on neurodiversity in higher education and technology of assessments, and Greek and Italian ones focus more on sensory, motor and autism applications.

Synthesis Matrix of AI Technology Integration

Table 3 outlines the complete synthesis matrix developed from the 27 selected studies, which includes for each study the research context, methodology, purpose, target disability category, the type of AI technology used, how the AI technology was integrated, and the target educational level. The AI technologies identified within the literature corpus can be divided into several repeating categories: GenAI and LLMs (such as ChatGPT, Gemini, GPT-4o, Claude) used mainly for lesson planning, creation of content and story adaptation; assessment and scoring based on machine learning and Bayesian knowledge tracing used to provide quick formative feedback; adaptive learning/intelligent tutoring systems used to personalize content presentation and decrease cognitive

load; and immersive/embodied technologies including robotics, VR and AR, and haptics, used to make science concepts concrete for those who have sensory processing difficulties or attention issues.

Table 3. Synthesis matrix of the 27 reviewed studies

Source	Country	Study type	Purpose	Target disability	AI technology	Integration mode	Education level
Asanaka et al. (2025)	USA	Qualitative/design	Improve STEM content accessibility in engineering courses using ML	Special education/STEM disabilities	ML models; multimodal LLMs	Document layout parsing & math accessibility conversion	Higher Ed/ K-12
Begel et al. (2025)	USA	Qualitative/experiential	Examine instructor experiences teaching AI to neurodiverse learners	Neurodiverse learners/autism	AI curriculum & ML modules	Inclusive AI teaching strategies & instructor PD	Higher education
Cecil and Gupta (2024)	USA	Experimental/single-subject	Evaluate XR and haptic systems on STEM learning for autistic students	ASD	VR; haptic VLE; AI agents	Immersive 3D environments with ABA/UDL haptic prompts	Middle & high school
Clark et al. (2025)	USA	Conceptual review	Review opportunities/risks of AI in large-scale science assessment	Students with disabilities (general)	GenAI; NLP; auto-scoring	Auto item generation, accessible test design & scoring	K-12 assessment
Estrada Palencia et al. (2025)	Colombia/Spain	Systematic review	Analyze AI, inclusive chemistry teaching, and TPACK in TPD	General special needs/LD	GenAI (ChatGPT); analytics; ANN	Lesson planning, TPD modules & teacher-behavior analysis	Basic ed/teacher Ed
Fränkel et al. (2026)	Germany	Systematic review	Evaluate digital media & AI in inclusive science teaching	SEN/LD/ASD	Adaptive tech; AR; AI tools	Linguistic simplification & multisensory learning support	Elementary & middle
Goyal and Chander (2026a)	India	Pre-post quantitative	Examine GenAI lesson-planning impact on pre-service teachers' UDL skills	Children with special needs (CWSN)	GenAI (ChatGPT, Gemini)	Learner-first prompt engineering & 5E lesson adaptation	Pre-service teacher ed
Goyal and Chander (2026b)	India	Qualitative/text analysis	Evaluate pedagogical/cultural quality of GenAI science stories	Visual impairment/SEND	GenAI (Gemini)	Three-tiered prompt engineering	Middle school
Howorth et al. (2025)	USA	Conceptual guide	Guide special education teachers using AI via SETT & UDL frameworks	ASD	Adaptive learning; NLP; AI assistants	Executive-function support & personalized scaffolding	K-12 special education
Islam et al. (2026)	USA/Australia	Conceptual review	Examine AI ethics and algorithmic fairness for neurodiverse talent in STEM	Neurodiversity/ASD/ADHD	Ethical AI frameworks	Bias mitigation & neuroinclusive curriculum design	Higher Education
Kotsari et al. (2026)	Greece	Quasi-experimental/mixed	Measure AI robotics & VR impact on science learning in autistic students	ASD	Edison V3 robots; VR simulations	Multisensory interaction & real-time feedback loops	Elementary special ed.
Kotsari and Smyrniou (2024)	Greece	Theoretical review	Review AI integration in special science education for autism	ASD	ITS; VR; BCI	Individualized instruction & sensory regulation	Primary education
Li et al. (2025)	China	Case study/technical	Investigate AI accessibility services in science museums for disabled visitors	Hearing, visual, intellectual, physical	Speech recognition; GenAI; AR/VR; tactile	Real-time sign-language translation & audio/tactile guides	Informal science/museum
Liyanage and Mallawattantiri (2025)	Sri Lanka/Australia	Systematic review	Propose unified multimodal AI/LLM framework for SEND STEM	SEND/ASD/ADHD	LLMs; adaptive AI; VR/AR	Multimodal input processing & adaptive scaffolding	K-12 STEM
Milakis et al. (2026)	Greece	Qualitative inquiry	Explore teacher perceptions of AI in inclusive STEAM classrooms	Gifted & special needs	Generative AI tools	Differentiated instruction & personalized STEAM tasks	Primary & middle
Pieriboni et al. (2026)	Italy	Systematic review	Review ICT & AI accessibility tools for STEM sensory/motor disabilities	Visual, hearing, cognitive, motor	GenAI; screen readers; OCR	Automated visual description & text simplification	K-12 & higher ed STEM
Pleasant and Morris (2026)	USA	Qualitative inquiry	Examine science teachers' critical perspectives on GenAI	General inclusive classrooms	GenAI (ChatGPT, Claude)	Content generation & critical pedagogical reflection	Teacher ed/ K-12

Table 3 (Continued).

Source	Country	Study type	Purpose	Target disability	AI technology	Integration mode	Education level
Quan et al. (2026)	China/ Malaysia/ UAE	Empirical quantitative	Evaluate validity/fairness of AI virtual labs & assessment algorithms	Diverse learner groups	Virtual labs; AI algorithms	Automated scoring & simulated virtual-lab feedback	Middle school science
Roski et al. (2024)	Germany	Cluster/ Methodological	Propose AI/SE framework linking ML analytics & UDL	Learning, visual, motor disabilities	Machine learning; BKT; analytics	Identifying learning barriers & bias mitigation	K-12 science education
Sumandya et al. (2026a)	Indonesia	Quantitative PLS-SEM	Examine how teachers' experiences and perspectives shape AI integration in STEM learning in inclusive schools	Inclusive-school students (SEND)	Adaptive AI; speech-to-text	Content personalization & lesson adaptation	Primary & middle teachers
Sumandya et al. (2026b)	Indonesia	Quantitative PLS-SEM	Examine teacher AI competencies in inclusive STEM pedagogy	Inclusive-school students	AI literacy tools; adaptive systems	Differentiated STEM teaching aligned with UDL	Primary & middle teachers
Sumandya et al. (2026c)	Indonesia	PLS-SEM & PLS-predict	Investigate teacher AI competence & self-efficacy on teaching capacity	Inclusive-school students	Adaptive quizzes; auto feedback	Cognitive-load reduction & multiple representations	Primary & middle teachers
Sumandya et al. (2026d)	Indonesia	Mixed SEM-ANN hybrid	Model digital culture, AI literacy & self-efficacy on teacher satisfaction	Inclusive-school students	Adaptive STEM tools; ANN	Digital-culture building & personalized learning	Inclusive-school teachers
Tazi et al. (2026)	USA/ Morocco	Conceptual/ policy	Review AISPED applications, teacher perceptions & ethical equity	Students with disabilities	Adaptive platforms; analytics	Predictive analytics & administrative-load reduction	K-12 & higher ed
Terrazas-Arellanes et al. (2025)	USA	Empirical ML assessment	Evaluate AI-MLS for scoring open-ended science assessments	Specific learning disability	Machine learning (AI-MLS); NLP	Rapid, unbiased scoring of performance-based science	Upper elementary (3-5)
Wang et al. (2023)	USA	Experiential/ program report	Report on a virtual CS/ML camp for high-school students with disabilities	Visual, hearing, physical	Python/ML; computer vision; JAWS	Direct AI/ML coding instruction with screen readers	High school
Wong et al. (2026)	USA	RCT/ simulation design	Test accessibility of GenAI UDL-transformed slides for neurodiversity	Dyslexia, ADHD, autism	LLMs (GPT-4o, Claude); RAG	UDL slide transformation & web accessibility	Higher education

Note. LD: Learning disability

A lesser amount of the reviewed papers uses NLP and computer vision technologies to create an accessible environment, for example for sign-language translation, screen reader, and speech-to-text services.

These are the ways that the technologies get incorporated into instruction based on four common functions:

- personalization or differentiation of content using AI's capability to tailor instruction according to individual learner characteristics,
- conversion or augmentation of existing materials (such as slides, documents or museum exhibits) into accessible form via AI,
- multimodal or embodied interactions with the use of AI-powered robotics or immersive technology providing real-life sensory experience of the scientific phenomena, and
- assessment and feedback where AI is involved in scoring or evaluation of students' work.

Notably, in the reviewed studies AI is generally positioned not as a replacement for teachers' judgement but as an instrument to be managed and monitored by teachers.

Thematic Clusters and Methodological Classification

In order to structure the literature above individual studies, the 27 analyzed papers were grouped into four thematic categories, as shown in **Table 4**, **Figure 4** and **Figure 5**. The biggest category, which includes nine studies (33.3% of total), is named teacher competence, AI literacy, and professional development and concerns the analysis of teacher technology acceptance, self-efficacy, and prompt engineering skills, and in terms of methodology is mostly represented by structural equation modeling (PLS-SEM and SEM-ANN) and pre-post quantitative researches involving relatively big groups of teachers. The second category, accessibility, UDL, and personalization (n = 8, 29.6%), mostly based on systematic reviews and random or simulation

Table 4. Thematic cluster breakdown and methodological distribution

Thematic cluster	n (%)	Dominant research methods	Key methodological characteristics
Teacher competence, AI literacy, & professional development	9 (33.3)	PLS-SEM, SEM-ANN, pre-post quantitative, text analysis	Large-sample teacher surveys, structural modeling, and prompt-engineering quality metrics
Accessibility, UDL, & personalization	8 (29.6)	Systematic reviews, RCT/simulation designs, qualitative inquiry	PRISMA-based reviews combined with experimental LLM-based transformations for neurodiversity personas
Immersive, multisensory, & robotic AI Technologies	5 (18.5)	Single-subject design, quasi-experimental, case study	Single-case designs (SCD) or pre-post control-group comparisons with autistic student cohorts
AI assessment, auto-scoring, & learning analytics	5 (18.5)	Machine-learning scoring (AI-MLS), cluster analysis	Algorithmic inter-rater reliability (QWK) and predictive validity on student science responses

Note. Percentages are calculated relative to N = 27 and may not sum exactly to 100% due to rounding

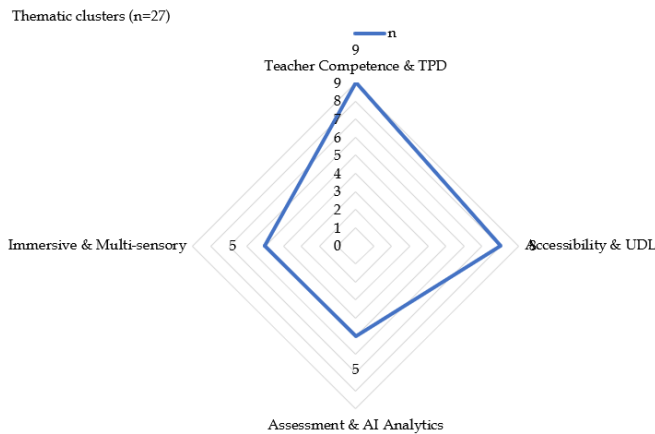


Figure 4. Combined thematic cluster breakdown (created by the authors based on data)

experiments, aims at estimating the ability of AI to change instructional materials, especially slides and documents, using LLMs with respect to certain neurodiversity personas.

The other two clusters are somewhat equal in size and have a more clear-cut focus on student level outcomes. The third cluster, immersive, multisensory, and robotic AI technologies (n = 5, 18.5%) consists mainly of single-subject or quasi-experimental research design, using usually small groups of autistic children and using pre- and post-comparisons or control groups. The fourth cluster, AI assessment, auto-scoring, and learning analytics (n = 5, 18.5%) utilizes machine-learning scoring algorithms and cluster analysis in order to measure the reliability of the algorithms, compared with human expert scoring of students' answers to scientific questions, mainly using quadratic weighted kappa (QWK) statistics.

Besides the thematic clusters, the methodological distribution of the corpus of papers (Figure 5) shows that the evidence base leans towards non-empirical research. There are systematic reviews, theories, frameworks or policies (n = 10, 37.0%), quantitative research including PLS-SEM models and automated scoring algorithms (n = 7, 25.9%) and qualitative research like case studies,

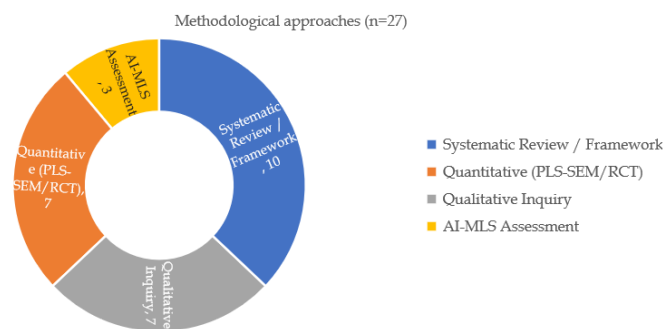


Figure 5. Methodological distribution (created by the authors based on data)

interviews or text analysis (n = 7, 25.9%). Only three papers are experimental, quasi-experimental or simulation-based (11.1%). Taken together, this classification suggests a field that is bifurcated between a teacher-centered, competency-building strand and a more technical, student- and assessment-centered strand, with accessibility and UDL research serving as a partial bridge between the two.

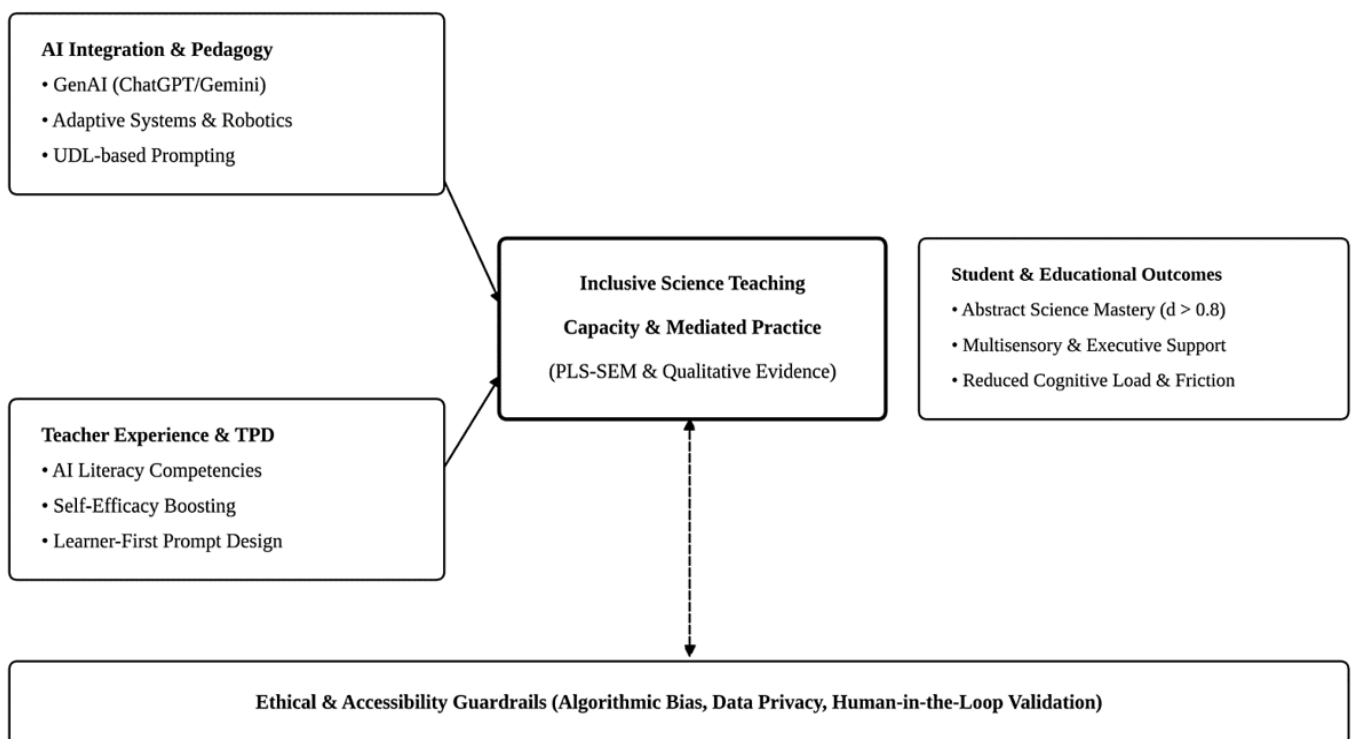
Empirical Findings, Ethical Guardrails, and Implications for Teacher Professional Development

In synthesizing the results of all the 27 studies in the literature review, we can create a structure in relation to four dimensions, including TPD and self-efficacy, student conceptual learning, formative assessment, and policy/ethics, presented in Table 5 and Figure 6.

Regarding the dimension of the teacher, the results of the structural equation model have found out that direct hands-on experience with AI tools and the digital culture of the school are much stronger factors influencing the adoption of AI in inclusive STEM education than just the ease of use with about 45% variance explained by digital culture and previous experience in Indonesian PLS-SEM studies (Sumandya et al., 2026a, 2026b) (possibly overlapping samples). In line with the finding above, structured scaffolded prompt-engineering training with a three-tiered 'learner-first' prompting approach significantly improved pre-service teachers' self-efficacy

Table 5. Structural framework of empirical findings, ethical guardrails, and TPD implications

Dimension	Key empirical findings	Ethical & technical guardrails	Actionable TPD implications
TPD & self-efficacy	Digital culture and prior experience explain 44.9% of variance in AI adoption; three-tiered prompting boosts UDL design skills.	Over-reliance risk; technostress and cognitive overload during training.	Shift TPD from one-off workshops toward sustained, experience-based prompt-engineering and UDL practice.
Student conceptual learning	VR, robotics, and haptic tools show large effect sizes ($d > 0.8$) for abstract science concepts among autistic students.	Sensory-overload risk; digital divide and device-availability constraints.	Incorporate multisensory AI tools into IEP goals with clear sensory-regulation protocols.
Formative assessment	AI-MLS reached substantial agreement (QWK = 0.72; single study) with expert scorers on open-ended science tasks.	Algorithmic bias against non-standard syntax/dialects; privacy leakage.	Use AI auto-scoring as a screening tool with teacher-in-the-loop validation for final grades.
Policy & ethics	Neuroinclusive frameworks require explicit bias audits and transparent data policies.	Lack of clear institutional policies and neurodiversity representation in training data.	Formulate district-level AI ethics guidelines prioritizing neurodiverse representation and data privacy.

**Figure 6.** Structural conceptual framework connecting AI-supported TPD, teacher self-efficacy, ethical guardrails, and inclusive science outcomes (created by the authors)

when designing lessons in alignment with UDL guidelines (Goyal & Chander, 2026a). Together, these findings suggest that professional development interventions built around passive exposure or one-off orientation sessions are unlikely to be sufficient; sustained, hands-on, experience-based training appears to be the more consequential lever.

Regarding the student experience, studies suggest large effect sizes ($d > 0.8$) of AI-supported robotics, VR simulations, and haptic feedback systems in facilitating comprehension of science abstractions among autistic children, like light reflection, density, and refraction, while simultaneously enhancing emotional regulation

and lowering executive function fatigue during learning (Cecil & Gupta, 2024; Kotsari et al., 2026). In the realm of assessments, AI-ML systems used to score students' responses to open-ended science questions at an elementary school level scored QWK of 0.72 with human scorers and allowed the reduction of teachers' grading load and timely provision of formative feedback (Terrazas-Arellanes et al., 2025).

Yet, there are always risks to any form of technological advance. Authors within the literature bring up the issue of algorithmic bias, model hallucination, and data privacy, and emphasize the importance of AI acting as an intermediary between the

student and the instructor and not replacing them (Clark et al., 2025; Islam et al., 2026; Tazi et al., 2026). The risks include sensory overload due to immersive technologies, lack of access due to device accessibility and the digital divide, algorithmic bias regarding non-standardized language and dialects in automated scoring, and generally lack of policy regarding neurodiversity and data privacy in special education with AI. Collectively, these results suggest a number of practical implications for the design of teachers' professional development programs, namely:

- (a) moving from isolated workshops to experience-based training in prompt engineering and lesson design in accordance with UDL principles,
- (b) integrating multi-sensory AI applications into IEPs in addition to sensory regulation procedures,
- (c) viewing AI-powered auto-scoring not as an ultimate verdict but as a means of screening that should be approved by teachers, and
- (d) creating institution-level AI ethics guidelines with neurodiversity and data protection at their forefront.

DISCUSSION

This study mapped the emerging body of research on how AI is being integrated into science education for students receiving special education services, and examined how this literature informs TPD needs, competencies, and practices. According to the findings, research addressing AI integration for SEND in science education, and for the professional development of the teachers who support them, has grown rapidly within the literature. The bibliometric findings clearly show that this field, represented by only a single study in 2023, came to account for 55.6% of the reviewed corpus by 2026. This trend may be linked to the spread of LLMs and GenAI tools after 2022, although the present data cannot establish such a relationship given the small annual counts, the incomplete 2026 data, and the general rise in AI publications. At the same time, this quantitative surge in publications makes it necessary to critically examine the deeper implications of AI for pedagogical quality and accessibility standards in special education science classrooms. Current trends in the literature indicate that research in this area is moving away from a fragmented structure toward a more cohesive, interdisciplinary field centered on special education teachers' professional development needs, AI literacy, and inclusive science teaching skills (Buzzi et al., 2025; Ibragimova et al., 2026; Pieriboni et al., 2026).

Looking at the geographic distribution of the studies, research based in the USA accounts for 40.7% of the corpus and focuses largely on machine learning assessment algorithms, VR and haptic learning systems, and accessibility standards at the higher education level (Asanaka et al., 2025). By contrast, studies conducted in

developing Asian countries such as Indonesia and India have tended to analyze teachers' AI self-efficacy and literacy, along with UDL practices in under-resourced inclusive classrooms, using quantitative modeling approaches such as PLS-SEM (Goyal & Chander, 2026a; Sumandya et al., 2026b). As for European states like Greece, Italy, and Germany, they have been focusing on educational robotics, physical accessibility of museums, and learning analytics approaches, which leads to an interdisciplinary application of the technology (Kotsari & Smyrniou, 2024; Pieriboni et al., 2026; Roski et al., 2024). It shows that integration of AI technologies is determined not only by technological infrastructure of each country, but also by a multidimensional structure depending on the socioeconomic situation and education policy of each state.

Concerning professional development of science teachers working with special needs students and their adoption of AI technology, it has become clear that institutional digital culture and practical experience play a decisive role. Findings obtained through PLS-SEM and ANN show that teachers' direct pedagogical experience and the school's internal digital culture carry far greater explanatory power than perceived ease of use of the technology itself (Sumandya et al., 2026a, 2026d). Traditional professional development models built around theoretical presentations or one-off orientation workshops appear insufficient for building teachers' capacity to integrate AI into their classrooms (Estrada Palencia et al., 2025). Reducing teachers' technostress and turning them into confident, effective practitioners of inclusive science teaching is only achievable through professional development programs that are ongoing, experiential, and grounded in direct classroom trial (Pleasants & Morris, 2026; Sumandya et al., 2026c). This points to the need for teacher education curricula to move beyond theoretical knowledge transfer and evolve toward practice-based AI literacy and critical inquiry skills.

Incorporating GenAI tools and LLMs into lesson planning has facilitated the practical application of UDL principles in special science education. A three-step prompt engineering approach (descriptive, contextual, and inclusive prompts) grounded in a 'learner-first' orientation enables teachers to develop materials that make science concepts more accessible and engaging for students with autism and other special educational needs (Goyal & Chander, 2026a, 2026b). With the help of AI, it is possible to create differentiated lesson scenarios, varied modes of presentation (visual, auditory, simplified text), and inclusive science stories in minutes, relieving teachers of their administrative and curricular burdens (Aldehami, 2022; Howorth et al., 2025; Wong et al., 2026). Indeed, as highlighted by Buzzi et al. (2025), personalized and adaptive learning technologies enhance students' motivation, engagement, and academic success in science. However, the necessity for

the teachers to critically assess the pedagogical validity and inclusiveness of the AI-generated material indicates the indispensability of the principle of 'human-supervised pedagogical design.'

Tangible, interactive, and multisensory AI technologies have produced positive outcomes with large effect sizes, particularly in helping students with ASD make sense of abstract science concepts. Quasi-experimental studies integrating educational robotics (such as the Edison Robot V3.0), EdScratch visual programming blocks, and VR simulations confirm significant gains in autistic students' academic achievement on abstract topics such as light, color, density, and biology (Cecil & Gupta, 2024; Kotsari et al., 2026). These concrete and predictable tools provide a safe learning environment for autistic students with sensory sensitivities, reducing executive function fatigue and supporting emotional regulation (Kotsari & Smyrniou, 2024). Multisensory interactions also spark students' scientific curiosity, encourage peer interaction in the classroom, and strengthen independent learning autonomy (Howorth et al., 2025; Liyanage & Mallawatantri, 2025). These findings demonstrate that in special science education, AI functions not merely as a software tool but as a holistic pedagogical partner that engages in physical and sensory learning channels.

In the context of accessibility and assistive technology, AI represents a strategic turning point in removing learning barriers faced by students with sensory and motor impairments in science and STEM. A five-year systematic review conducted by Pieriboni et al. (2026) documents that ICT and AI play a critical role in designing accessible course materials and adaptive systems within the WCAG framework. For students with visual impairments, tools such as dynamic image descriptions, tactile graphics (Chart4Blind), and voice-based lab assistants are being used, while real-time AI sign language translation and automatic captioning systems are being developed for students who are deaf or hard of hearing (Li et al., 2025; Pieriboni et al., 2026). However, Buzzi et al. (2025) emphasize the important drawback, stating that even though there are automatic descriptions produced by LLMs of complex science pictures, chemical equations, and charts, semantic mistakes and imperfections in such descriptions remain relevant, which means that the established accessibility guidelines are not yet mature enough. It highlights the necessity to use the co-design approach, which will include special education professionals, science teachers, and people with disabilities.

AI-supported assessment and automatic scoring systems hold the potential to fundamentally transform formative assessment processes into inclusive science classrooms. AI-MLS showed substantial agreement (QWK = 0.72 in one study) with expert human raters when evaluating open-ended science responses from students with SLD (Terrazas-Arellanes et al., 2025). Such

automatic scoring systems considerably reduce teachers' assessment workload and time pressure, while giving students immediate, unbiased, and structured feedback (Clark et al., 2025; Quan et al., 2026). That said, using automated assessment systems within standardized test formats that lack reasonable accommodations carries the risk of inaccurately measuring the cognitive processes of students with disabilities (Roski et al., 2024). AI scoring systems should therefore be designed not as independent decision-makers but as a first-pass screening and feedback mechanism that supports teachers' pedagogical judgment, following a 'teacher-in-the-loop' model.

The expanding presence of AI in special science education brings with it serious concerns, and correspondingly necessary safeguards, around data ethics, algorithmic fairness, and student privacy. Because neurodivergent individuals are underrepresented in training datasets, current AI systems and LLMs risk misclassifying atypical language patterns or developmental differences as 'errors' (Islam et al., 2026; Tazi et al., 2026). As underscored in the studies by Pieriboni et al. (2026) and Buzzi et al. (2025), the ethical, privacy, and algorithmic transparency dimensions are frequently overlooked in the process of scaling up accessible technologies, placing the data security of students with special needs at risk. Over-reliance on AI tools may also weaken students' critical thinking, peer collaboration, and problem-solving skills (Milakis et al., 2026; Pleasants & Morris, 2026). To guard against these risks, schools and district authorities need to carry out neurodiversity-focused fairness audits and formally adopt clear ethical guidelines.

A theoretical synthesis of all the reviewed studies suggests that AI should not be positioned as a substitute for the teacher in special science education, but rather as a 'co-mediator' that supports teacher agency. Drawing together social constructivism, Vygotsky's (1978) zone of proximal development, the SETT framework, and TPACK, it becomes clear that AI functions as a cognitive scaffold (Estrada Palencia et al., 2025; Goyal & Chander, 2026a; Howorth et al., 2025). When teachers use AI tools, they are able to carry out complex UDL adaptations and inclusive lesson designs well beyond what they could accomplish independently (Sumandya et al., 2026b). As conceptualized by Kotsari et al. (2026), this interaction forms a 'distributed cognition' model in which human and AI agents work in tandem. Ultimately, the success of AI integration depends less on the technology itself than on the teacher's ability to translate it into the classroom through a humane, ethical, and empathy-driven pedagogical approach.

Despite the valuable insights it offers, this bibliometric and content analysis study is subject to several methodological and structural limitations. To begin with, the review was limited to English-language records indexed in Scopus, WoS, and ERIC; studies

published in other languages or indexed elsewhere may therefore have been missed. Because no restriction was placed on document type, the corpus also includes conference papers, a book chapter, and preprints (Sumandya et al., 2026a; Tazi et al., 2026), which have not necessarily undergone peer review, and their findings should be interpreted with caution. Furthermore, as the set of studies dealing with AI, special education, and science education is in its early development stages, quite a number of empirical samples used self-reported surveys as their source of data. Most AI applications examined involved short-term interventions, and empirical classroom trials tracking the longitudinal durability of learning outcomes remain limited (Cai et al., 2026; Kotsari et al., 2026; Pieriboni et al., 2026). This limitation is reinforced by the methodological distribution of the corpus: only 11.1% of the included studies employed experimental or quasi-experimental designs, so claims about learning gains, including the large effect sizes reported for autistic learners, rest on a small number of studies with limited samples. In addition, consistent with the mapping aim of the review, no formal quality or risk-of-bias appraisal was conducted; the included studies were therefore weighed equally regardless of methodological rigor. Finally, a substantial proportion of the empirical studies included focused specifically on ASD and SLD, which limits the generalizability of the findings to the full range of special education populations, including students with physical, multiple, or severe intellectual disabilities.

CONCLUSION AND RECOMMENDATIONS

This study has provided a comprehensive picture of the global scope, methodological designs, technological trends, and professional development implications of research on AI integration into science teaching within special education. The 27 full-text studies reviewed confirm that, in special education science classrooms, AI functions as far more than a single type of technological innovation; it operates as a multidimensional systemic tool that supports teacher self-efficacy, gives concrete form to UDL principles, and helps neurodivergent students make sense of abstract science concepts. GenAI tools and ‘learner-first’ prompt engineering protocols have visibly strengthened teachers’ capacity to personalize and make lesson content accessible, while tangible technologies such as educational robotics, VR, and haptic systems have produced meaningful gains in autistic students’ academic achievement, curiosity, and classroom participation. The empirical findings further demonstrate that teachers’ adoption of AI tools is shaped not simply by hardware access, but primarily by institutional digital culture, professional experience, and self-efficacy beliefs.

At the same time, this study has clearly surfaced the ethical, technical, and pedagogical risks that accompany the unique opportunities AI offers and that cannot be overlooked. Semantic inaccuracies in the description of complex science visuals, graphs, and formulas (Buzzi et al., 2025; Pieriboni et al., 2026), together with algorithmic bias in training datasets and breaches of data privacy, stand out as key factors that could threaten equity in inclusive education. Sustainable success can only be achieved when AI systems are designed not to replace the teacher but as a ‘distributed cognition partner’ that supports the teacher’s pedagogical guidance, human interaction, and ethical oversight. In sum, this study shows that AI-driven transformation in special science education can serve an equitable and inclusive future for all students only when it is supported by teacher-centered professional development policies, ethical oversight mechanisms, and interdisciplinary collaboration.

Ministries of education and education administrators should shift teacher training and professional development policy away from hardware-focused approaches and toward ongoing, experiential AI literacy programs. Professional development courses for special education science teachers should be restructured to include modules on ‘learner-first’ prompt engineering, UDL-based differentiated lesson planning, AI-supported formative assessment, and ethical data literacy. In addition, schools and education districts should formally adopt neurodiversity-focused ethical use principles and oversight protocols to safeguard the data security of students with atypical developmental profiles and to prevent algorithmic bias. School administrations should encourage peer feedback-based professional learning communities where teachers can safely experiment with AI tools in their classrooms and should ensure equitable access to the necessary hardware.

Future research should move beyond short-term orientation interventions and focus on mixed-methods longitudinal studies that examine the long-term durability of AI-supported inclusive science teaching on students’ cognitive, sensory, and social development. Researchers should also carry out larger-scale trials that include special education populations beyond autism and learning disabilities, such as students with physical, hearing, visual, and multiple disabilities. In technology development processes, co-design models bringing together AI engineers, special education specialists, science educators, and individuals with disabilities should be adopted to develop high-precision, semantically accurate, open-source AI accessibility tools for science formulas and complex diagrams. Finally, there is a need for international comparative research that can reveal the dynamics of AI adoption in special education science classrooms across different cultural and socio-economic contexts.

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Ethical statement: This study is a bibliometric and content analysis study based on publicly available published literature. Therefore, it does not involve any human participants, animals, or sensitive personal data, and consequently does not require any ethical approval.

AI statement: No generative AI or AI-based tools were used in this study.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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