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Digital Education Fronts 2026

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Abstract

As information technology keeps evolving and advancing, digital education has become a core engine driving global educational transformation. The value of digital education keeps rising in reforming teaching organization patterns, broadening access to premium educational resources and reducing the imbalance in educational development. In this context, systematically identifying and dynamically tracking research fronts in digital education helps to precisely grasp new directions for educational development under technological transformation, providing theoretical support for policy-making, academic research, and practical application.

In 2025, the editorial office of *Frontiers of Digital Education* took the lead in setting up a project team on research fronts of digital education and published *Digital Education Fronts 2025*, which has drawn widespread

‡ The details of the project team are shown in Appendix A.

global attention since it was released. In 2026, the project team carries on with this work to maintain continuous tracking. The main process for this year's research includes systematically sorting and selecting global digital education frontiers and critical fronts, accurately interpreting their core connotations, constructing and optimizing a framework for critical front research, and deeply analyzing the intrinsic logical connections and dynamic evolutionary paths among these research fronts.

This report consists of three main sections. Section 1 outlines the research framework, including the methodologies for data retrieval, the mechanisms of cross-institutional collaboration, and the selection procedure of critical research fronts. Section 2 provides an overview of the research situation in the field of digital education. Section 3 focuses on the top 10 critical fronts, with detailed insights supported by empirical cases and trend forecasting. These are interpreted through multiple perspectives, including technological evolution, policy alignment, and emergent ethical challenges. This report aims to offer a timely, reliable and practical reference for the development of global digital education, thereby supporting the academic innovation and practical implementation in this area.

1. Background and Methodological Framework

1.1 Background

Nowadays, technological iteration in digital education continues to accelerate, emerging research topics are constantly appearing, and cross-disciplinary integration trends are becoming increasingly significant. Breakthroughs in large-scale AI models, large-scale application of educational agents, iterative upgrades in immersive teaching experiences, and the accelerated implementation of global digital education policies are collectively driving multi-dimensional and in-depth development in this field. To this end, the project team of digital education fronts continues to track global research developments in digital education, selecting and interpreting critial research fronts in this field, aiming to deliver precise, forward-looking academic perspectives and decision-making references for policymakers, scholars and practitioners engaged in digital education worldwide.

In 2026, adhering to the established research framework, the project team adjusts the research time frame to 2020–2025. It further optimizes the data processing and analytical models to compile a set of continuous and comparable annual research reports on critical fronts in the field of digital education, thereby facilitating the dynamic iteration and ongoing refinement of the knowledge system for research in this area.

1.2 Methodological Framework

This study adopts a mixed-method approach combining quantitative bibliometric analysis and qualitative expert evaluation, aiming to present key research directions in digital education from an objective and comprehensive perspective. The basic research process is: literature retrieval, data analysis, and expert evaluation.

Literature retrieval: Library and information science experts use literature retrieval techniques, combined with keywords, journal lists, conference lists, etc., provided by digital education experts, to develop search formulas, define the research scope, and retrieve papers in the field of digital education.

Data analysis: Co-citation clustering is used to form literature cluster topics, discover critical fronts, and analyze the core papers behind each critical front to obtain characteristics such as development trends and geographical distribution.

Expert evaluation: Critical fronts are gradually selected through methods such as screening, name revision, and expert seminars. At the same time, subject expert nominations and revisions are used to compensate for the lag in published literature data.

Regarding data sources, this study uses the Web of Science™ Core Collection database of Clarivate Analytics as the data source. Based on previous research foundations and expert opinions in the digital education field, the retrieval strategy is further optimized and the search formula adjusted. A systematic search is conducted for global digital education-related literature from 2020 to 2025, retrieving nearly 90,000 papers, effectively ensuring comprehensive retrieval results and laying a solid data foundation for subsequent critical front identification, analysis, and research.

Through detailed analysis of papers published in the global digital education field over the past six years and their citation patterns, the project team identified cutting-edge critical fronts. First, highly cited papers were selected from the nearly 90,000 digital education-related papers retrieved earlier. Then, these selected highly cited papers were matched with highly cited papers in the Essential Science Indicators (ESI) research fronts formed based on co-citation cluster analysis, resulting in 98 ESI research fronts in digital education, identified as research critical fronts in this field. The formation of these critical fronts does not rely on manual classification and labeling of literature but is based on the knowledge network formed by mutual citations among paper authors, focusing on critical fronts and trends in global digital education. On this basis, algorithmic clustering and expert evaluation are further combined to screen out the top ten critical fronts with the greatest influence.

1.3 Selection Process for the Top 10 Critical Fronts in Digital Education

The selection of the Top 10 Critical Fronts in Digital Education is based on a standardized system with multiple rounds of interaction and progressive layering, supported by data and scientific methods. Based on previous research, the research team continuously optimizes the process to enhance its scientific, systematic, and precise nature. The selection process includes three core stages.

1.3.1 Data Retrieval

Based on journal papers in the Science Citation Index Expanded (SCIE) and Social Sciences Citation Index (SSCI) from the Web of Science™ database, as well as conference papers from the Conference Proceedings Citation Index (CPCI), a mapping relationship between the digital education discipline system and Web of Science™ subject categories was constructed to obtain a list of academic journals and conferences in the digital education field. Combined with expert nominations, multiple rounds of review and revision, the search formula was optimized and finalized, ultimately retrieving nearly 90,000 digital education-related papers. On this basis, focusing on the "Education & Educational Research" field, 27,799 papers were obtained, covering 58 research fronts and involving 329 core papers, collectively forming the main research object of this study.

1.3.2 Algorithmic Clustering

Using various algorithmic models such as natural language processing and co-word analysis, in-depth analysis and topic mining were conducted on 329 core papers. Multiple sets of initial topic clusters were generated respectively, and the core papers, high-frequency terms, and cluster strength indicators corresponding to each topic cluster were output. On this basis, experts in the digital education field were organized to systematically identify, compare, analyze, and fuse the output results of different algorithmic models, ultimately determining 15 candidate critical fronts.

1.3.3 Expert Evaluation

Experts in the digital education field were organized to conduct multiple rounds of evaluation of the 15 candidate critical fronts, assessing the academic frontier nature, practical impact, and development trends of each critical front. During the evaluation process, topics with overlapping content or intersecting boundaries were merged, topics that were too finely divided were deduplicated or integrated, and topics with insufficient representativeness were eliminated. After multiple rounds of optimization and adjustment, Digital Education Fronts 2026 were finally determined.

2. Global Research Landscape in Digital Education

The digital transformation of education and the educational application of generative AI (GenAI) are core issues in current global educational development. Research in related digital education fields focuses on areas such as improving the smart literacy of teachers and students, upgrading educational infrastructure, transforming teaching processes, accelerating teaching automation, and exploring teaching laws, profoundly influencing the development of digital education. This chapter systematically reviews global research achievements in the digital education field from 2020 to 2025, presenting a panoramic view of academic hot spots and development trends in this field through multi-dimensional literature analysis, providing a macro perspective for grasping the development direction of digital education research.

Overall, research activity in the digital education field continued to increase from 2020 to 2025, with the annual number of papers showing an overall growth trend, rising from 2,507 papers in 2020 to 5,761 papers in 2025. In terms of category normalized citation impact (CNCI), the overall impact of papers in the digital education field has always been higher than the average for all disciplines. Among them, the CNCI index in this field reached 2.46 in 2023, a periodic high point. Although the CNCI index in 2024 and 2025 declined slightly, it remained significantly higher than the average for all disciplines, reflecting the strong overall impact, prominent frontier nature, and high international recognition of research in the digital education field. Overall, from 2020 to 2025, the scale of research in digital education continued to expand, and the overall quality of papers remained at a high level, showing a trend of simultaneous quantitative and qualitative growth (see Figure 1).

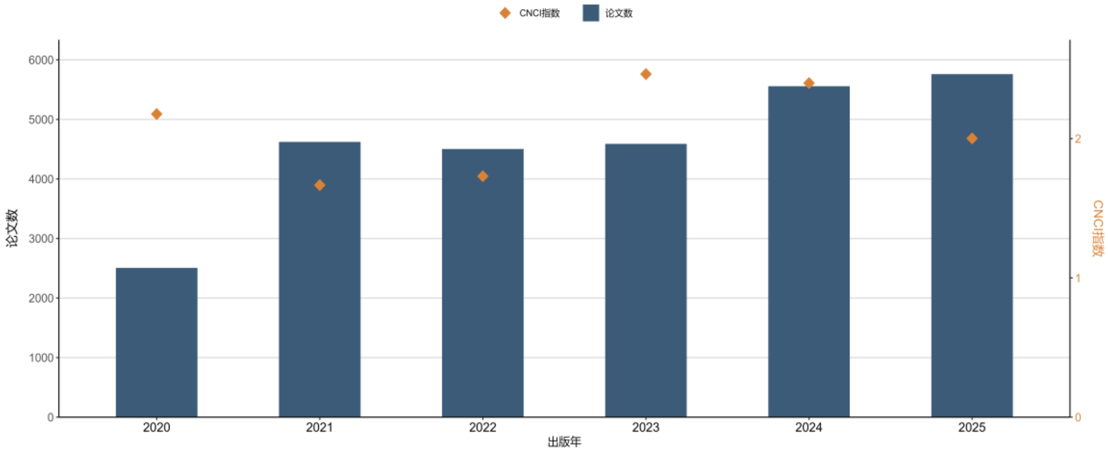

Figure 1 Annual number of papers and CNCI index in the field of digital education (2020–2025).

High-impact papers refer to papers ranked in the top 10% by citation frequency within a specific discipline, year, and document type. From 2020 to 2025, the proportion of high-impact papers in the digital education field generally showed a declining trend. In 2020, the proportion of high-impact papers reached a periodic high of 31.1%, showing strong research leadership. From 2021 to 2024, the proportion remained relatively stable. It declined to 15.9% in 2025. This trend indicates that while the overall research output in the digital education field has expanded in recent years, further efforts are still needed to cultivate high-level, breakthrough research results (see Figure 2).

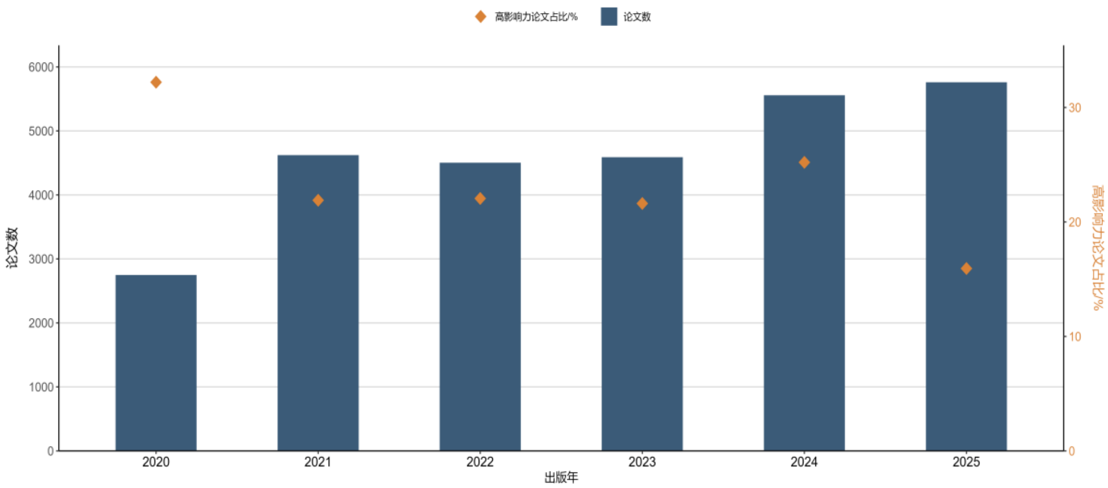

Figure 2 Annual number of papers and precentage of high-impact papers in digital education (2020–2025).

Internationally collaborative papers are an important indicator of the degree of international cooperation in academic research, reflecting the level of participation in international academic exchange and the international influence of research. From 2020 to 2025, the proportion of internationally collaborative papers in the digital education field generally showed an upward trend, rising from 19.7% in 2020 to 23.8% in 2025. Since 2023, the proportion of internationally collaborative papers has remained above 21%, indicating increasingly close transnational academic ties in digital education. Overall, with the continuous growth in the number of internationally collaborative papers, the level of international cooperation in digital education research has also steadily improved, and the trend towards internationalization is becoming increasingly evident (see Figure 3).

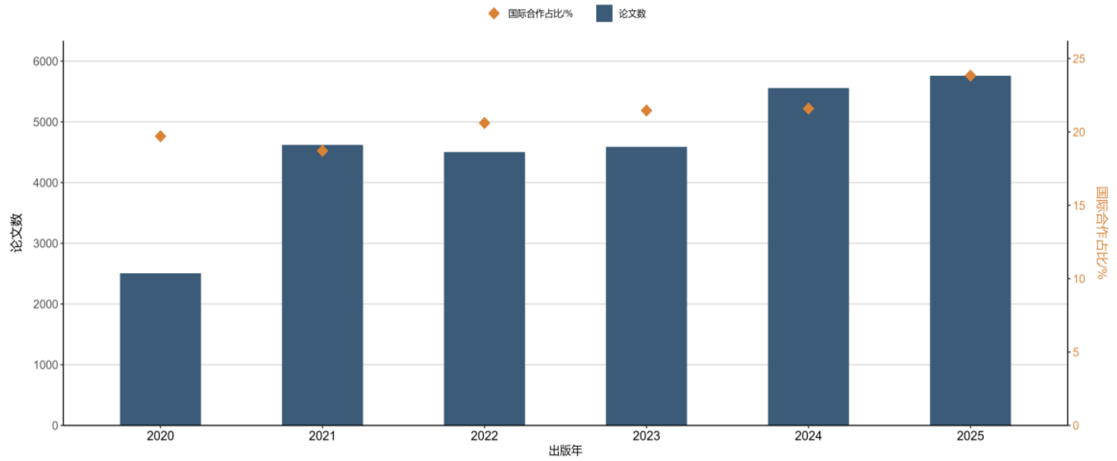

Figure 3 Annual number of papers and precentage of international collaborations in digital education (2020–2025).

In terms of the number of publications and paper impact of various countries, from 2020 to 2025, the impact of papers from most countries was higher than the average for all disciplines. Among them, China and the USA held a leading position in the number of publications, with 5,137 and 4,977 papers respectively, significantly higher than other countries; the UK ranked third globally with 3,493 papers. Chinese scholars demonstrated strong comprehensive strength in both the quantity and quality of papers, ranking first in both the number of publications and the CNCI index. Australia ranked second in CNCI index with 3.22, and the UK ranked third with 2.65, indicating their strong academic influence (see Figure 4).

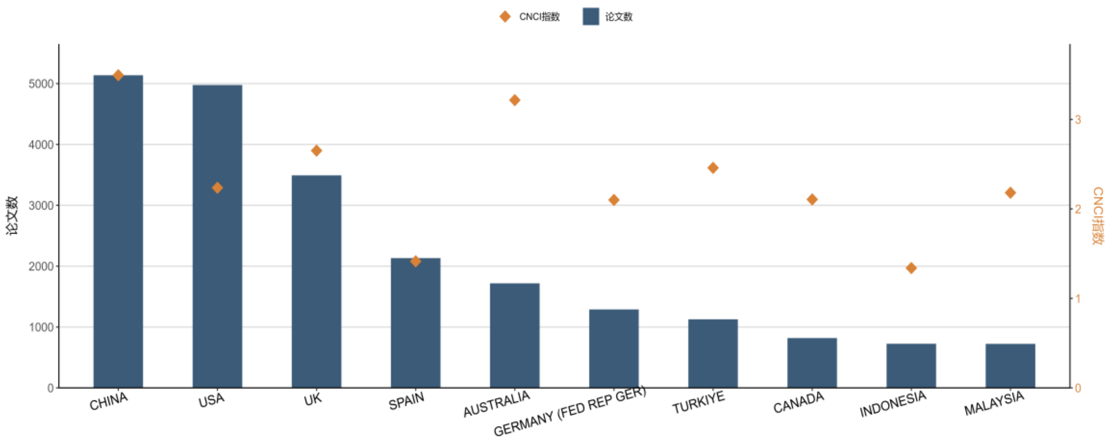

Figure 4 Top 10 countries by number of papers in digital education and their CNCI indexes (2020–2025).

In terms of the proportion of high-impact papers, there are obvious differences among major publishing countries in the digital education field from 2020 to 2025. China ranked first among the top ten countries with 35.8% high-impact papers, demonstrating strong high-level output capacity. Australia had 32.1% high-impact papers, and the UK had 27.6%, both showing high research leadership (see Figure 5).

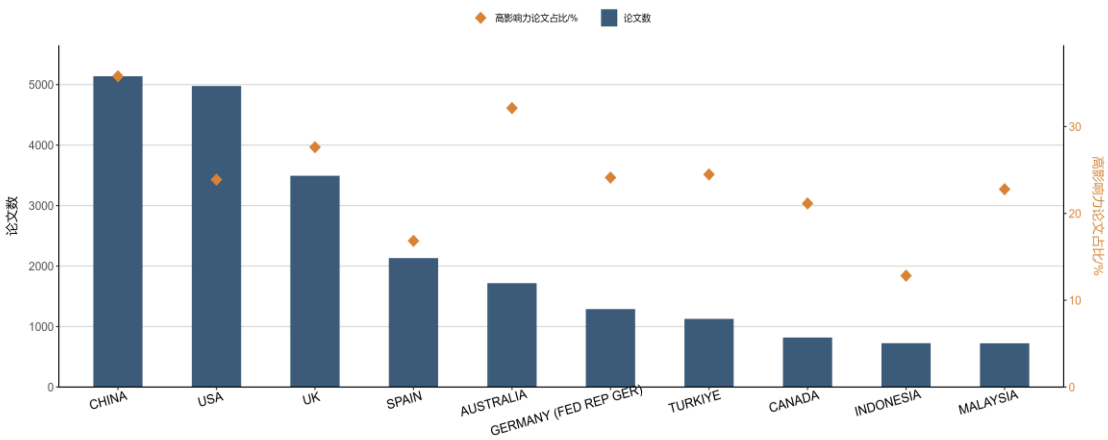

Figure 5 Top 10 countries by number of papers in digital education and their precentages of high-impact papers (2020–2025).

Regarding internationally collaborative papers, the overall level of international collaboration among major publishing countries in the digital education field from 2020 to 2025 was relatively high, but there were obvious differences between countries. The UK ranked first with 51.6% of its papers being internationally collaborative. Malaysia and Australia followed with 50.1% and 45.8%, respectively. In contrast, although China and the USA ranked high in the number of publications, their potential for international collaboration still needs to be explored (see Figure 6).

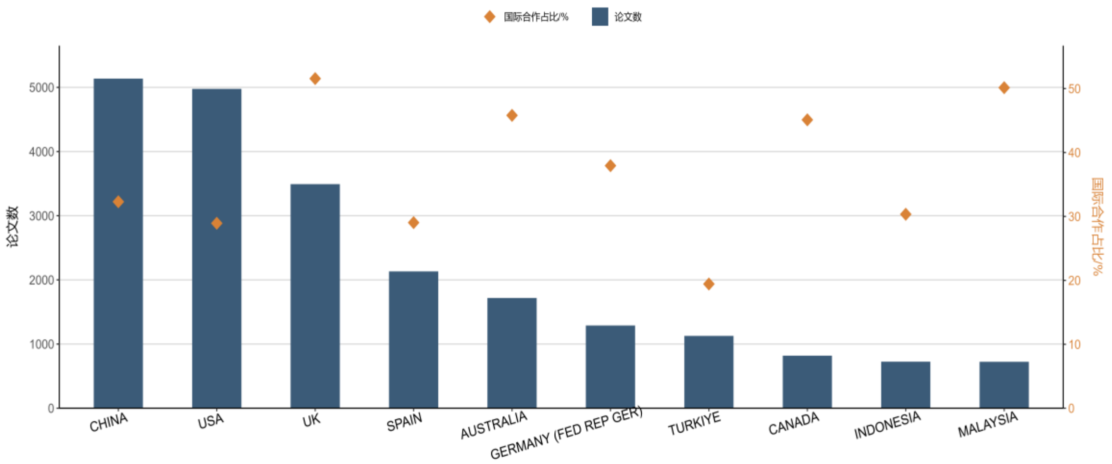

Figure 6 Top 10 countries by number of papers in digital education and their precentages of international collaborations (2020–2025).

From 2020 to 2025, the annual number of papers from the top 10 countries in digital education publications generally showed a growth trend. As shown in Figure 7, the growth trends of different countries can be divided into significant growth and stable growth categories. China and the USA showed significant growth in the number of papers; China's number of papers continued to rise after surpassing the USA in 2023, exceeding 1,300 papers in 2025. The number of papers from the remaining countries generally maintained steady growth, with the UK and Spain showing relatively obvious fluctuations, with annual paper numbers in the range of

400–600. Countries such as Australia, Germany, and Turkey showed more stable numbers, generally below 300 papers per year.

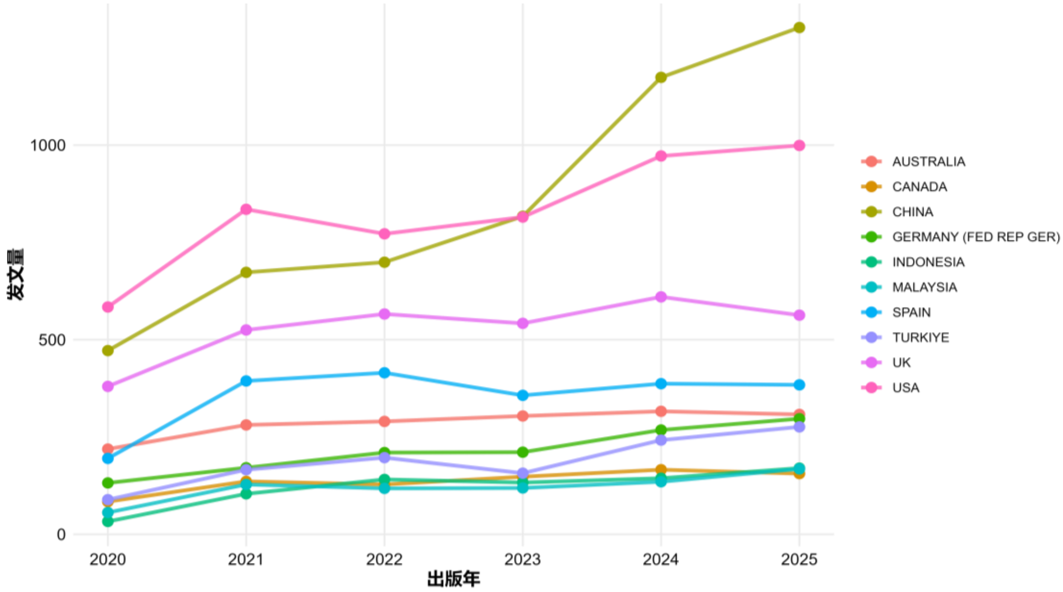

Figure 7 Trend of the annual number of papers from the top 10 countries in digital education (2020–2025)

3. Top 10 Critical Fronts in Digital Education

3.1 Overview

The Top 10 Critical Fronts in Digital Education 2026 are selected based on the number of core papers and citation data from 2020 to 2025. Through clustering of keywords and core terms extracted from abstracts and full texts, high-growth, high-value research directions are identified.

The Top 10 Critical Fronts in Digital Education 2026 include: human–machine collaboration drives smart teaching paradigm shifts, human–machine interaction reveals fundamental logic of learning cognition, risk perception defines scope of digital technology application, teaching competence influences high-quality digital transformation of education, interdisciplinary teachingrealizes in-depth integration of technology and humanities, educational robots become a new cornerstone of smart education, adaptive learning systems accelerate transformation of learning scenarios, collaborative ai governance shapes global educational security, immersive interactive technology reshapes future learning form, self-directed learning ability reflects essential characteristics of digital education (see Table 1). Among these, the number of core papers, total citations, and average citations per paper indicate the level of research activity to a certain extent; the mean publication year reflects the development trend of the research. Table 2 shows the annual publication volume of core papers for each of the 2026 critical fronts.

Table 1 Top 10 critical fronts in digital education 2026

No.	Top 10 fronts in digital education	Number of core papers	Total citations	Average citations per paper	Mean publicat-ion year
1	Human–machine collaboration drives smart teaching paradigm shifts	97	6,208	64.00	2023.8
2	Human–machine interaction reveals fundamental logic of learning cognition	55	3,906	71.02	2024.3
3	Risk perception defines scope of digital technology application	54	4,618	85.52	2024.6
4	Teaching competence influences high-quality digital transformation of education	50	3,646	72.92	2024.2
5	Interdisciplinary teaching realizes in-depth integration of technology and humanities	47	4,057	86.32	2023.7
6	Educational robots become a new cornerstone of smart education	40	2,370	59.25	2023.4
7	Adaptive learning systems accelerate transformation of learning scenarios	32	3,161	98.78	2023.8
8	Collaborative AI governance shapes global educational security	27	1,962	72.67	2024.0
9	Immersive interactive technology reshapes future learning form	21	1,586	75.52	2022.0
10	Self-directed learning ability reflects essential characteristics of digital education	20	1,366	68.30	2023.4

Table 2 Number of core papers published annually on the top 10 critical

No.	Top 10 fronts in digital education	2020	2021	2022	2023	2024	2025
1	Human–machine collaboration drives smart teaching paradigm shifts	3	1	6	15	49	23
2	Human–machine interaction reveals fundamental logic of learning cognition	0	0	0	5	32	18
3	Risk perception defines scope of digital technology application	0	0	0	0	22	32
4	Teaching competence influences high-quality digital transformation of education	1	0	10	22	2	15
5	Interdisciplinary teaching realizes in-depth integration of technology and humanities	2	2	2	6	25	10
6	Educational robots become a new cornerstone of smart education	2	0	6	11	15	6
7	Adaptive learning systems accelerate transformation of learning scenarios	0	3	1	5	12	11
8	Collaborative AI governance shapes global educational security	0	0	0	6	16	5
9	Immersive interactive technology reshapes future learning form	4	4	7	1	4	1
10	Self-directed learning ability reflects essential characteristics of digital education	2	1	2	2	9	4

Core issues from 2025, such as interdisciplinary integration, learning behavior cognition, and ethical governance of digital education, are all continued and deepened in the 2026 critical fronts, confirming the academic leading value of digital education research frontiers. Furthermore, from the perspectives of data characteristics and content focus, the critical fronts have undergone significant changes, reflecting the rapid development of digital education research and highlighting the importance of tracking these critical fronts.

3.1.1 Trends in Data Characteristics of the Critical Fronts

Compared with 2025, the top 10 critical fronts for 2026 show two major changes in data characteristics: First, the distribution of core papers across critical fronts is more balanced, indicating that global digital education research is moving towards a more in-depth and diversified pattern. Second, the annual trend in the number of core papers directly reflects the cutting-edge direction of digital education research. The concentrated explosive growth of core papers for some research critical fronts in the past two years indicates that the critical front selection more accurately captures trends in global digital education research.

3.1.2 Trends in Content Focus of the Critical Fronts

The main changes in the content focus of research critical fronts are manifested in the following three aspects.

First, the core tracks of digital education research remain stable and continue to deepen. Critical fronts from 2025, such as GenAI accelerating interdisciplinary integration, global co-governance redefining ethical boundaries in digital education, and digital education transforming cognition of learning behaviors, correspond respectively to and connect with 2026 critical fronts such as human-AI collaboration initiating a new paradigm shift in smart teaching, AI collaborative governance concerning the global landscape of educational security, and human-computer interaction revealing the deep logic of learning cognition. This reflects the coherence and continuity of the main lines of digital education research, as well as the progressive deepening of research content.

Second, digital education research delves into the discovery of practical patterns and core capacity building, with new critical fronts indicating a shift in research trends. Specifically, research on GenAI adoption risk perception has experienced explosive growth in 2024 and 2025, becoming an important indicator of the rapid diffusion and application of AI technology in education. Second, it is clear that educational robots (whether chatbots or physical robots) have become basic equipment for smart teaching; smart technology has become the intellectual power in education. Third, research on teacher digital literacy has been further refined, emphasizing the key role of teachers' smart teaching competence. Fourth, research on self-regulated learning strategies has been added, emphasizing the importance of learners' agency in the context of technological empowerment. These new critical fronts indicate that AI educational applications have become unstoppable, and research on factors determining the success or failure of applications—such as teachers' and students' attitudes towards AI technology, the accessibility of AI technology, teacher competence, learner self-control, and the patterns of human-AI collaborative teaching and learning—has become the main content of global digital education research.

Third, research critical fronts converge on core tracks, with some sub-areas being integrated and optimized. Among them, research content with specific educational stage characteristics, such as vocational education, has been incorporated into a broader research framework and is no longer listed as an independent critical front, achieving a coordinated upgrade of research perspectives. Research related to the metaverse has been integrated into the research scope of immersive interactive technology reshapes future learning modalities, reflecting the concentration of research resources on core areas and the trend of research content becoming more convergent and focused.

3.2 Top 10 Critical Fronts in Digital Education: Interpretation

3.2.1 Human–Machine Collaboration Drives Smart Teaching Paradigm Shifts

The paradigm shift in smart teaching driven by human–machine collaboration refers to a new model oriented toward cognitive development rather than centered on knowledge transmission. This transformation occurs against the backdrop of GenAI, learning analytics, multimodal perception, and other technologies being continuously integrated into educational contexts. Enabled by in-depth collaboration between teachers and intelligent systems, teaching evolves from the execution of pre-set procedures to a dynamically generated and continuously optimized process through sustained interaction among multiple subjects—teachers, students, and machines. Its essence lies in the systematic reconstruction of teaching relationships, feedback mechanisms, and knowledge construction approaches.

In terms of development trajectory, research progress in this field closely aligns with the process of digital transformation in education. Early studies primarily relied on blended learning, flipped classrooms, and virtual simulation experiments to expand the temporal and spatial boundaries of learning and gradually break the physical constraints of traditional classrooms. With the advancement of learning analytics and adaptive systems, research focus shifted from extending learning spaces to optimizing internal teaching processes, emphasizing data-driven precise intervention and dynamic regulation. Since 2023, the rapid development of GenAI has enabled human–machine collaboration to penetrate core teaching links, driving fundamental changes in teaching content generation, interaction structures, and cognitive support pathways. This marks a transition from technology enhancement to paradigm reconstruction in teaching methodologies. Currently, research in this field centers on the core logic of reconstructing teaching paradigms via human–machine collaboration in the intelligent era, focusing on the following four directions.

First, learning spaces evolve from hybrid spaces to intelligently enhanced scenarios. Existing research indicates that blended learning and flipped classrooms have preliminarily restructured learning time and space, yet they remain essentially a formal integration of online and offline elements. The integration of AI technologies endows learning environments with real-time perception and dynamic response capabilities to learners' states, driving a shift from static learning spaces to intelligently enhanced scenarios. In such contexts, intelligent tutoring systems and adaptive learning platforms dynamically adjust learning paths and teaching scaffolds based on learners' behavioral performance, cognitive load, and emotional states, enabling more accurate personalized learning. This not only significantly boosts learner engagement but also fosters the development of higher-order cognitive skills to a certain extent. However, the adaptability and stability of such systems across complex disciplines and diverse learner groups require further validation.

Secondly, teaching interaction advances from data-driven precision teaching to cognition regulation embedded with precision. The development of learning analytics has facilitated data-driven teaching decisions, yet early studies focused on tracking learning behaviors and predicting learning outcomes, primarily characterizing learning effectiveness through superficial indicators such as task click-through and completion rates. However, this behavior-centric analytical paradigm fails to uncover learners' inherent cognitive mechanisms in knowledge construction, nor can it support in-depth teaching interventions. Thus, research perspectives have shifted from behavioral representation to cognitive interpretation, focusing on key variables such as cognitive load, metacognitive strategies, and learning regulation processes. For instance, some studies integrate self-regulated learning perspectives with learning analytics to explore learners' use of strategies and cognitive regulation mechanisms during task execution. Others combine adaptive learning systems with dynamic scaffolds to support learners in adjusting paths and optimizing strategies. Additional research attempts to integrate multi-source data in intelligent learning environments for refined learning process diagnosis, enabling more targeted teaching interventions. These developments reflect a shift in teaching processes from optimizing models driven by overt behaviors to constructing mechanisms centered on internal cognitive regulation; teaching logic has evolved from operational concerns of what to teach and how to teach to cognitive inquiries into how to facilitate learning behaviors.

Furthermore, knowledge construction transitions from one-way transmission to human–machine co-creation. Human–machine co-creation reshapes knowledge production, with value deriving not only from collaborative outputs but also from the co-creation process itself, which becomes a core learning component. Early studies viewed AI primarily as an auxiliary tool for generating learning resources and providing instant feedback. Enhanced conversational interaction capabilities have enabled AI to participate directly in knowledge construction, evolving into a learning partner with cognitive scaffolding functions. Teaching has thus transformed from a content-centered knowledge transmission model to a dynamically constructed process driven by problem-solving and dialogue. Knowledge acquisition, no longer limited to passive reception, emerges and reorganizes through continuous interaction among teachers, students, and AI. This shift presents new challenges: over-reliance on AI-generated content may impair independent thinking skills, and balancing passive generation with active reasoning has become a core research priority.

Finally, teacher-student relationships evolve from teacher-dominated to shared responsibility between teachers and students. On one hand, teachers' roles have shifted from knowledge transmitters to learning activity designers, data interpreters, and innovation facilitators. In the triadic structure of teachers, students, and machines, teachers are no longer the sole source of knowledge. Instead, they coordinate human–machine interactions through instructional design, implement precise interventions via data interpretation, and foster students' critical thinking and innovation through value guidance. This transformation elevates teachers' professional value in complex learning environments while imposing higher demands on their digital literacy and technology integration capabilities. On the other hand, learners have evolved from passive recipients to active decision-makers, in-depth questioners, and resource co-constructors. A core challenge in this transition lies in the dual dilemma of teachers' willingness to delegate authority and students' ability to assume learning responsibilities. Currently, human–machine collaborative teaching models remain largely teacher-led. Future research must prioritize teacher-student co-governance and even explore learner-led teaching models in specific contexts. Teaching activities will no longer be organized solely by teachers but by multi-subject collaborative paradigms.

The reconstruction of new teaching paradigms through human–machine collaboration yields multifaceted educational significance. First, it supports the cultivation of higher-order thinking and complex problem-solving skills, shifting learning from knowledge acquisition to cognitive development. Second, it creates intelligently enhanced scenarios that enable continuous learning across pre-class, in-class, and post-class stages, transforming teaching from discrete activities to systematic operations. Third, it expands access to high-quality educational resources to a certain extent, offering new pathways for educational equity.

In this research area, the top 3 countries by core paper output are China, the USA, and Iran; the top 3 countries by citations are China, the USA, and the Netherlands; the top 3 countries by average citations per paper are Netherlands, Republic of Korea, and the USA. Among major core paper output countries, China and the USA exhibit the highest international collaboration. Institutions ranking top three in core publications are The University of Hong Kong, Nanjing Normal University, and Education University of Hong Kong; those ranking top three in average citations per paper are Open University of the Netherlands, Wageningen University, and The Hong Kong Baptist University. Among major core-producing institutions, The Chinese University of Hong Kong demonstrates the most extensive collaboration with other institutions. Countries ranking top three in citing core papers are China, the USA, and Türkiye; institutions ranking top 3 in citing core papers are The Education University of Hong Kong, The Chinese University of Hong Kong, and The University of Hong Kong.

Table 3 Major countries producing core papers on human–machine collaboration drives smart teaching paradigm shifts

Order	Country	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	China	52	53.61	5,769	110.94	2024.0
2	USA	11	11.34	1,527	138.82	2023.6
3	Iran	9	9.28	970	107.78	2024.2
4	Republic of Korea	6	6.19	969	161.50	2023.0
4	UK	6	6.19	487	81.17	2024.3
6	Australia	5	5.15	232	46.40	2024.8
7	Netherlands	4	4.12	1,042	260.50	2024.0
7	Germany	4	4.12	384	96.00	2024.5
9	Canada	3	3.09	355	118.33	2024.3
9	Pakistan	3	3.09	173	57.67	2024.7

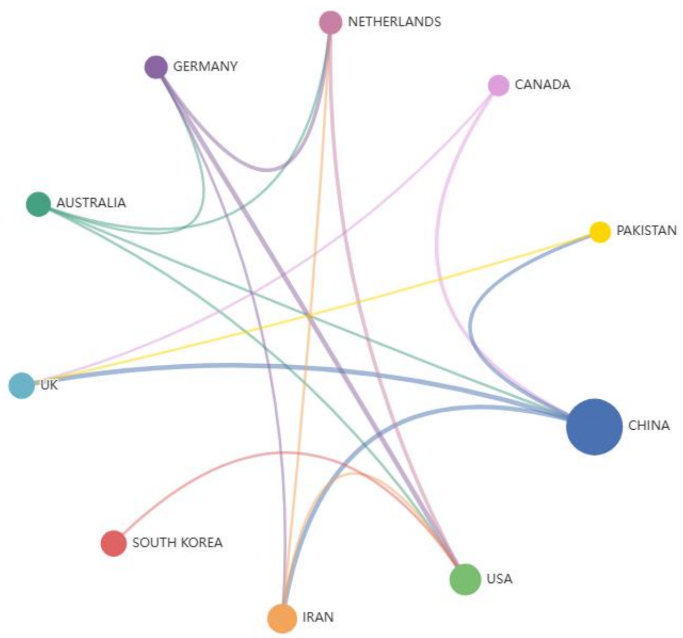

Figure 8 Collaboration network among major countries producing core papers on human–machine collaboration drives smart teaching paradigm shifts

Table 4 Major institutions producing core papers on human–machine collaboration drives smart teaching paradigm shifts

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	The University of Hong Kong	8	8.25	1,413	176.62	2023.2
1	Nanjing Normal University	8	8.25	827	103.38	2023.6
3	The Education University of Hong Kong	6	6.19	841	140.17	2024.2
4	Golestan University	5	5.15	628	125.60	2024.0
4	The Chinese University of Hong Kong	5	5.15	376	75.20	2024.6
6	The Hong Kong Polytechnic University	4	4.12	576	144.00	2023.5
6	Zhejiang University	4	4.12	246	61.50	2024.2
8	Open University Netherlands	3	3.09	860	286.67	2024.7

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
8	Wageningen University and Research	3	3.09	860	286.67	2024.7
8	The Hong Kong Baptist University	3	3.09	725	241.67	2023.7

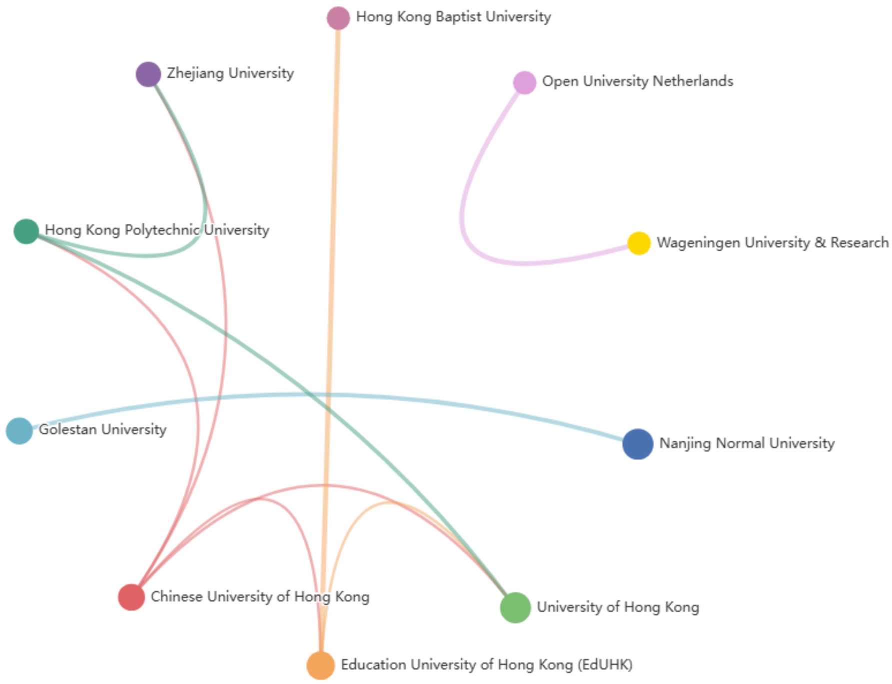

Figure 9 Collaboration network among major institutions producing core papers on human–machine collaboration drives smart teaching paradigm shifts

Table 5 Major countries citing core papers on human–machine collaboration drives smart teaching paradigm shifts

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	China	2,782	36.49	2024.8
2	USA	942	12.35	2024.5
3	Türkiye	405	5.31	2025.0
4	UK	384	5.04	2024.6
5	Spain	361	4.73	2024.1

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
6	Malaysia	340	4.46	2024.6
7	Australia	304	3.99	2024.6
8	Germany	296	3.88	2024.4
9	Saudi Arabia	292	3.83	2024.5
10	Republic of Korea	283	3.71	2024.7

Table 6 Major institutions citing core papers on human–machine collaboration drives smart teaching paradigm shifts

Order	Institution	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	The Education University of Hong Kong	177	2.32	2024.8
2	The Chinese University of Hong Kong	141	1.85	2024.8
3	The University of Hong Kong	136	1.78	2024.4
4	Zhejiang University	99	1.30	2025.0
5	Central China Normal University	95	1.25	2024.5
6	East China Normal University	94	1.23	2024.9
7	Beijing Normal University	92	1.21	2024.8
8	The Hong Kong Polytechnic University	84	1.10	2024.8
9	Nanjing Normal University	70	0.92	2024.5
10	Universiti Sains Malaysia	67	0.88	2024.6

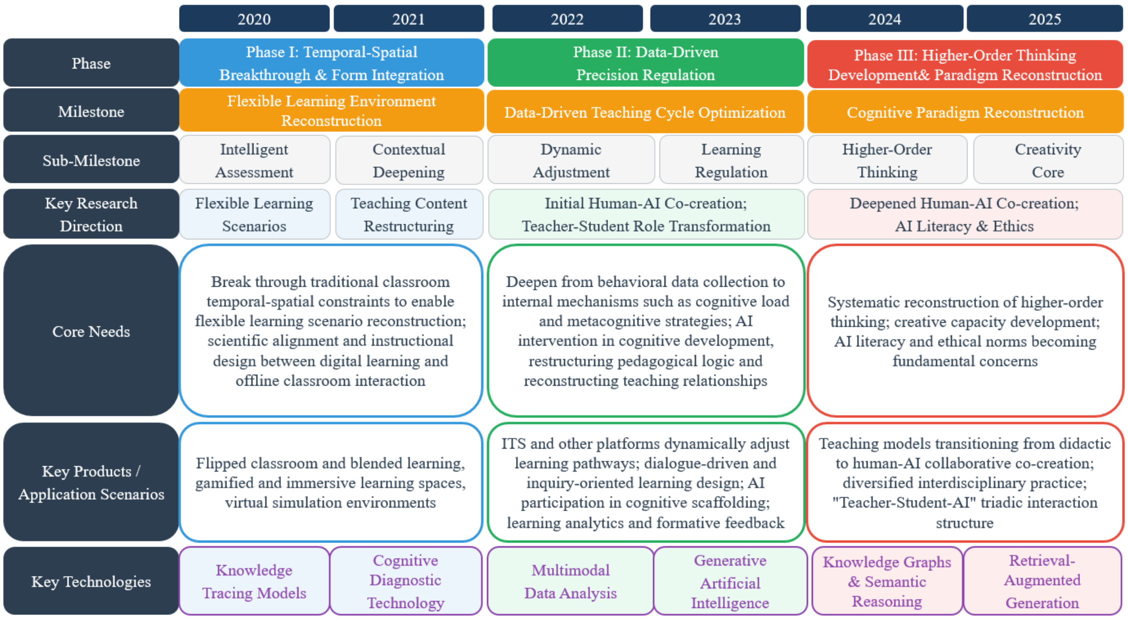

Figure 10 Development roadmap for human–machine collaboration drives smart teaching paradigm shifts

Figure 10 illustrates the development roadmap for human–machine collaboration drives smart teaching paradigm shifts. Before 2020, research on this hotspot focused on scattered technology-assisted exploration, with blended learning and flipped classrooms in preliminary practice. Technology applications were limited to simple online-offline integration, lacking a systematic human–machine collaborative teaching framework.

From 2020 to 2021, research entered a phase of temporal-spatial breakthrough and formal integration. Blended learning, flipped classrooms, and virtual simulation technologies freed traditional classrooms from temporal-spatial constraints, driving flexible reconstruction of learning spaces. The emergence of data analytics and intelligent tutoring systems enabled initial data-driven precision teaching, laying a practical foundation for cognitive regulation.

From 2022 to 2023, research shifted focus to data-driven and cognition regulation. The launch of ChatGPT in late 2022 sparked a wave of educational transformation, deepening research along five dimensions: first, learning spaces evolved from static environments to intelligently enhanced scenarios; second, Intelligent Tutoring Systems (ITS) and adaptive platforms can dynamically adjust learning paths; third, teaching evaluation expanded from collecting behavioral data to analyzing internal mechanisms such as cognitive load and metacognitive strategies; fourth, teaching content took initial shape as human–machine co-creation; fifth, teachers' roles evolved into learning designers and data interpreters. During this period, challenges related to technology integration barriers, ethics, and equity became increasingly prominent.

2024–2025 marks the phase of cognition regulation and paradigm reconstruction, characterized by explosive growth in literature. Research focuses on systematic reconstruction of higher-order thinking, reshaping creativity connotations through human–machine co-creation assessment frameworks, transforming teaching models from rote instruction to collaborative co-creation, diversifying interdisciplinary practical spaces, and advancing AI literacy and ethical norms. Human–machine collaborative teaching has thus transitioned from technology enhancement to paradigm reconstruction.

As paradigm reconstruction accelerates, deeper structural tensions have surfaced. First, there is a risk of eroding cognitive agency. Overreliance on AI-generated content may undermine learners' capacity for independent reasoning. A critical imperative is to guide learners in leveraging intelligent systems while preserving critical thinking, and to strike a balance between passive content generation and active reasoning—both essential for meaningful knowledge construction. Second, there exists a reciprocal tension in teacher–student role transformation. A central challenge concerns teachers' willingness to cede instructional authority and learners' readiness to take ownership of their learning. This dual dilemma of willingness and capability represents a major bottleneck for advancing paradigm reconstruction beyond superficial adjustments.

Future research and practice can progress along three interrelated dimensions. First, advance research on multimodal interaction mechanisms to develop more intuitive, responsive human–machine interaction environments. Second, refine human–machine collaboration frameworks to clarify roles and responsibilities among teachers, students, and intelligent systems, thereby transitioning instructional organization from teacher-centered to multi-agent collaborative models. Third, establish longitudinal, process-oriented assessment systems to monitor the systematic development of higher-order thinking, foster AI literacy and ethical awareness, and build robust institutional safeguards to sustain long-term paradigm transformation.

3.2.2 Human–Machine Interaction Reveals Fundamental Logic of Learning Cognition

Understanding how learning behaviors actually occur has long been a core inquiry in educational science. The continuous evolution of digital environments has created unprecedented research opportunities for exploring this question. As learners interact with digital platforms and intelligent tools, they generate continuous, fine-grained behavioral traces that render cognitive processes observable. This enables researchers to transcend the limitations of traditional laboratory paradigms and systematically examine the inherent mechanisms of learning cognition in authentic educational settings. From early log analyses on online learning platforms, to cognitive process tracking in adaptive systems, and further to the examination of interactions with GenAI, digital technologies have consistently expanded the observational scope of learning cognition research and deepened its theoretical foundations. Research in this field offers threefold value: at the process level, it helps reconstruct the pathways of knowledge construction and deep understanding in real-world tasks; at the mechanism level, it clarifies the boundaries and principles of human–machine cognitive complementarity through systematic comparisons between human teachers and intelligent pedagogical agents;

at the developmental level, it reveals the cumulative effects of prolonged digital tool use on learners' cognitive abilities, motivational structures, and psychological well-being.

Research in this field exhibits clear clustering characteristics. First, research contexts are highly concentrated on language learning, particularly foreign language learners using large language models for language acquisition, writing support, feedback reception, and classroom interaction. Second, theoretical frameworks are relatively unified, with Self-Determination Theory and the Technology Acceptance Model repeatedly employed to explain relationships among AI acceptance, cognitive processes, anxiety, resilience, and other constructs. Third, diverse research methods—observational studies, mixed-methods designs, and real-classroom interventions—are widely adopted, with the research focus shifting from effectiveness testing (by asking "Is the tool effective?") to mechanism identification (by asking "Under what conditions does AI facilitate or hinder learning?").

Driven by advances in big data technologies, digital learning environments have been widely implemented, enabling systematic collection and analysis of learner behavioral traces and providing a solid data foundation for learning cognition research. The emergence of GenAI has further opened new research avenues. On one hand, researchers have developed a heightened awareness of exploring interaction processes, with the question “How exactly does learning cognition unfold in human–machine interaction?” attracting widespread attention and inspiring numerous studies on cognitive mechanisms in AI-mediated contexts. On the other hand, GenAI has significantly lowered the technical barriers to developing digital learning support environments. Researchers no longer rely on complex adaptive system engineering but can rapidly construct controlled experimental settings in authentic teaching contexts. This shift has substantially reduced research costs while greatly enhancing the feasibility and timeliness of investigations.

Current research in this field advances along three key strands. First, micro-level examination of cognitive processing mechanisms in digital interactions. Early studies, drawing on online platform logs and questionnaires, focused on how learning motivation and emotional experiences influence cognitive engagement. In recent years, attention has shifted to specific tasks such as AI-assisted writing and feedback reception, analyzing learning processes under AI support. Second, systematic comparisons of human and machine roles in educational contexts. Following the emergence of GenAI, comparative analyses of the quality of AI-supported versus human teaching, along with explorations of underlying mechanisms, have become one of the most active research topics. Third, longitudinal tracking of the effects of prolonged digital tool use on individual cognitive and psychological development. Studies investigate both the cumulative benefits of AI-assisted learning for critical thinking, creativity, and complex problem-solving, and potential risks, including mechanisms of AI dependency, longitudinal associations between excessive AI use and anxiety or depression, and the erosion of cognitive autonomy through prolonged AI reliance.

In this research area, the top 3 countries by core paper output are China, Iran, and the UK; the top 3 countries by citations are China, Iran, and Philippines; the top 3 countries by average citations per paper are Philippines, Republic of Korea, and Canada. Among major core paper output countries, China and Iran exhibit the highest international collaboration. Institutions ranking top 3 in core publications are The Chinese University of Hong Kong, The Education University of Hong Kong, and Golestan University; those ranking top 3 in average citations per paper are The University of Hong Kong, North China University of Water Resources and Electric Power, and Nanjing Normal University. Among major core-producing institutions, The Chinese University of Hong Kong and The Education University of Hong Kong demonstrate the most extensive collaboration with other institutions. Countries ranking top three in citing core papers are China, the USA, and Türkiye; institutions ranking top 3 in citing core papers are The Education University of Hong Kong, The Chinese University of Hong Kong, and The University of Hong Kong.

Table 7 Major countries producing core papers on human–machine interaction reveals fundamental logic of learning cognition

Order	Country	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	China	37	67.27	4,299	116.19	2024.3
2	Iran	11	20.00	720	65.45	2024.6
3	UK	5	9.09	143	28.60	2024.8
4	Republic of Korea	2	3.64	378	189.00	2024.0
4	Canada	2	3.64	234	117.00	2024.5
4	USA	2	3.64	232	116.00	2024.0
4	Malaysia	2	3.64	92	46.00	2024.5
4	Australia	2	3.64	79	39.50	2024.5
4	Oman	2	3.64	41	20.50	2025.0
10	Philippines	1	1.82	390	390.00	2023.0

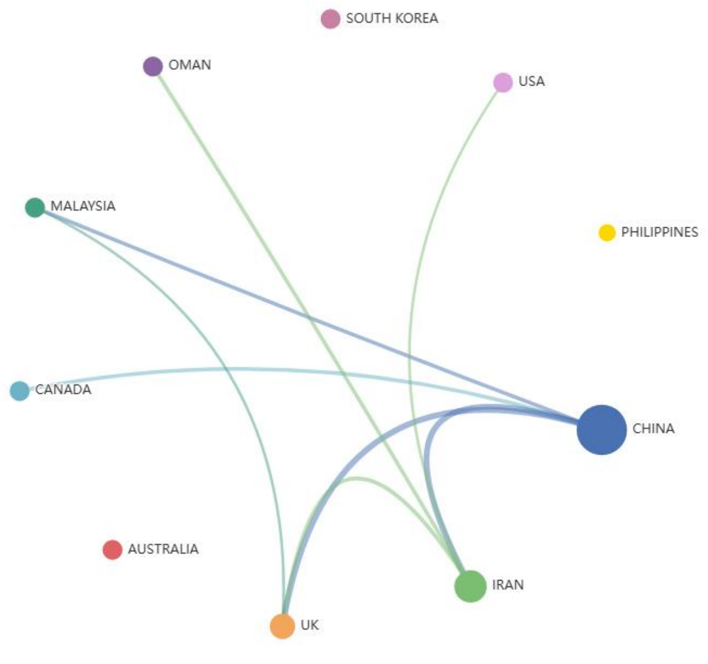

Figure 11 Collaboration network among major countries producing core papers on human–machine interaction reveals fundamental logic of learning cognition

Table 8 Major institutions producing core papers on human–machine interaction reveals fundamental logic of learning cognition

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	The Chinese University of Hong Kong	9	16.36	781	86.78	2024.6
2	The Education University of Hong Kong	6	10.91	568	94.67	2024.3
3	Golestan University	5	9.09	419	83.80	2024.4
4	The University of Hong Kong	4	7.27	1,334	333.50	2023.8
4	North China University of Water Resources and Electric Power	4	7.27	507	126.75	2024.5
4	University of Exeter	4	7.27	82	20.50	2025.0
7	Nanjing Normal University	3	5.45	356	118.67	2024.3
7	Huainan Normal University	3	5.45	172	57.33	2025.0
7	Soochow University (Suzhou, China)	3	5.45	172	57.33	2025.0
7	Hunan University of Science and Technology	3	5.45	40	13.33	2025.0

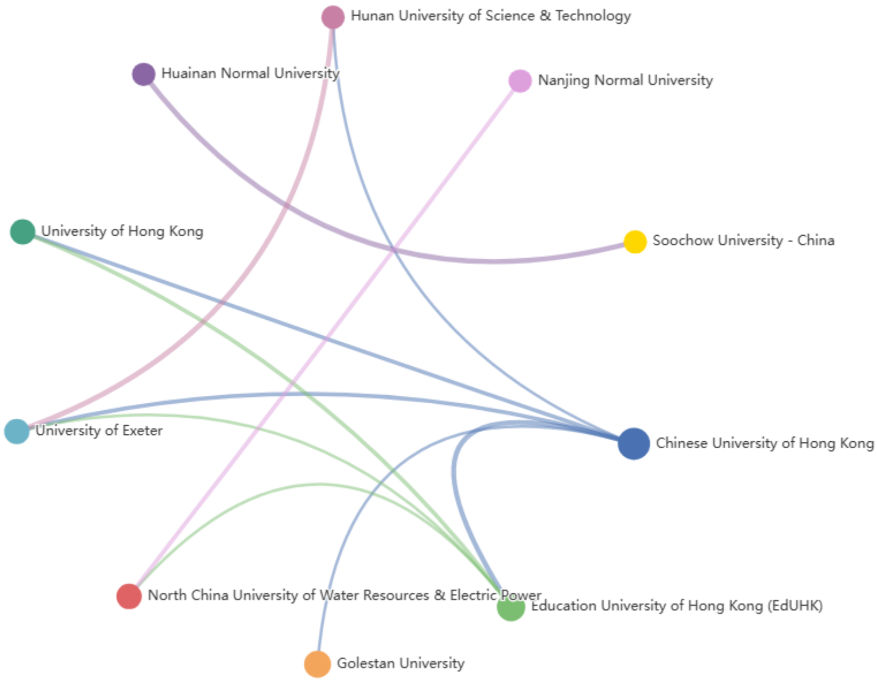

Figure 12 Collaboration network among major institutions producing core papers on human–machine interaction reveals fundamental logic of learning cognition

Table 9 Major countries citing core papers on human–machine interaction reveals fundamental logic of learning cognition

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	China	1,753	43.42	2025.1
2	USA	484	11.99	2025.0
3	Türkiye	222	5.50	2025.2
3	UK	222	5.50	2025.1
5	Malaysia	200	4.95	2025.1
6	Australia	171	4.24	2025.1
7	Saudi Arabia	149	3.69	2024.9
8	Republic of Korea	139	3.44	2025.0
8	Spain	139	3.44	2025.1
10	Iran	134	3.32	2025.1

Table 10 Major institutions citing core papers on human–machine interaction reveals fundamental logic of learning cognition

Order	Institution	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	The Education University of Hong Kong	128	3.17	2025.0
2	The Chinese University of Hong Kong	98	2.43	2025.0
3	The University of Hong Kong	84	2.08	2024.9
4	Zhejiang University	74	1.83	2025.2
5	Beijing Normal University	62	1.54	2025.1
6	Universiti Sains Malaysia	53	1.31	2025.1
7	East China Normal University	49	1.21	2025.0
8	The Hong Kong Polytechnic University	46	1.14	2025.1
9	Central China Normal University	41	1.02	2025.3
10	Nanyang Technological University	38	0.94	2025.1

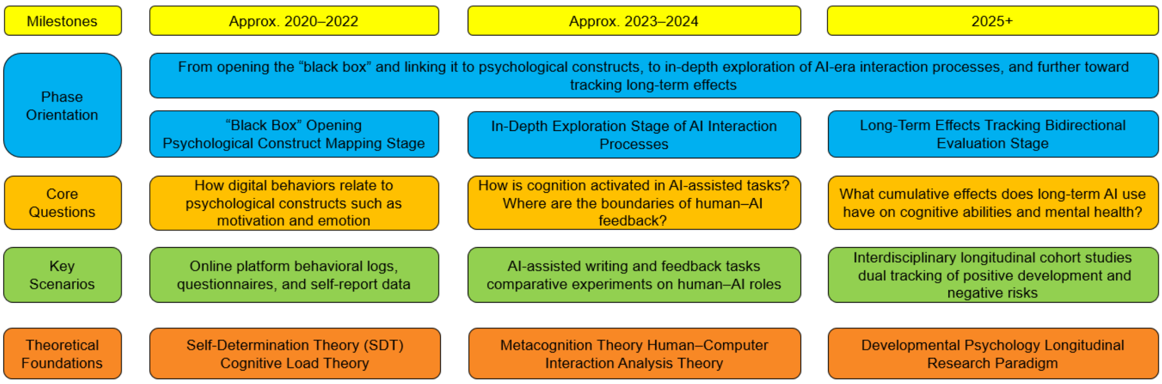

Figure 13 Development roadmap for human–machine interaction reveals fundamental logic of learning cognition

Figure 13 presents the development roadmap for human–machine interaction reveals fundamental logic of learning cognition. Research in this domain can be divided into three phases.

Phase I (2020–2022): unpacking the black box by linking psychological constructs. Research centered on online learning platforms, using behavioral logs and questionnaire data to establish systematic associations between digital interaction behaviors and learners' internal psychological constructs. Path relationships among motivational structures, emotional experiences (enjoyment, anxiety, self-efficacy), and engagement behaviors were initially clarified. The core objective of this phase was to validate the proposition that digital interactions influence learning performance not through extrinsic technological variables but via affective and belief systems. Its key contribution lies in rendering implicit learning cognition processes partially observable and providing a stable conceptual framework, variable system, and measurement tools for subsequent research.

Phase II (2023–2024): delving into interactions by exploring process mechanisms in the ai era. The large-scale adoption of GenAI tools fundamentally reshaped core research questions in this field. Studies shifted focus from measuring outcome variables to examining task interaction processes themselves. On one hand, research on AI-assisted writing, academic revision, and feedback reception employed metacognitive theory, self-regulated learning frameworks, and task engagement theory to analyze how learners formulate queries, revise outputs, and evaluate or adopt AI suggestions. The focus evolved from whether to use AI to how to interact effectively with AI. On the other hand, human–machine role comparison became a prominent theme, with differences, complementarities, and boundaries between AI feedback, peer feedback, and teacher feedback emerging as frequent topics. Concurrently, research methods evolved notably, with real-classroom interventions, mixed-methods designs, and process-based evidence collection gaining widespread adoption. This shift reflects a transition from static correlational analyses to fine-grained examinations of interaction mechanisms, scaffolding design, and task processes.

Phase III (2025 onward): tracking long-term effects by dual examination of benefits and risks. Research perspectives expanded from single-task and cross-sectional measurements to long-term, multi-wave longitudinal tracking. On one hand, scholars continue to assess the cumulative benefits of AI-assisted learning for critical thinking, creativity, complex problem-solving, and sustained engagement, further exploring conditions for sustainable personalized learning and just-in-time scaffolding under GenAI. On the other hand, issues such as AI dependency, fcognitive offloading, diminished originality, mental health risks, and weakened learning autonomy have been explicitly integrated into the core research agenda. Studies have begun investigating mechanisms of problematic AI use and dynamic relationships between AI dependency and psychological states like anxiety and depression. This indicates that research in this field will no longer focus unilaterally on learning enhancement but address governance-oriented questions: under what conditions do benefits materialize? Who bears the costs? How should boundaries be defined? The dual examination of positive benefits and negative risks defines the most distinctive feature of this phase.

Looking ahead, future research will prioritize five key directions: first, fine-grained process analysis based on dialogue logs, revision trajectories, and multimodal data; second, integrated development of AI literacy, prompt literacy, and critical thinking; third, functional division and optimal combination of feedback sources—teachers, peers, and AI; fourth, personalized scaffolding, customizable learning experiences, and context-aware intervention mechanisms; fifth, identification of longitudinal causal relationships concerning AI dependency, ethical judgment, cognitive autonomy, and psychological well-being. Overall, human–machine interaction research will gradually shift from effectiveness validation to mechanism modeling and boundary governance.

3.2.3 Risk Perception Defines Scope of Digital Technology Application

As GenAI penetrates educational settings at an accelerating pace, stakeholders' risk perceptions regarding technology use have emerged as a decisive factor shaping its adoption boundaries within education. Two interrelated forces constantly interact: the pursuit of enhanced efficiency, user-friendly experience and innovative support; and profound concerns about privacy breaches, content bias, ambiguous accountability and cognitive degradation. Accordingly, the integration of GenAI into education is far more than a mere technical adaptation; it represents a behavioral decision-making process as technology becomes deeply embedded in human cognition and social contexts. Even when GenAI demonstrates clear efficiency advantages, significant disparities may persist in adoption willingness between teachers and students, giving rise to paradoxes such as high proficiency with limited uptake or functional availability without practical use. The core of this paradox lies in risk perception acting as a bottom-line constraint, continually balancing against perceived utility. Together, these two factors determine the extent, intensity and modalities of GenAI deployment in education.

Against this core rationale, research in this field advance along two principal directions. One strand investigates multifaceted determinants shaping GenAI adoption and implementation, encompassing usage preferences, external institutional support, AI literacy and tool-specific characteristics. By examining how these factors differentially influence individual adoption intentions, research scope has expanded beyond teachers to include student populations. The other strand centers on validating real-world application outcomes across specific contexts, evaluating performance metrics, experiential perceptions and higher-order thinking development, while probing contextual variations and functional boundaries of GenAI effectiveness in authentic, diverse educational environments.

Current research in this area concentrates on three pivotal dimensions—adoption rationale, influencing factors and contextual deployment—mirroring distinctive application logics that differentiate GenAI integration from conventional educational technology adoption.

In terms of adoption rationale, scholarly focus has shifted from technical usability and ease of use toward considerations of practical feasibility and contextual appropriateness. Traditional technology acceptance models emphasize perceived ease of use and usefulness as primary drivers of adoption, often marginalizing risk considerations. Given GenAI's black-box nature and its potential to challenge human agency, perceived risks become salient in teaching practice. This shift redirects inquiry from whether GenAI performs well to whether it can be safely and appropriately employed. Consequently, perceived risk evolves from a passive side effect to an active determinant of adoption decisions. Furthermore, research distinguishes hierarchical risk dimensions, including content-related hazards such as hallucination and factual inaccuracy, and normative risks involving academic integrity and privacy protection. This evolution signals a transition from utility prioritization to a balanced evaluation of risks and benefits.

Regarding influencing factors, research has expanded from a singular focus on teachers' experiential perceptions toward integrated analysis of both teacher and student perspectives. Early technology adoption research implicitly assumes a unidirectional diffusion model, positioning teachers as gatekeepers. Studies thus explored teacher-specific traits and external supports as key determinants. However, GenAI disrupts this paradigm: student engagement with the technology often surpasses that of teachers in certain contexts, transforming students from passive recipients into influential agents of educational technology integration. Consequently, students' risk boundaries in GenAI use, alongside teachers' attitudes toward its deployment, have become critical indicators of meaningful educational embedding. This transition reflects a shift from teacher-centric frameworks toward dual-agent perspectives.

With respect to contextual deployment, research highlights context-specific teaching scenarios, emphasizing risk perception's differential role in boundary delineation. Earlier studies focused broadly on general acceptance levels, measuring adoption intentions while neglecting how contextual heterogeneity triggers and modulates risk perception. Empirical evidence indicates greater risk tolerance and more permissive adoption boundaries in low-stakes settings such as classroom drills. In contrast, high-stakes contexts including examinations and competitions activate heightened vigilance regarding content authenticity, accountability and academic integrity, thereby narrowing acceptable use boundaries. Notably, identical GenAI tools may elicit divergent adoption rationales and usage strategies for the same user across different scenarios. Current research has begun quantifying differential risk perceptions in academic writing, programming instruction, assessment design and research assistance. This evolution reflects a shift from generalized acceptance models toward context-embedded boundary identification, underscoring how risk perception dynamically delineates acceptable, appropriate and cautious deployment parameters in specific educational contexts.

In this research area, the top 3 countries by core paper output are China, Iran, and the USA; the top 3 countries by citations are China, Iran, and Malaysia; the top 3 countries by average citations per paper are Czechia, Russia, and Malaysia. Among major core paper output countries, China exhibits the highest international collaboration. Institutions ranking top 3 in core publications are The Education University of Hong Kong, The Chinese University of Hong Kong, and Golestan University; those ranking top 3 in average citations per paper are Nanjing Normal University, East China Normal University, and Zhejiang University of Technology. Among major core-producing institutions, The Chinese University of Hong Kong demonstrates the most extensive collaboration with other institutions. Countries ranking top three in citing core papers are China, the USA, and Türkiye; institutions ranking top 3 in citing core papers are The Education University of Hong Kong, The Chinese University of Hong Kong, and East China Normal University.

Table 11 Major countries producing core papers on risk perception defines scope of digital technology application

Order	Country	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	China	31	57.41	2,179	70.29	2024.6
2	Iran	7	12.96	545	77.86	2024.7
3	USA	6	11.11	353	58.83	2024.8
4	Australia	4	7.41	248	62.00	2024.8
4	UK	4	7.41	225	56.25	2024.8
6	Malaysia	3	5.56	382	127.33	2024.3
6	Canada	3	5.56	244	81.33	2024.3
6	Pakistan	3	5.56	173	57.67	2024.7
9	Czech	2	3.70	356	178.00	2024.5
9	Russia	2	3.70	272	136.00	2024.5

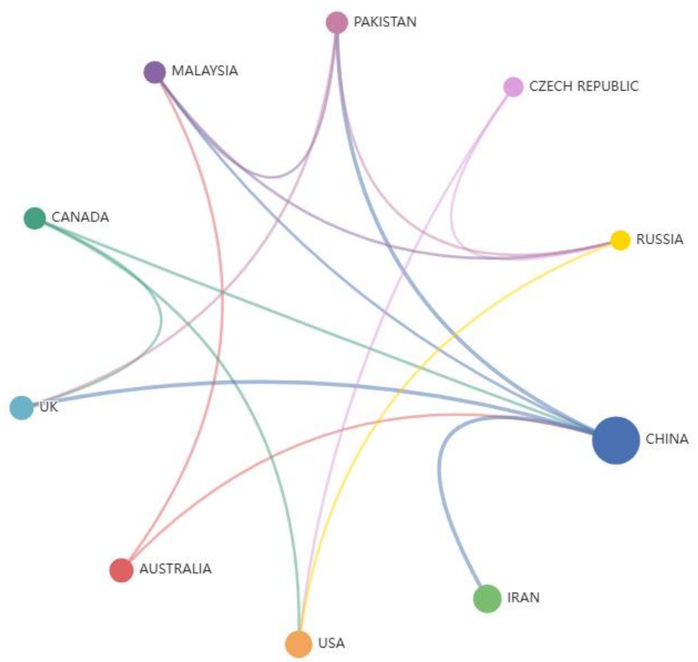

Figure 14 Collaboration network among major countries producing core papers on risk perception defines scope of digital technology application

Table 12 Major institutions producing core papers on risk perception defines scope of digital technology application

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	The Education University of Hong Kong	7	12.96	497	71.00	2024.4
2	The Chinese University of Hong Kong	6	11.11	545	90.83	2024.7
2	Golestan University	6	11.11	529	88.17	2024.7
4	North China University of Water Resources and Electric Power	4	7.41	421	105.25	2024.8
4	The University of Hong Kong	4	7.41	190	47.50	2024.5
6	Nanjing Normal University	2	3.70	265	132.50	2024.5
6	East China Normal University	2	3.70	232	116.00	2025.0
6	Zhejiang University of Technology	2	3.70	232	116.00	2025.0
6	Allameh Tabataba'i University	2	3.70	208	104.00	2024.5
6	University of Toronto	2	3.70	164	82.00	2024.5

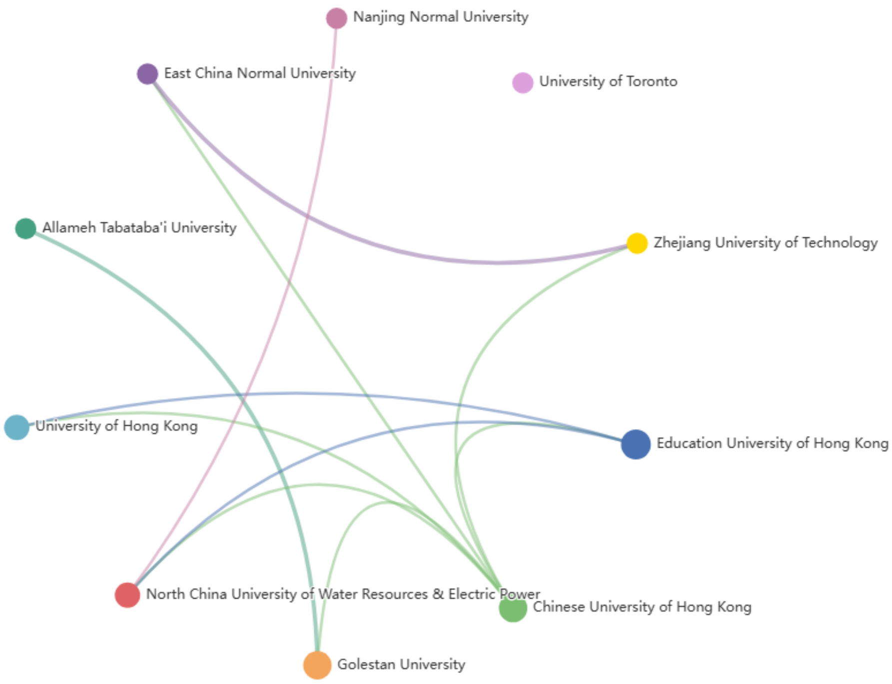

Figure 15 Collaboration network among major institutions producing core papers on risk perception defines scope of digital technology application

Table 13 Major countries citing core papers on risk perception defines scope of digital technology application

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	China	1,212	47.44	2025.3
2	USA	241	9.43	2025.3
3	Türkiye	145	5.68	2025.3
4	UK	140	5.48	2025.2
5	Malaysia	133	5.21	2025.3
6	Saudi Arabia	127	4.97	2025.2
7	Australia	97	3.80	2025.3
8	Republic of Korea	92	3.60	2025.3
8	Spain	92	3.60	2025.2
10	Iran	84	3.29	2025.2

Table 14 Major institutions citing core papers on risk perception defines scope of digital technology application

Order	Institution	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	The Education University of Hong Kong	72	2.82	2025.3
2	The Chinese University of Hong Kong	64	2.50	2025.1
3	East China Normal University	55	2.15	2025.1
4	Beijing Normal University	42	1.64	2025.3
5	Zhejiang University	36	1.41	2025.4
6	The University of Hong Kong	33	1.29	2025.1
7	University of Patras	32	1.25	2025.3
8	The Hong Kong Polytechnic University	31	1.21	2025.3
9	Central China Normal University	30	1.17	2025.3
9	Nanjing Normal University	30	1.17	2025.0
9	North China University of Water Resources and Electric Power	30	1.17	2025.1

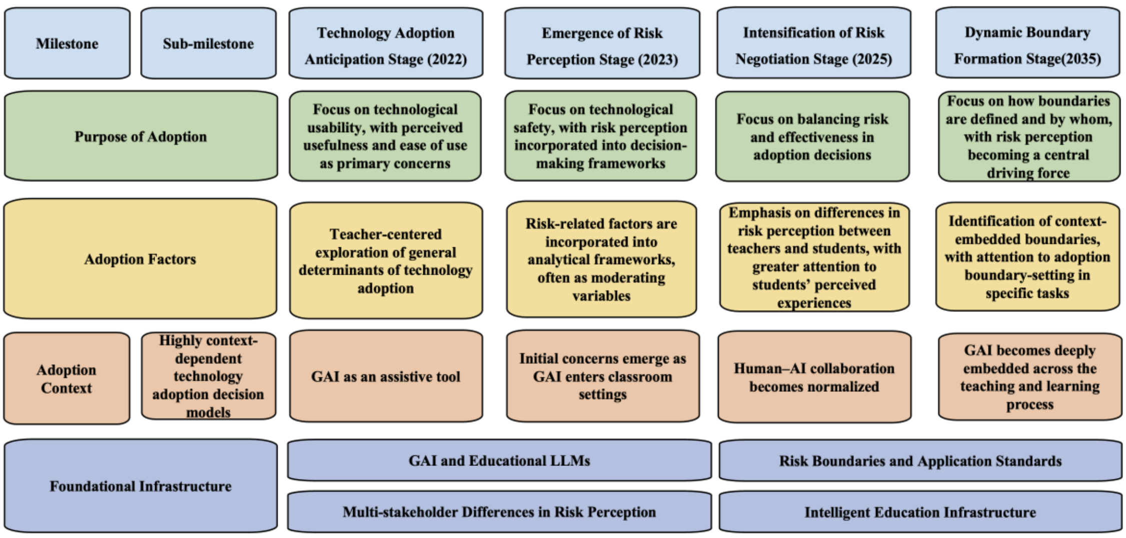

Figure 16 Development roadmap for risk perception defines scope of digital technology application

Figure 16 illustrates the development roadmap for risk perception defines scope of digital technology application. As GenAI integrates into educational practice, stakeholder risk perceptions and adoption boundaries have evolved progressively—from initial neglect to heightened vigilance, from deliberative trade-offs to formalized boundary-setting. Based on existing research and future projections, this evolutionary trajectory unfolds across four distinct phases.

Phase I constitutes a period of technology adoption assessment. GenAI functions primarily as an auxiliary tool, remaining peripheral to core classroom instruction. Scholarly work largely adheres to conventional acceptance frameworks, prioritizing perceived usability and ease of use, while risk considerations remain marginal. Adoption decisions during this stage are overwhelmingly driven by efficiency imperatives.

Phase II marks the emergence of risk perception. As GenAI enters mainstream classroom use, its opaque operational mechanisms and output uncertainty trigger initial awareness of potential hazards. Research focus shifts from technical functionality to safety considerations. Risk perception enters analytical frameworks but remains a secondary or moderating factor, with teachers developing cautious yet tentative usage strategies.

Phase III witnesses intensified risk-benefit trade-offs. Human–machine collaboration becomes normalized within teaching practice, with risk and utility accorded equal importance. Three pivotal shifts characterize this phase: adoption rationale evolves from utility prioritization to balanced risk-benefit evaluation; influencing factors expand from teacher-centric to dual-agent perspectives; contextual deployment transitions from generalized acceptance to context-specific boundary identification.

Phase IV entails dynamic boundary formalization. GenAI becomes deeply embedded across all teaching stages, with risk perception elevated to a foundational determinant of adoption decisions. Research focus shifts from descriptive adoption patterns to normative inquiries regarding boundary delineation authority and mechanisms. Emphasis is placed on defining context-specific acceptable, appropriate and cautious deployment parameters, establishing tiered and differentiated usage guidelines.

3.2.4 Teaching Competence Influences High-Quality Digital Transformation of Education

Intelligent teaching competence refers to teachers' comprehensive ability to effectively integrate AI into instructional design, teaching implementation, learning assessment, and personalized support within evolving educational contexts. It requires understanding the fundamental logic of AI, recognizing its appropriate boundaries, and engaging in continuous reflection, dynamic adjustment, and optimization of teaching practices. This construct comprises two core dimensions: teachers' ability to understand, adopt, and integrate AI in educational settings; teachers' capacity to make informed pedagogical decisions, adapt their teaching, and maintain professional agency when AI technologies are embedded in instructional practice, guided by educational goals, instructional principles, and student development needs. The development of such professional capabilities is critical not only for leveraging technology to enhance educational quality but also for advancing intelligent education from "technological access" toward "pedagogical reconstruction".

Empirical evidence indicates that teachers' exposure to AI has increased significantly, explorations of AI-supported teaching practices have become increasingly active, and application scenarios have continued to expand. These applications are mainly concentrated in areas such as language teaching, writing feedback, curriculum development, and personalized tutoring. Research on teaching competence has evolved from digital literacy and information-based instructional capabilities toward digital competence, AI literacy, and ICT-based teaching competence, shifting focus from technological usability to effective pedagogical application. This underscores intelligent teaching competence as a key issue and benchmark for evaluating digital transformation in education.

Research in this domain mainly focuses on the following three aspects.

First, research examines teachers' perceptions, technical proficiency, and practical application of AI, identifying critical factors shaping instructional use. Technical competence has expanded beyond tool operation to encompass understanding, critical judgment, integration, and reflective practice. Findings reveal generally low-to-moderate levels of AI knowledge and pedagogical translation skills, with substantial variation across teacher groups. Adoption and usage patterns are shaped not only by technological accessibility but also by perceived utility, ease of use, pedagogical beliefs, and trust in technology.

Second, research focuses on cultivating teachers' integrated capabilities to optimize and innovate instruction with AI, strengthen awareness of human–AI collaborative teaching, and establish practice-oriented competency frameworks. A central requirement is deep technology–pedagogy integration in authentic tasks. Current research emphasizes contextualized and task-specific applications across different disciplines, instructional goals, and classroom processes. While technology augments instruction, it places higher demands on teachers’ judgment, instructional design, interactional organization, and feedback skills. Development has shifted from technical proficiency toward authentic human–AI practices in authentic teaching contexts.

Third, research assesses teachers’ psychological dynamics and subjective influences on AI-enabled education. Findings show perceived utility, technological trust, and self-efficacy enhance adoption, while AI anxiety, risk concerns, and uncertainty inhibit classroom implementation. Higher self-efficacy, resilience, and emotional regulation correlate with greater satisfaction, engagement, and professional well-being. GenAI-based teching interventions can enhance teachers' confidence and motivation to some extent. Psychological adaptation provides internal support, while professional development offers external pathways for sustained competence growth.

In this research area, countries leading in core publications include China, Iran, the USA, and the UK; the top 3 countries by citations are China, Iran, and Australia; the top 3 countries by average citations per paper are Switzerland, Finland, and Republic of Korea (Table 15). Among the major core-producing countries in terms of core paper output, the USA shows the highest level of international collaboration (Figure 17). The top core-producing institutions include Nanjing Normal University and North China University of Water Resources and Electric Power; the top 3 institutions by average citations per paper are The Education University of Hong Kong, The Hong Kong Baptist University, and University of Oulu (Table 16). Among the major core papers producing institutions, North China University of Water Resources and Electric Power, Golestan University, and The Chinese University of Hong Kong demonstrate the most extensive collaboration (Figure 18). Countries ranking top 3 in citing core papers are China, the USA, and Türkiye (Table 17); institutions ranking top 3 in citing core papers are The Education University of Hong Kong, The Chinese University of Hong Kong, and The University of Hong Kong (Table 18).

Table 15 Major countries producing core papers on teaching competence influences high-quality digital transformation of education

Order	Country	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	China	29	58.00	3,388	116.83	2024.2
2	Iran	5	10.00	627	125.40	2023.8
2	USA	5	10.00	392	78.40	2024.4
2	UK	5	10.00	344	68.80	2024.4
5	Germany	4	8.00	302	75.50	2024.2
6	Australia	3	6.00	576	192.00	2023.0
6	Pakistan	3	6.00	173	57.67	2024.7
8	Switzerland	2	4.00	436	218.00	2024.0
8	Finland	2	4.00	426	213.00	2024.0
8	Repulic of Korea	2	4.00	396	198.00	2023.0

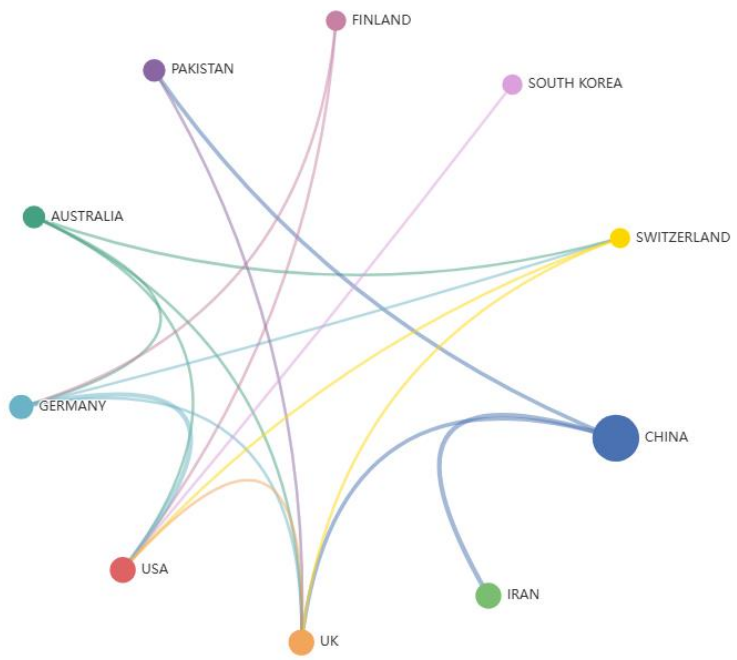

Figure 17 Collaboration network among major core-producing countries on teaching competence influences high-quality digital transformation of education

Table 16 Major institutions producing core papers on teaching competence influences high-quality digital transformation of education

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	Nanjing Normal University	5	10.00	574	114.80	2023.4
1	North China University of Water Resources and Electric Power	5	10.00	361	72.20	2025.0
3	The Education University of Hong Kong	4	8.00	976	244.00	2023.5
3	Golestan University	4	8.00	558	139.50	2023.8
4	The University of Hong Kong	4	8.00	420	105.00	2024.2
6	The Hong Kong Baptist University	3	6.00	725	241.67	2023.7
6	Xi'an Jiaotong University	3	6.00	269	89.67	2024.0
6	The Chinese University of Hong Kong	3	6.00	173	57.67	2024.7
9	University of Oulu	2	4.00	426	213.00	2024.0
9	Korea University	2	4.00	396	198.00	2023.0

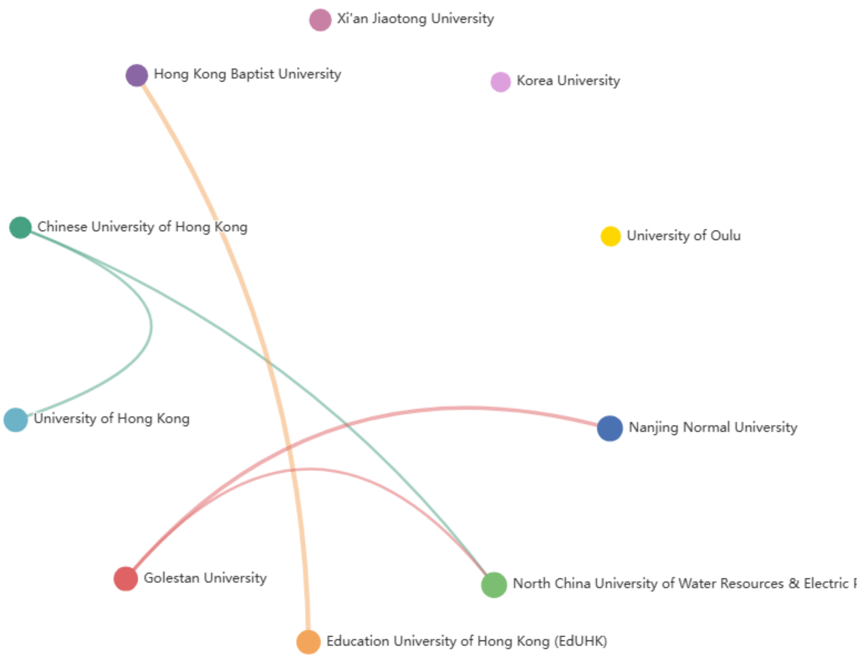

Figure 18 Collaboration network among major core-producing institutions on teaching competence influences high-quality digital transformation of education

Table 17 Major countries citing core papers on teaching competence influences high-quality digital transformation of education

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	China	1,764	38.72	2024.9
2	USA	494	10.84	2024.9
3	Türkiye	296	6.50	2025.0
4	Spain	248	5.44	2024.4
5	Malaysia	198	4.35	2024.9
6	UK	194	4.26	2024.8
7	Saudi Arabia	161	3.53	2024.7
8	Australia	157	3.45	2024.7
9	Germany	156	3.42	2024.5
10	Iran	146	3.20	2024.8

Table 18 Major institutions citing core papers on teaching competence influences high-quality digital transformation of education

Order	Institution	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	The Education University of Hong Kong	123	2.70	2025.0
2	The Chinese University of Hong Kong	94	2.06	2025.0
3	The University of Hong Kong	74	1.62	2024.9
4	Nanjing Normal University	68	1.49	2024.4
5	The Hong Kong Polytechnic University	56	1.23	2025.1
6	Golestan University	54	1.19	2024.8
7	North China University of Water Resources and Electric Power	52	1.14	2024.8
7	Zhejiang University	52	1.14	2025.2
9	Beijing Normal University	50	1.10	2024.9
10	East China Normal University	47	1.03	2024.9

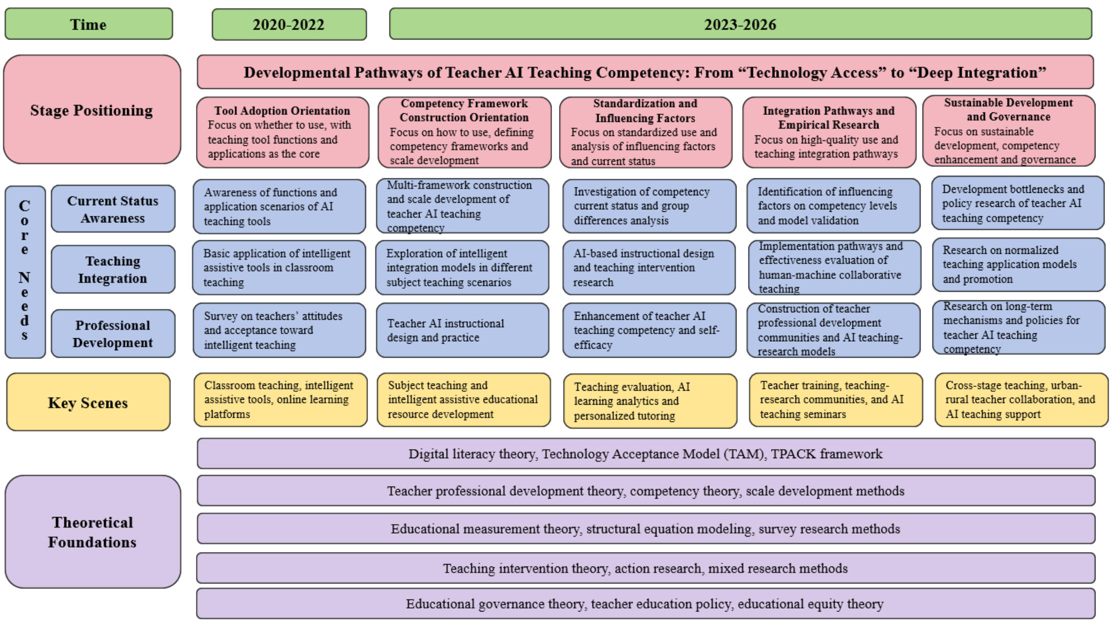

Figure 19 Development roadmap for teaching competence influences high-quality digital transformation of education

Figure 19 illustrates the development trajectory of research on intelligent teaching competence, progressing across two main phases. During the period of 2020–2022, research centered on the transition from digital teaching capabilities to intelligent teaching capabilities, covering key topics such as teachers' digital competence, online teaching ability, and technology integration skills. Research focused on whether teachers possess the basic conditions for using smart tools, examining their adoption willingness, influencing factors, and relationship with digital literacy. At this stage, smart teaching tools mainly served as supplementary support, and research on intelligent teaching competence remained in the conceptual introduction and exploratory phase.

During the period of 2023–2026, research entered the phase of competency framework restructuring driven by GenAI. Beyond measuring attitudes and intentions, studies focused on reconstructing teacher competency structures, developing measurement tools, designing career development paths, and exploring practical models. Emerging concepts such as AI literacy, GenAI competence, intelligent TPACK, and ethical competence signaled the shift of research focus from digital to intelligent teaching. Meanwhile, AI gradually evolved from peripheral support to core assistance in teaching. How to organize human–machine collaborative teaching and maintain professional leadership became core research themes, marking the transition from exploratory research to systematic construction.

Future research will advance toward ethics and higher-order thinking development, with GenAI as core support to promote critical thinking cultivation, formulate AI ethics guidelines, and construct human-centered frameworks. Despite progress, multiple challenges remain. Teachers' competence upgrading lags behind technological iteration, creating gaps in practical application. Structural imbalances across regions and cohorts affect educational equity. Training systems lack integrated pathways. Moving forward, research will shift toward human–machine collaborative capacity building, prioritizing replicable equitable models, standardized assessments, and ethical governance frameworks to support high-quality education transformation.

3.2.5 Interdisciplinary Teaching Realizes In-Depth Integration of Technology and Humanities

Compared with traditional subject-based education, interdisciplinary teaching reconstructs learners' cognition from fragmented subject knowledge to systematic thinking by integrating multi-disciplinary perspectives, enabling learners to address complex real-world problems more effectively. In this process, learners need to synthesize cross-domain and multi-modal information such as data, images and texts, driving instructional design and inquiry-based learning to adopt interdisciplinary integration models. AI-enabled interdisciplinary teaching has shifted practice from superficial knowledge combination toward systematic transformation marked by deep dynamic coupling of technology, discipline and humanities. This transition is reflected in several aspects: disciplinary boundaries extend from natural sciences such as engineering, programming and mathematics to bidirectional construction with humanities and social sciences including art, politics, economics, philosophy and history; disciplinary roles evolve from instrumental media to critical practice of ontological learning; pedagogical focus moves from group averages to the complex internal dynamics of individual learners; learning contexts expand toward seamless, comprehensive connectivity. Current research in this field centers on three core themes: constructing systematic frameworks for interdisciplinary teaching to deepen coupling among technology, discipline and humanities; developing affective-cognitive co-regulation interventions to explore emotion as a key driver of cognitive growth; leveraging lightweight AI tools, with STEM project-based learning as the core, to examine connection models between formal and informal learning contexts.

Solving complex real-world problems requires integrating multi-disciplinary knowledge and skills. This demand stems not only from educational efforts but also from the inherent need of real-world complexity for interdisciplinary thinking. The deepening of interdisciplinary teaching aligns with global strategies to enhance future workforce competencies and strengthen international competitiveness. For decades, most countries have regarded STEM education as a core policy instrument for driving economic growth and maintaining technological leadership. Against rapid technological iteration and blurring industrial boundaries, single-discipline knowledge can no longer meet the demands of complex professional roles for integrated analysis, problem restructuring and innovative design capabilities. By integrating scientific inquiry, engineering design and mathematical modeling, STEM education cultivates systematic thinking and collaborative skills essential for real-world professional contexts, nurturing high-caliber talent for the future.

With rapid AI advancement, interdisciplinary teaching practice has undergone four key shifts. Disciplinary boundaries keep expanding, extending from early focus on natural sciences to humanities and social sciences, achieving bidirectional construction between domains. Supporting disciplines evolve from instrumental use to ontological learning. GenAI breaks cognitive barriers between subjects, enabling disciplines like art to move beyond serving as mere tools for interdisciplinary integration, toward deeper understanding of disciplinary ontology. This not only fosters exploration of disciplinary essence but also advances critical and innovative practice in localized and cross-cultural contexts. Pedagogical focus moves from group averages to individual learners' internal dynamics. In integrated STEM tasks, learners with diverse backgrounds show distinct strategies for activating prior knowledge, grasping new concepts and synthesizing information. GenAI shifts instructional support from designing for the majority to modeling for individuals, helping learners bridge knowledge gaps and build integrated understanding. Learning contexts expand comprehensively, extending to communities, maker spaces and science venues. Cross-context project design promotes collaborative application of interdisciplinary knowledge, effectively breaking boundaries of learning environments.

Current research on interdisciplinary teaching exhibits three characteristics. First, construction of systematic theoretical frameworks. Early studies drew on general educational and psychological frameworks, offering initial guidance for interdisciplinary teaching but failing to fully address complexities of cognition, disciplinary heterogeneity and human–machine collaboration. By developing specialized interdisciplinary models integrating epistemology, psychology and pedagogy, frameworks have evolved beyond superficial content integration, forming systems centered on embodied, generative and environment-supported cognition, with dynamic coupling of technology, discipline and humanities as the core goal. Second, advancing affective-cognitive co-regulation strategies. Research focuses on dynamic changes in epistemic emotions such as curiosity, confusion and surprise triggered by confrontation tasks in STEM problem-solving, elevating emotion as a key driver of cognitive development.

Evidence shows significant positive correlation between achievement and knowledge transfer, highlighting integration of learning and emotional experience. AI integration positively impacts learners' cognitive, affective and social engagement, with emotional dynamics shaping academic involvement depth and persistence. Interdisciplinary learning demands stronger affective-cognitive coordination; effective design must stimulate both cognitive conflict and positive emotion to foster deep knowledge integration and transfer. Third, deep integration of informal learning and interdisciplinary practice. Lightweight AI tools lower barriers to informal learning participation and decision-making. Integrated STEM project-based learning enables exploration of effective connections between formal and informal learning. This approach avoids fragmentation and disorder in interdisciplinary practice, validates informal learning outcomes within formal systems, and reinforces classroom knowledge through informal practice, achieving deep alignment of content, process and goals.

Future research on interdisciplinary teaching requires breakthroughs in three key directions. Renewing assessment systems is a top priority. Current assessments focus on single-subject mastery or final outputs, failing to capture process characteristics of interdisciplinary understanding and engineering design. There is an urgent need for practical formative assessment tools, accompanied by clear criteria and teacher guidelines. Research design should incorporate longitudinal tracking and multi-modal data integration to reveal long-term development trajectories of interdisciplinary competence, using real-time data such as facial expressions, physiological signals and behavioral logs to map cognitive and affective dynamics during problem-solving. Diversifying samples and contexts is equally critical. Future studies should cover diverse cultural backgrounds, educational stages and disciplines, emphasizing implementation in rural or resource-limited settings, and examining moderating effects of teachers' content knowledge, beliefs and external support on curriculum delivery.

In this research area, countries leading in core publications include China and USA; the top 3 countries by citations are China, Australia, and the USA; the top 3 countries by average citations per paper are Australia, France, and India. Among major core-producing countries, China and the USA show extensive international collaboration. The top 3 institutions in core publications are The Chinese University of Hong Kong, Xi'an Jiaotong University, and The Education University of Hong Kong; the top 3 institutions by average citations per paper are North China University of Water Resources and Electric Power, Peking University, and University of Macau. Among major core-producing institutions, The Chinese University of Hong Kong, The Education University of Hong Kong, and Peking University demonstrate the most extensive collaboration. Countries ranking top 3 in citing core papers are China, the USA, and the UK;

institutions ranking top 3 are The Chinese University of Hong Kong, The Education University of Hong Kong, and The University of Hong Kong.

Table 19 Major countries producing core papers on interdisciplinary teaching realizes in-depth integration of technology and humanities

Order	Country	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	China	29	61.70	2,987	103.00	2024.0
2	USA	7	14.89	843	120.43	2023.6
3	Australia	4	8.51	1,028	257.00	2022.2
3	UK	4	8.51	629	157.25	2023.8
3	Iran	4	8.51	281	70.25	2025.2
6	New Zealand	3	6.38	251	83.67	2024.0
6	Republic of Korea	3	6.38	251	83.67	2024.0
6	Türkiye	3	6.38	242	80.67	2023.7
6	Japan	3	6.38	237	79.00	2024.0
10	France	2	4.26	466	233.00	2023.0
11	India	2	4.26	466	233.00	2023.0

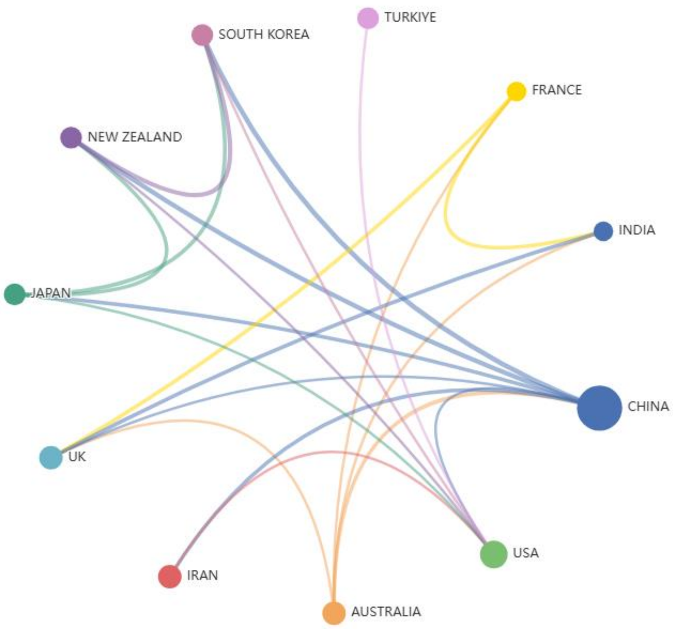

Figure 20 Collaboration network among major core-producing countries on interdisciplinary teaching realizes in-depth integration of technology and humanities

Table 20 Major institutions producing core papers on interdisciplinary teaching realizes in-depth integration of technology and humanities

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	The Chinese University of Hong Kong	5	10.64	575	115.00	2023.8
2	Xi'an Jiaotong University	4	8.51	371	92.75	2024.0
2	The Education University of Hong Kong	4	8.51	323	80.75	2024.5
4	North China University of Water Resources and Electric Power	3	6.38	420	140.00	2024.3
4	University of Macau	3	6.38	362	120.67	2023.7
4	Nanjing Normal University	3	6.38	356	118.67	2024.3

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
4	Auckland University of Technology	3	6.38	251	83.67	2024.0
4	Kyung Hee University	3	6.38	251	83.67	2024.0
4	Golestan University	3	6.38	219	73.00	2025.0
10	Peking University	2	4.26	271	135.50	2024.5

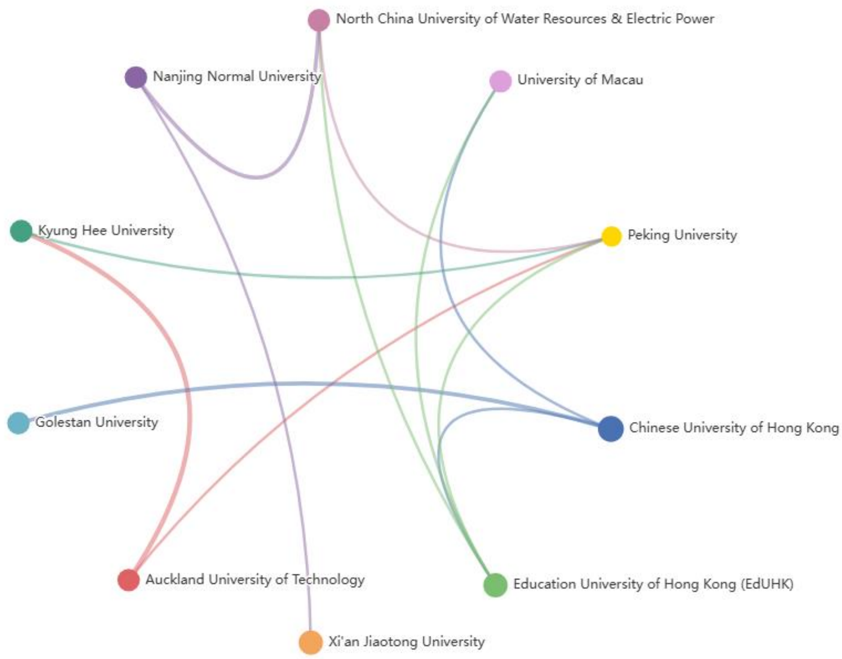

Figure 21 Collaboration network among major core-producing institutions on interdisciplinary teaching realizes in-depth integration of technology and humanities

Table 21 Major countries citing core papers on interdisciplinary teaching realizes in-depth integration of technology and humanities

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	China	1893	39.31	2024.8
2	USA	603	12.52	2024.6
3	UK	277	5.75	2024.7
4	Malaysia	253	5.25	2024.8

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
5	Spain	242	5.03	2024.3
6	Turkiye	241	5.01	2024.9
7	India	224	4.65	2024.6
8	Australia	205	4.26	2024.6
9	Republic of Korea	196	4.07	2024.9
10	Germany	168	3.49	2024.4

Table 22 Major institutions citing core papers on interdisciplinary teaching realizes in-depth integration of technology and humanities

Order	Institution	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	The Chinese University of Hong Kong	131	2.72	2024.3
2	The Education University of Hong Kong	112	2.33	2024.7
3	The University of Hong Kong	65	1.35	2024.5
4	The Hong Kong Polytechnic University	62	1.29	2025.0
5	University of Macau	61	1.27	2024.8
6	Universiti Sains Malaysia	52	1.08	2025.0
7	Beijing Normal University	47	0.98	2024.8
7	Zhejiang University	47	0.98	2025.1
9	Nanjing Normal University	44	0.91	2024.5
9	National Taiwan University of Science and Technology	44	0.91	2024.1

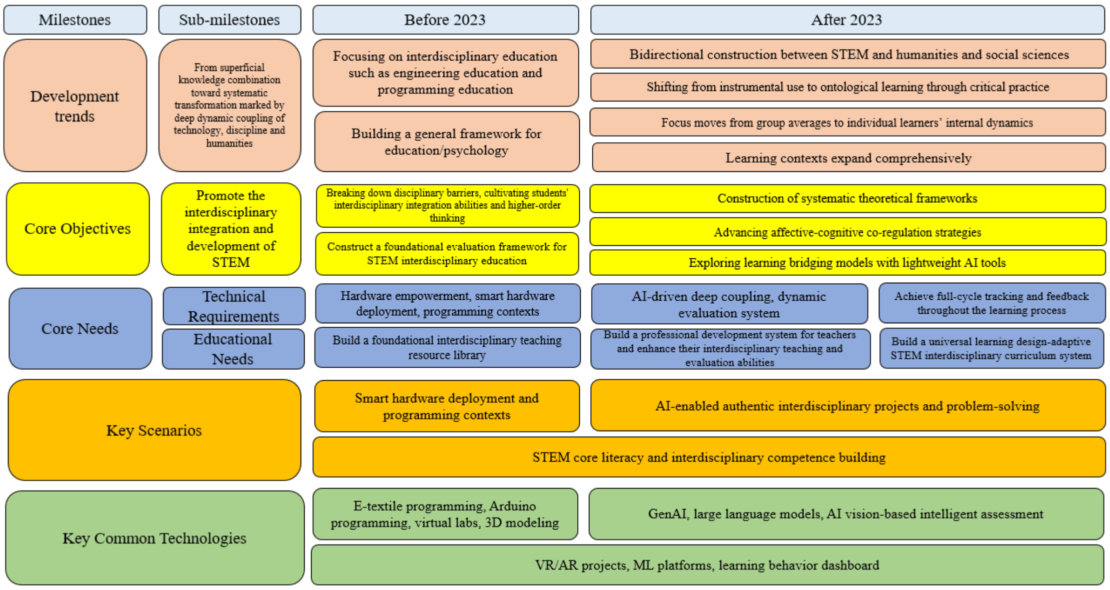

Figure 22 Development roadmap for interdisciplinary teaching realizes in-depth integration of technology and humanities

Figure 22 illustrates the development roadmap for interdisciplinary teaching realizes in-depth integration of technology and humanities. Before 2023, interdisciplinary teaching centered on hardware empowerment, focusing on smart hardware deployment and programming contexts, establishing foundational frameworks for STEM education. While marked by superficial knowledge combination, this phase laid practical groundwork for AI-driven deep coupling.

After 2023, rapid AI advancement ushered interdisciplinary teaching into a new era of AI-enabled deep integration and comprehensive expansion. GenAI and large language models became core drivers, elevating interdisciplinary teaching from traditional knowledge synthesis to alignment with humanities and social sciences, and making AI-enabled authentic interdisciplinary projects central applications.

In the future, research will continue evolving toward deep dynamic coupling of technology, discipline and humanities, fostering ontological and personalized interdisciplinary learning ecosystems.

3.2.6 Educational Robots Become a New Cornerstone of Smart Education

Educational robots are specialized intelligent educational systems with interactive perception capabilities, designed to support specific teaching and learning activities. They include physical robots such as programming robots (e.g., Lego Mindstorms, Bee-Bot) and social robots (e.g., NAO, Pepper), as well as screen-based virtual agents, like teacher-developed chatbots for specific subjects and multi-role teaching agents. With the widespread adoption and deeper integration of AI, educational robots have expanded beyond programming education into multi-subject and interdisciplinary teaching contexts. The boundary between physical and virtual forms is increasingly blurred, and together they constitute the intelligent interactive foundation for teaching and learning. Physical robots are gaining speech and emotion-recognition capabilities, while virtual robots can perceive classroom environments via sensing devices. A new integrated form of educational robots combining virtuality and physicality is gradually taking shape. If AI represented by large models is the infrastructure driving digital transformation in education, various educational robots are critical components of this infrastructure. They are evolving from auxiliary tools into indispensable daily teaching equipment, becoming a new digital foundation embedded in formal curricula, covering all educational stages and supporting interdisciplinary teaching.

Research indicates that educational robots have significant positive effects on developing computational thinking, supporting language learning, and fostering social-emotional competence. These effects are particularly prominent in STEAM subjects, early grades, and teaching practices for children with special educational needs such as autism spectrum disorder. Meanwhile, the indiscriminate use of AI to replace interpersonal support between teachers and students, or among peers may raise ethical risks such as increased learner loneliness. Additionally, conversational AI is evolving from a simple cognitive Q&A tool into a dual-channel support system combining cognitive and affective support. AI-generated feedback and teacher feedback are complementary in terms of their areas of focus and types of feedback, making human–machine collaborative teaching ecosystems a more promising direction. Future research urgently needs to shift from short-term evaluation of effectiveness to explanation of underlying mechanisms and longitudinal follow-up studies. It requires coordinated breakthroughs in sustainable evidence, scalable implementation, governable ethics and assessable outcomes, alongside progress in building teachers' human–machine collaboration capabilities and ethical governance frameworks. This will provide systematic support for educational robots to become a new cornerstone of smart education.

Educational robots are shifting from tool-based applications to standard provision. Since LEGO's U.S. division introduced physical educational robots in 1998, they have mainly served as tools for visualizing thinking in programming learning and STEAM project-based learning in basic education, used in programming courses, STEAM competitions and extracurricular activities. In 2016, chatbots gained popularity in European and American universities, supporting admissions inquiries, timetable inquiries and course selection recommendations. By late 2022, ChatGPT burst onto the scene, and GenAI-powered chatbots (conversational agents) were rapidly adopted in teaching and learning contexts across educational stages and subject areas, with multi-agent teaching applications growing rapidly. Against this backdrop, a large number of empirical studies targeting various teaching scenarios have emerged. Current research in this field centers on three main dimensions.

First, research scope extends from effectiveness validation to impact boundary identification. After years of empirical accumulation, the positive effects of educational robots have been confirmed by multi-source evidence. Meta-analyses show educational robots produce significant positive outcomes in fostering computational thinking, supporting language learning and developing social-emotional competence, with stronger effects in STEAM subjects and early grades. Research focus is shifting from verifying technical effectiveness to exploring impact boundaries, reflected in three aspects. Evaluation of teaching effectiveness has expanded from a narrow cognitive focus on knowledge acquisition to multiple dimensions including learning behavior, emotional experience and cognitive engagement. Some studies show conversational AI exerts a significant mediating effect on learners' emotional regulation, well-being, and willingness to communicate. Research explores the value of educational robots for children with special needs, examining compensatory support in cognition, social interaction, emotion and behavior. Research also investigates impacts on teacher-student relationships, noting over-reliance on AI may lead to negative outcomes such as increased loneliness and reduced sense of belonging. This highlights that developing educational robots as a foundation requires balancing technological instrumentality with social relationality, integrating technology application with the essence of education.

Second, functional positioning shifts from cognitive Q&A to dual cognitive-emotional support. This transition manifests in three aspects. On the virtual side, educational chatbots and conversational AI agents are the fastest-growing form of educational robots. Language-related activities are their most common application scenarios, evolving from general Q&A tools into learning partners supporting writing, outlining, revision and polishing. Voice-enabled chatbots expand interaction from text to voice and images. Research on knowledge and emotional scaffolding confirms conversational AI is evolving from single cognitive support into a dual cognitive-emotional system. On the physical side, integration of large language models and affective computing transforms physical robots from passive programmable platforms into intelligent learning partners with contextual awareness and personalized feedback. AI-driven physical robots support complex scenarios such as empathy training in patient–doctor communication. At the convergence, virtual-physical boundaries blur. Physical robots extend teaching presence via digital twins, and integration of conversational AI and physical robots is giving rise to a new generation of hybrid intelligent educational robots with natural language understanding and emotional interaction.

Third, development model shifts from individual teacher exploration to comprehensive ecosystem construction. Teachers are the key actors in advancing educational robots toward becoming a foundation for intelligent education, with adoption willingness and teaching capabilities directly determining integration effectiveness. Research suggests that a more promising direction lies not in replacing teachers with AI, but in building collaborative teaching ecosystems in which teachers and AI work together. Studies show AI and teacher feedback complement each other in focus and type, with conversational AI evolving from independent replacement to collaboration in teacher-led ecosystems. Research also shows that students and teachers hold divergent views on the appropriate boundaries of AI use in educational settings, while most schools have yet to establish clear usage policies or meaningful professional development support for teachers. This means developing educational robots as a foundation requires not only enhancing individual teacher capabilities but also building systematic support ecosystems covering competence standards, training models, assessment systems and usage norms.

In this research area, the top 3 countries by core paper output are China, USA, and Republic of Korea; the top 3 countries by citations are China, Republic of Korea, and the USA; the top 3 countries by average citations per paper are Saudi Arabia, the UAE, and China. Among major core-producing countries, the USA exhibits the highest international collaboration. The top 3 institutions in core papers are The University of Hong Kong, The Hong Kong Polytechnic University, and Southeast University (China); the top 3 institutions by average citations per paper are The Education University of Hong Kong, The Hong Kong Baptist University, and The University of Hong Kong. Among major core-producing institutions, The Hong Kong Polytechnic University demonstrates the most extensive collaboration. Countries ranking top 3 in citing core papers are China, the USA, and Türkiye; institutions ranking top 3 are The Education University of Hong Kong, The University of Hong Kong, and The Chinese University of Hong Kong.

Table 23 Major countries producing core papers on educational robots become a new cornerstone of smart education

Order	Country	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	China	18	45.0	3,304	183.56	2023.4
2	USA	6	15.0	682	113.67	2023.7
3	Republic of Korea	5	12.5	775	155.00	2023.2
4	Saudi Arabia	2	5.0	513	256.50	2023.5
4	UAE	2	5.0	505	252.50	2023.5
4	Cyprus	2	5.0	330	165.00	2022.0
4	Australia	2	5.0	153	76.50	2024.0
4	Iran	2	5.0	121	60.50	2024.5
4	Germany	2	5.0	74	37.00	2024.5
4	Türkiye	2	5.0	52	26.00	2025.0

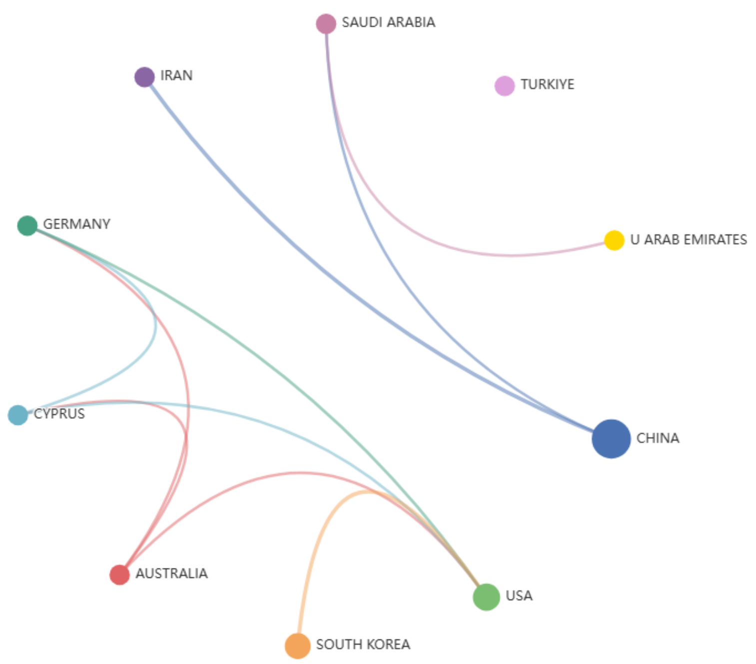

Figure 23 Collaboration network among major core-producing countries on educational robots become a new cornerstone of smart education

Table 24 Major institutions producing core papers on educational robots become a new cornerstone of smart education

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	The University of Hong Kong	4	10.0	979	244.75	2022.8
2	The Hong Kong Polytechnic University	3	7.5	504	168.00	2023.3
2	Southeast University (China)	3	7.5	282	94.00	2023.7
4	National Taiwan University of Science and Technology	2	5.0	436	218.00	2022.5
4	Taipei Medical University	2	5.0	436	218.00	2022.5
4	Beijing Institute of Technology	2	5.0	181	90.50	2023.5
4	Chung-Ang University	2	5.0	166	83.00	2023.0
4	Zhejiang University	2	5.0	105	52.50	2024.5
4	The Chinese University of Hong Kong	2	5.0	92	46.00	2025.0
10	The Education University of Hong Kong	1	2.5	568	568.00	2023.0
10	The Hong Kong Baptist University	1	2.5	568	568.00	2023.0

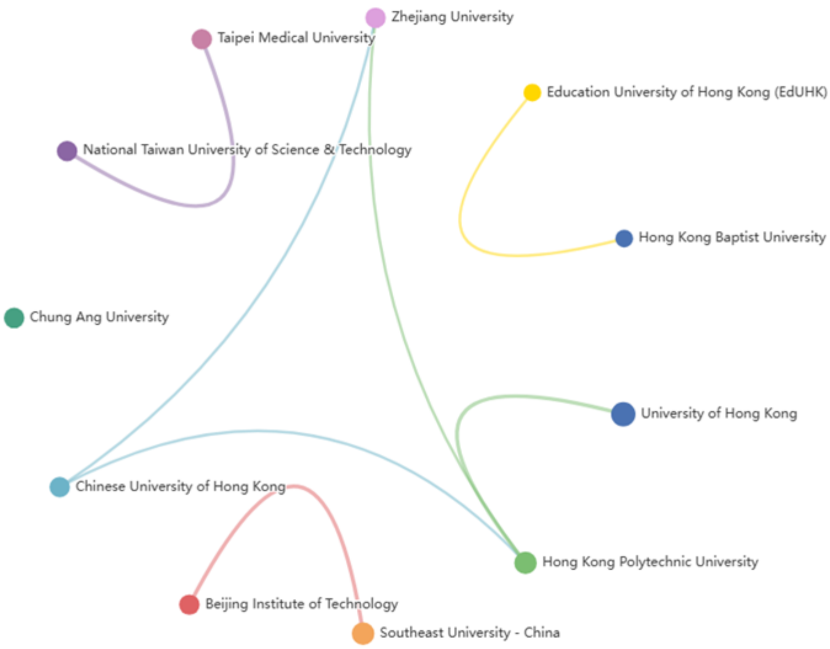

Figure 24 Collaboration network among major core-producing institutions on educational robots become a new cornerstone of smart education

Table 25 Major countries citing core papers on educational robots become a new cornerstone of smart education

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	China	1,599	38.11	2024.8
2	USA	554	13.20	2024.5
3	Türkiye	254	6.05	2025.0
4	UK	209	4.98	2024.6
5	Saudi Arabia	184	4.39	2024.6
6	Republic of Korea	177	4.22	2024.6
7	Spain	170	4.05	2024.2
8	Malaysia	162	3.86	2024.5
9	Australia	153	3.65	2024.7
10	Germany	141	3.36	2024.4

Table 26 Major institutions citing core papers on educational robots become a new cornerstone of smart education

Order	Institution	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	The Education University of Hong Kong	127	3.03	2024.4
2	The University of Hong Kong	98	2.34	2024.3
3	The Chinese University of Hong Kong	78	1.86	2024.8
4	Zhejiang University	71	1.69	2024.8
5	Beijing Normal University	61	1.45	2024.5
5	The Hong Kong Polytechnic University	61	1.45	2024.8
7	East China Normal University	51	1.22	2024.8
8	Central China Normal University	48	1.14	2024.9
9	Nanyang Technological University	42	1.00	2024.5
10	National Taiwan University of Science and Technology	34	0.81	2024.1

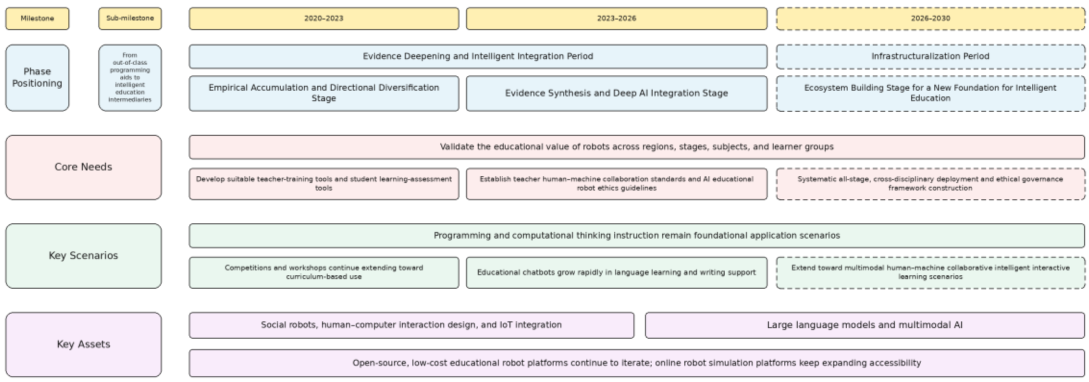

Figure 25 Development roadmap for educational robots become a new cornerstone of smart education

Figure 25 illustrates the development roadmap for educational robots become a new cornerstone of smart education. Before 2020, educational robots matured as tools for programming learning and the cultivation of computational thinking. From 2020 to 2023, the field entered empirical accumulation and direction diversification, expanding to language learning, distance education, special education and creativity development. Research explored situated presence, instructional support, and emotional support under conditions of uneven teaching-staff distribution, with meta-analyses providing systematic evidence. From 2023 to 2026, accelerated AI integration drove evidence synthesis and the deep integration of AI into subject teaching, with chatbots growing rapidly and robots evolving into intelligent teaching partners. Looking ahead (2026–2030), the field will formally enter a stage of ecosystem construction centered on infrastructuralization and the establishment of a new foundation for intelligent education. This stage will take multimodal human–robot collaborative tasks as its core scenario, substantially extending the frontiers of intelligent interactive learning. On the demand side, the focus will shift toward systematic, large-scale deployment spanning all educational stages and bridging multiple disciplines, accompanied by the concurrent development of a corresponding ethical governance framework. On the infrastructure side, open-source low-cost educational robotics platforms and online robot simulation platforms will undergo continuous iteration and expansion, providing robust technical feasibility to support the large-scale infrastructuralization of educational robotics.

Educational robots are becoming a new smart teaching cornerstone, yet challenges remain. Realizing this requires sustainable evidence, scalable implementation, ethical governance and assessable outcomes. In terms of evidence, existing studies focus mainly on short-term interventions and lack cross-semester longitudinal tracking, providing insufficient grounds for the sustained-effect judgments required for routine deployment. In terms of implementation, structural barriers—including inadequate basic equipment, limited instructional time, lack of technical support, and insufficient funding for computing power—constrain teachers' adoption willingness; regional disparities in equipment costs and teaching staff conditions risk widening the digital divide and undermining the goal of equalizing public services. In terms of ethics, emerging risks such as children's anthropomorphic perceptions of robots, learner behavioral misconduct, and the credibility of AI-generated content threaten the ethical legitimacy of institutionalized use. In terms of standards, standardized assessment systems for educational-robot learning outcomes and curricular competency progression frameworks remain at an early stage, hindering curriculum-standard alignment and outcome certification. Future research must prioritize mechanism interpretation and long-term tracking, advancing teacher development, equitable models, assessment tools and ethical frameworks for systematic support.

Overall, educational robots are evolving from demonstration tools into regular intelligent education resources. Their effectiveness depends not only on continued advances in AI capabilities, but even more critically on synchronized progress in evidence-based research, teacher support, curriculum alignment and ethical governance.

3.2.7 Adaptive Learning Systems Accelerate Transformation of Learning Scenarios

With advances in GenAI and multimodal perception technologies, research focus on adaptive learning systems is shifting. Adaptive learning systems emphasize "tailored to individual learners", delivering learning support aligned with individual differences and evolving learner needs. Current research centers more closely on authentic learning processes, exploring how to interpret learner behavior, deliver timely interventions, and adjust support strategies in complex contexts.

In recent years, research priorities in this field have shifted toward multi-dimensional state perception, real-time intervention, and the adaptive evolution of systems for learning processes. Key research themes include emotion recognition, cognitive load monitoring, learning engagement analysis, conversational support, multimodal large models, and immersive learning environments. This evolution marks adaptive learning systems moving from simple content recommenders to integrated systems combining perception, decision-making, feedback, assessment, and continuous optimization. Core capabilities now encompass understanding real-time learner states, determining intervention timing, and refining system functions dynamically across complex scenarios.

Research in this field centers on three key directions. First, modeling multi-dimensional learner states. This line of inquiry focuses on system perception and learner modeling modules. Systems conduct multi-dimensional modeling of learner states, covering emotion recognition, cognitive load assessment, learning engagement analysis, motivation identification, and autonomy profiling. Leveraging facial recognition, text and dialogue analysis, multimodal signal processing, and physiological monitoring, systems build detailed, dynamic learner profiles.

Second, adaptive mechanisms for real-time intervention and dynamic feedback. Research centers on system decision-making and adaptive intervention modules. Beyond content recommendation, studies focus on intervention timing, delivery modes, channels, and support strategies. System evolution reflects a shift from static content delivery to integrated dynamic feedback, emotional scaffolding, task difficulty adjustment, and conversational support. Dialogue agents, automated writing evaluation, and adaptive assessment have become major research focuses.

Third, evolutionary mechanisms for sustained system optimization across diverse contexts. Research emphasizes system architecture and continuous adaptation in dynamic learning environments. Cloud-based adaptive learning and mobile context-aware adaptation are emerging approaches, enabling iterative updates under dynamic data, complex scenarios, and multi-task conditions. Continuous learning theory highlights balancing stability and plasticity for iterative system improvement. Ethical risks and data privacy are also growing research concerns.

This research field exhibits four key characteristics. First, iteration of adaptive learning systems involves more than technical addition; core logic shifts from simple content recommendation to process-oriented dynamic support. Second, learner models evolve toward multi-dimensional integration of emotion, cognition, behavior, and context, enabling finer-grained perception. Third, feedback, assessment, and conversational support modules become dynamically integrated under new technical frameworks. Fourth, adaptive learning systems emerge as stable, continuously optimized learning infrastructures for complex environments. Critical challenges include ethical risks, data privacy, algorithm bias, limited interpretability, cross-cultural adaptability, and the potential weakening of teachers' roles.

In this research area, countries with prominent core paper output include China, Iran, the UK, and the USA; the top 3 countries by citations are China, the UAE, and Saudi Arabia; the top 3 countries by average citations per paper are Saudi Arabia, the UAE, and Republic of Korea. Among major core-producing countries, China, Iran, the USA, and the UAE show extensive international collaboration. Leading core-producing institutions include The Education University of Hong Kong, The Chinese University of Hong Kong, and Central China Normal University; the top 3 institutions by average citations per paper are Tsinghua University, Princess Nourah bint Abdulrahman University, and Zayed University. Among major core-producing institutions, The Education University of Hong Kong and The Chinese University of Hong Kong demonstrate the most extensive collaboration. Countries ranking top 3 in citing core papers are China, the USA, and the UK; institutions ranking top 3 are The Chinese University of Hong Kong, The Education University of Hong Kong, and Zhejiang University.

Table 27 Major countries producing core papers on adaptive learning systems accelerate transformation of learning scenarios

Order	Country	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	China	13	40.62	1,640	126.15	2023.9
2	Iran	4	12.50	258	64.50	2024.8
3	USA	3	9.38	340	113.33	2024.0
3	UK	3	9.38	349	116.33	2024.3
5	UAE	2	6.25	428	214.00	2024.0
5	Republic of Korea	2	6.25	322	161.00	2022.5
5	Greece	2	6.25	217	108.50	2024.5
5	Portugal	2	6.25	209	104.50	2024.5
5	Germany	2	6.25	60	30.00	2025.0
10	Saudi Arabia	1	3.12	412	412.00	2023.0

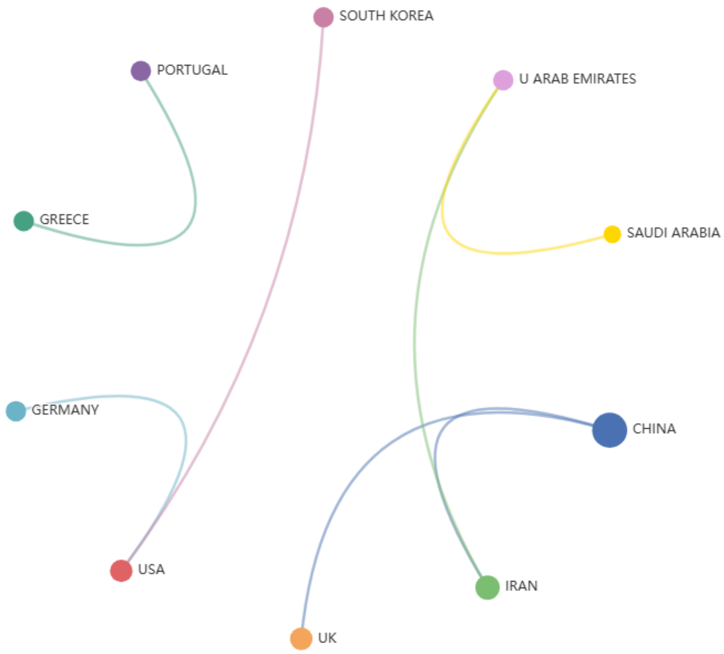

Figure 26 Collaboration network among major core-producing countries on adaptive learning systems accelerate transformation of learning scenarios

Table 28 Major institutions producing core papers on adaptive learning systems accelerate transformation of learning scenarios

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	The Education University of Hong Kong	3	9.38	349	116.33	2024.3
1	The Chinese University of Hong Kong	3	9.38	330	110.00	2023.7
1	Central China Normal University	3	9.38	121	40.33	2024.0
4	University of Patras	2	6.25	217	108.50	2024.5
4	Golestan University	2	6.25	181	90.50	2025.0
6	Tsinghua University	1	3.12	578	578.00	2024.0
6	Princess Nourah bint	1	3.12	412	412.00	2023.0

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
	Abdulrahman University					
6	Zayed University	1	3.12	412	412.00	2023.0
6	Lingnan University	1	3.12	251	251.00	2023.0
6	Zurich University of Applied Sciences	1	3.12	200	200.00	2021.0

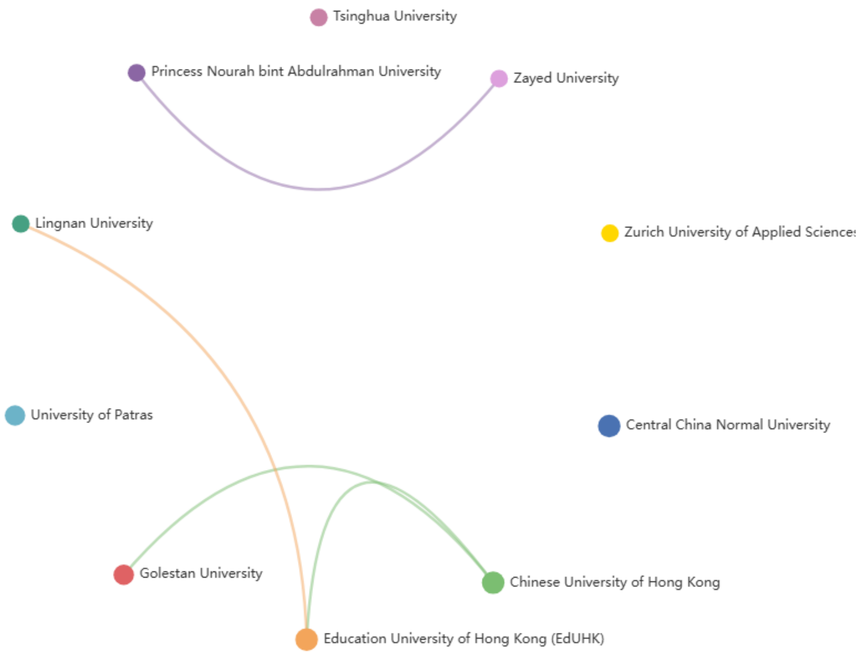

Figure 27 Collaboration network among major core-producing institutions on adaptive learning systems accelerate transformation of learning scenarios

Table 29 Major countries citing core papers on adaptive learning systems accelerate transformation of learning scenarios

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	China	1,518	42.40	2024.9
2	USA	392	10.95	2024.7
3	UK	160	4.47	2024.8
4	Republic of Korea	157	4.39	2024.7

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
5	Saudi Arabia	154	4.30	2024.6
5	Türkiye	154	4.30	2024.9
7	Spain	149	4.16	2024.5
8	Malaysia	143	3.99	2024.8
9	Australia	129	3.60	2024.8
10	Germany	121	3.38	2024.7

Table 30 Major institutions citing core papers on adaptive learning systems accelerate transformation of learning scenarios

Order	Institution	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	The Chinese University of Hong Kong	70	1.96	2024.3
2	The Education University of Hong Kong	64	1.79	2024.8
3	Zhejiang University	56	1.56	2024.9
4	The University of Hong Kong	55	1.54	2024.4
5	Nanyang Technological University	50	1.40	2025.0
6	University of Patras	47	1.31	2025.2
7	East China Normal University	46	1.28	2024.8
8	Chinese Academy of Sciences	44	1.23	2024.8
9	Tsinghua University	43	1.20	2025.2
10	Beijing Normal University	40	1.12	2024.7

Sub-theme	Adaptive Learning Systems Accelerate the Transformation of Learning Scenarios			
Phase Positioning	Basic Adaptation Construction Phase	Emerging Interactive Expansion Phase	Deepening State Perception Phase	Multimodal Integration and System Reconstruction Phase
Core Features	Based on blended learning and online platforms, focuses on resource recommendation and pathway differentiation. The system initially identifies differences in learners' abilities and emphasizes whether it can effectively support learning.	Extending to teaching and peer agents, the system shifts from two-dimensional content adaptation to immersive environments, such as VR and the metaverse, and from resource distribution to scenario embedding.	Generative AI is incorporated into content generation and affective scaffolding. Based on behavioral, textual, and physiological data, the system understands learner states and provides dynamic interventions. Moving toward process-oriented support.	Within the framework of large multimodal models, content, support, and assessment are integrated. Neurophysiological signal monitoring is introduced. Emphasizing human–machine collaboration and ethical governance.
Key Scenarios	Blended learning, online platforms, adaptive gamification, etc.	Language learning, educational chatbots, VR/the metaverse, etc.	Learning management systems, MOOCs, conversational scaffolding, etc.	Multimodal science education, writing feedback, neuroadaptive learning, etc.
Key Issues	Personalized pathways, digital support design, learning style identification, etc.	Dialogue agent roles, interaction styles, personalized feedback, immersive support, etc.	Generative content and feedback, knowledge and affective scaffolding, cognitive load regulation, etc.	Applications of large multimodal models, perception and load management, human–machine boundaries, etc.

Figure 28 Development roadmap for adaptive learning systems accelerate transformation of learning scenarios

Figure 28 illustrates the development roadmap of adaptive learning systems across four key phases.

Phase I: Basic adaptation construction period. Research centered on blended learning, online platforms, and gamified design, establishing initial adaptive mechanisms for resource recommendation and path differentiation based on learning styles, abilities, and preferences. Systems functioned primarily as structured learning tools.

Phase II: Interactive expansion germination period. Systems evolved from within-platform content distribution and task adaptation to rich interaction, integrating dialogue, voice, and contextual guidance. Interactions became more companionable, responsive, and context-embedded.

Phase III: State perception deepening period. GenAI shifted focus to learning processes, including emotion, engagement, cognitive load, and dialogue performance. Through knowledge scaffolding, affective scaffolding, dynamic feedback, and state recognition, adaptive learning systems provide more fine-grained support and regulation. At this stage, they gradually develop the ability to understand and intervene in the learning process.

Phase IV: Multimodal integration and system reconstruction period. Multimodal large models, neurophysiological sensing, human–machine collaboration and system governance become increasingly interconnected.

Adaptive learning systems begin to integrate multiple functions within a unified framework, including content generation, multimodal representation transformation, and real-time state monitoring, gradually evolving into complex, multimodal, and collaborative intelligent learning support systems.

3.2.8 Collaborative AI Governance Shapes Global Educational Security

AI governance in education refers to the process of normative guidance, risk prevention, accountability coordination and value shaping around AI design, development, introduction and application in education. It focuses on AI's potential impacts on academic integrity, educational equity and data security.

With AI penetrating the entire teaching and learning process, educational AI governance is gradually shifting from external constraints such as legal provisions and organizational norms toward a comprehensive governance model combining group consensus, AI literacy development and multi-party coordination. Current research in this field focuses on three aspects. The connotation of AI literacy extends beyond knowledge memorization and basic tool operation to integrated capabilities in human–machine collaboration. AI ethical governance shifts from external regulation toward teachable and assessable educational goals, becoming a core component of AI literacy. GenAI widens the digital divide from access gaps to skill and usage disparities, creating complex governance challenges for educational equity.

Current research on educational AI governance is no longer limited to risk prevention. It explores whether technological development can serve educational goals such as fostering morality, academic integrity, equity and holistic student development. Synergistic AI governance and stakeholder capacity building enhance understanding, judgment and responsible use of AI, laying a foundation for the stable and sustainable development of education in the smart era. Current research in this field focuses on three core directions.

First, capacity building extends from knowledge understanding and tool operation to responsible use. With GenAI integrated into teaching, academic writing and language learning, developing learners' responsible

AI use has become a core issue. The connotation of AI literacy is evolving, expanding from knowledge comprehension and tool operation to multi-dimensional competencies including effective use, critical judgment, ethical assessment and adaptive regulation in human–machine collaboration. Empirical studies show that the real impact of AI hinges on learners' ability to craft effective prompts, evaluate outputs, identify risks, revise responses and maintain independent thinking. With advances in scale development and validation, AI literacy is recognized as a measurable, stratifiable and intervenable competency. It evolves into a human–machine collaborative capability for complex problem-solving, making responsible use a core objective.

Second, AI ethical governance shifts from rule-making to capacity building. From the perspective of AI ethics governance, the research focus shifts from external regulation to educational goals that are both cultivable and assessable. The research centres on pathways for the responsible integration of AI in education, as developed through the following three key dimensions. First, research deepen into academic integrity and usage boundaries. The widespread application of AI has directly impacted writing authenticity, the principle of independent completion, and traditional writing competency assessment systems. The common attention in research is: in the process of AI-assisted learning, how should educational systems redefine the relationships among reasonable use, originality, and effective learning. Second, attention to the risks and trustworthiness of AI systems is growing. Research has found that AI poses risks in areas such as hallucinated outputs and value biases. These risks ofen manifest in seemingly coherent and authoritative forms, making them difficult to identify. Therefore, the extent to which AI should intervene in high-stakes scenarios such as assessment, feedback, and knowledge support has become a key research focus. Third, there is a growing consensus on incorporating responsible use into AI literacy frameworks. Existing research argue that the responsible use of AI should be embedded within learners' core competency development systems, carrying equal importance to knowledge understand and skill application. It is evident that the core of AI ethics governance is shifting from principle-based advocacy toward cultivable and assessable educational objectives. This indicates that educational practice must further promote the transformation of AI ethics govenance standards into curriculum design, instructional activities, and assessment methods, enhancing the contextual adaptability, operability, and consistency of relevant implementation standards to ensure their effective realization. Moreover, given that teachers serve as key organizers of AI application in instructional practice, it is also necessary to strengthen research on teachers' capacities for ethical judgement and pedagogical guidance in AI application.

Third, the digital divide extends from access gaps to skill and usage disparities. Research indicates that the emergence of AI does not equate to the equalization of educational opportunities; on the contrary, AI may exacerbate existing educational disparities and resource stratification. On the one hand, it offers new opportunities for personalized learning support and learning resource compensation; on the other hand, the effectiveness of AI application depends heavily on infrastructure, family support and user capabilities. Furthermore, if the systems harbor deficiencies such as data bias, cultural bias, or inadequate contextual adaptation, the digital divide may be further widened. Existing research primarily focuses on three dimensions. First, access disparities arising from differing digital infrastructure conditions. Device availability, network quality, and platform accessibility directly affect whether learners can enter AI-supported learning environments, and inter-group imbalances in digital infrastructure do not naturally disappear with the proliferation of AI. Second, competency differences are gradually emerging as a new critical differentiating factor. Under similar access conditions, differences among learners in digital literacy, information judgement, prompt use, self-learning and technology acceptance significantly affect the effectiveness of their AI use. Third, disparities at the levels of usage purpose and resources are becoming increasingly apparent. More research shows that even when presented with the same AI tools, different groups exhibit varying behaviors and receive differing levels of learning support, and such disparities are closely related to learners' family support resources and school guidance. Currently, the digital divice is extending further in the direction of competency differentiation, necessitating targeted competency cultivation and institutional support for different groups. Future research should be grounded in local realities and strengthen the study of urban-rural disparities, regional development imbalances, and socioeconomic background differences, so as to enhance the practical relevance of educational equity research.

In this research area, countries with prominent core paper output include China, Australia, the UK and the USA; the top 3 countries by citations are China, the UK and Philippines; the top 3 countries by average citations per paper are the UK, China and Philippines. Among major core-producing countries, the UK and Australia show the most extensive international collaboration. Leading core-producing institutions include Central Queensland University, National University (Philippines) and Allameh Tabataba'i University; the top 3 institutions by average citations per paper are University of Plymouth, The University of Hong Kong and The Education University of Hong Kong. Among major core-producing institutions, Golestan University, Allameh Tabataba'i University and North China University of Water Resources and Electric Power demonstrate the most extensive collaboration. Countries ranking top 3 in citing core papers are China, the USA and the UK. Institutions ranking top 3 in citing core papers are The Education University of Hong Kong, The Chinese University of Hong Kong, and The University of Hong Kong.

Table 31 Major countries producing core papers on collaborative AI governance shapes global educational security

Order	Country	Number of core papers	Percentage of core papers/%	Total citations	Average citations per paper	Mean publication year
1	China	9	33.33	2,349	261.00	2023.9
2	Australia	6	22.22	432	72.00	2024.2
3	UK	4	14.81	1,289	322.25	2024.2
3	USA	4	14.81	409	102.25	2023.8
5	Philippines	2	7.41	434	217.00	2024.0
5	Iran	2	7.41	258	129.00	2024.5
5	Malaysia	2	7.41	202	101.00	2024.0
5	India	2	7.41	118	59.00	2024.0
5	Germany	2	7.41	69	34.50	2024.5
5	Latvia	2	7.41	69	34.50	2024.5

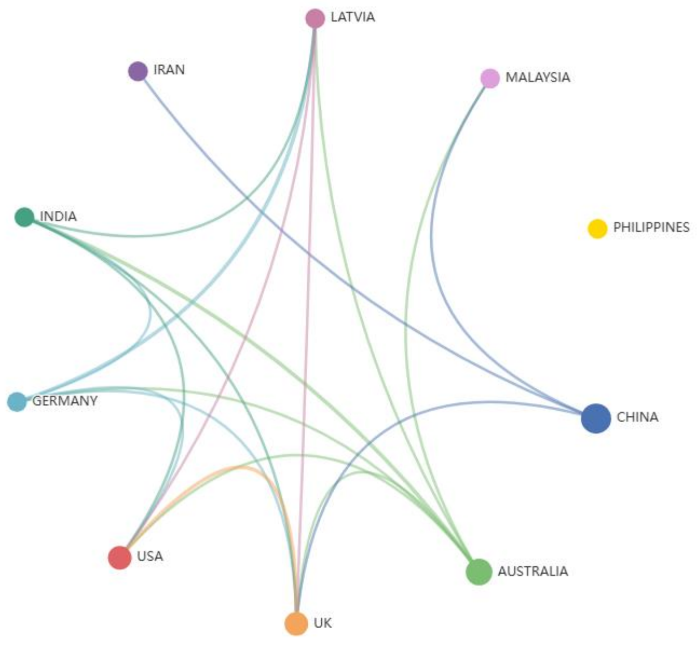

Figure 29 Collaboration network among major core-producing countries on collaborative AI governance shapes global educational security

Table 32 Major institutions producing core papers on collaborative AI governance shapes global educational security

Order	Institution	Number of core papers	Percentage of core papers/%	Total citations	Average citations per paper	Mean publication year
1	Central Queensland University	3	11.11	245	81.67	2024.0
2	National University Philippines	2	7.41	434	217.00	2024.0
2	Allameh Tabataba'i University	2	7.41	258	129.00	2024.5
2	Golestan University	2	7.41	258	129.00	2024.5
2	North China University of Water Resources and Electric Power	2	7.41	117	58.50	2025.0
2	Riga Stradins University	2	7.41	69	34.50	2024.5
2	University of Munich	2	7.41	69	34.50	2024.5
8	University of Plymouth	1	3.70	1,171	1,171.00	2024.0
8	The University of Hong Kong	1	3.70	952	952.00	2023.0
8	The Education University of Hong Kong	1	3.70	568	568.00	2023.0

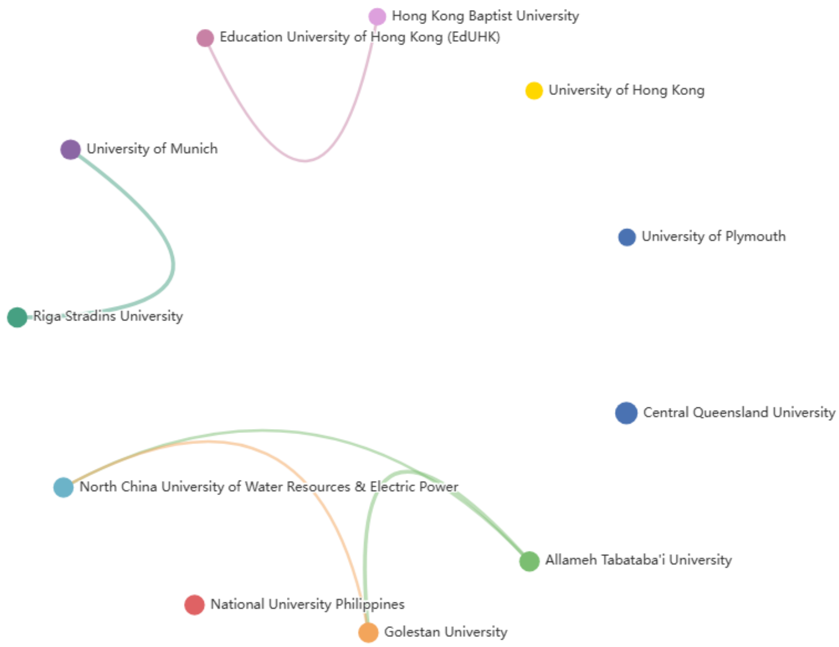

Figure 30 Collaboration network among major core-producing institutions on collaborative AI governance shapes global educational security

Table 33 Major countries citing core papers on collaborative AI governance shapes global educational security

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	China	1441	32.84	2025.1
2	USA	658	15.00	2024.8
3	UK	267	6.08	2024.9
4	Türkiye	252	5.74	2025.0
5	Australia	247	5.63	2024.8
6	Germany	176	4.01	2024.7
7	Malaysia	163	3.71	2024.9
7	Saudi Arabia	163	3.71	2024.8
7	Spain	163	3.71	2024.9
10	Republic of Korea	135	3.08	2024.9

Table 34 Major institutions citing core papers on collaborative AI governance shapes global educational security

Order	Institution	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	The Education University of Hong Kong	94	2.14	2024.9
2	The Chinese University of Hong Kong	72	1.64	2025.0
3	The University of Hong Kong	61	1.39	2024.8
3	Zhejiang University	61	1.39	2025.1
5	The Hong Kong Polytechnic University	52	1.19	2025.0
6	East China Normal University	49	1.12	2024.9
7	Beijing Normal University	37	0.84	2025.1
7	Nanyang Technological University	37	0.84	2025.0
9	Monash University	33	0.75	2025.0
9	University of Patras	33	0.75	2025.3

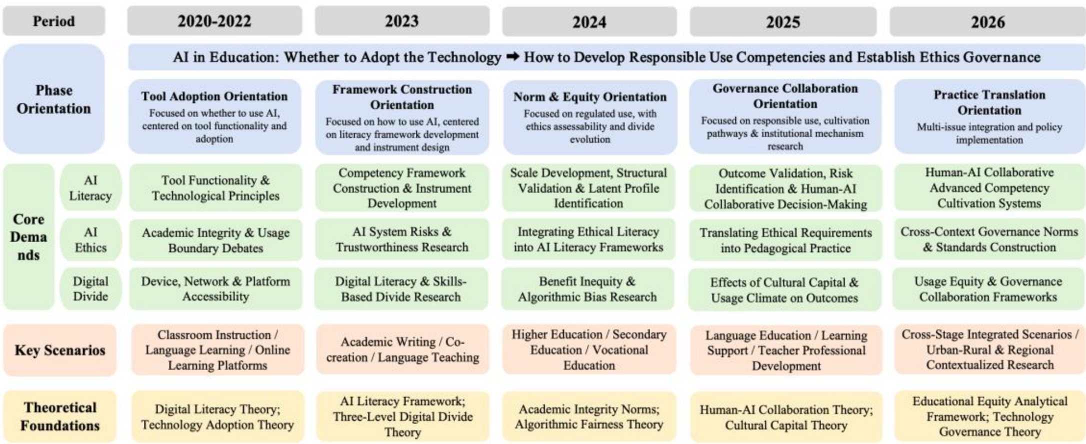

Figure 31 Development roadmap for collaborative AI governance shapes global educational security

Figure 31 illustrates the development roadmap. From 2020 to 2022 AI governance research in educational settings was generally characterised by a tool-adoption orientation. Studies during this period mainly focused on the supportive functions of AI in education the underlying technological principles and the conditions for access and use with core research topics centred on AI use and its application scenarios.

Since 2023, the rapid integration of GenAI into educational and instructional contexts has transformed AI from an auxiliary tool into a deeply embedded supportive tool involved in writing question-answering feedback assessment and other educational processes. This shift has pushed AI governance research in educational settings from technology adoption towards the construction of capability frameworks with increasing attention to how AI can be used effectively and how responsible AI use should be defined.

In 2024, as GenAI became further embedded across teaching learning and assessment processes related research expanded to key issues of normative and equitable use including AI literacy frameworks risk analysis and the digital divide.

In 2025, AI governance research in educational settings further demonstrated a collaborative governance orientation. Research attention shifted towards multi-stakeholder collaborative governance issues arising from the deep integration of GenAI into teaching learning support and teacher professional development. Key concerns included outcome verification risk identification and the cultivation of human–AI collaborative decision-making capacity. This stage emphasised the need to establish clearer divisions of responsibility and coordination mechanisms among teachers students technological systems and educational organisations.

In 2026, AI governance research moved towards an implementation-oriented stage of practice transformation with the research focus shifting to the development of implementable systems frameworks and standards. Relevant studies continued to address the construction of human–AI collaborative higher-order capability development systems cross-scenario governance norms and standards and frameworks for AI use equity and governance coordination. Research also gradually expanded to integrated cross-stage educational scenarios and context-specific studies in urban–rural regional settings.

Overall, the deep integration of GenAI has driven AI governance research in educational settings from an initial focus on technology adoption and boundaries of use towards a comprehensive governance stage characterised by the co-development of collaborative governance and capacity building.

3.2.9 Immersive Interactive Technology Reshapes Future Learning Paradigms

Immersive interactive technology refers to a category of technologies centered on extended reality (XR), which includes virtual reality (VR), augmented reality (AR), and mixed reality (MR). Its core function is to transcend the boundary between the physical world and the digital virtual world, thereby enabling users to experience a strong sense of presence and embodied interaction.

In digital education, research on immersive interactive technology focuses on three core areas. First, it explores how immersive technologies such as VR and AR support the development of metaverse-based learning environments, creating highly embodied and interactive learning experiences. Second, it investigates how immersion and interactivity shape learners' cognitive and affective processes, including interest, motivation, cognitive load, and embodied experience, thereby influencing learning processes and learning performance. Third, it examines how immersive learning spaces transform teaching practices, with attention to teachers' technological readiness, instructional design strategies, and integration approaches with existing education systems.

Empirical findings show that immersive learning environments significantly enhance learners' interest, emotional engagement, and knowledge retention. However, overall learning effectiveness depends primarily on instructional design rather than the technology itself. While immersion and interactivity facilitate learning through embodied experience and virtual scenarios, overly complex interfaces or excessive emotional arousal can distract learners, increase cognitive load, and impair knowledge transfer. Current research examines how immersive interactive technology moderates teaching strategies. Future studies will focus on embodied cognition-based immersive environment design, adaptive learning pathways, real-time feedback mechanisms, multimodal integration, and ecological support for teachers' technological readiness. The ultimate goal is to build highly embodied, personalized, and cohesive learning ecosystems that reduce cognitive load, activate learners' agency, and deepen knowledge construction.

As a key driver of digital transformation, immersive interactive technology is evolving from standalone VR applications toward integrated VR, AR, and MR solutions, continuously advancing learning paradigms. Multimodal sensory experiences and embodied interactions shift learners from passive knowledge recipients to active explorers and meaning constructors. Research confirms that immersive interactive technology exerts significantly positive effects on science education and the development of learners' specific competencies, outperforming traditional lectures and unguided practical activities. Nonetheless, it faces challenges such as excessive cognitive load and novelty effect interference, and learning outcomes remain highly dependent on instructional design. Therefore, rigorous systematic evaluation and instructional design research are essential to fully unlock the educational potential of immersive interactive technology.

Current research centers on three main aspects. First, it explores the mechanisms through which immersive interactive technology influences cognition and emotion. Grounded in cognitive-affective immersion learning models, studies examine how immersion and interactivity shape learning processes and outcomes through mediating variables such as interest, motivation, self-efficacy, embodied experience, and cognitive load, revealing interactions between technology and learners' psychological factors. Second, it focuses on the design and optimization of instructional strategies in immersive learning environments. Research validates the effectiveness of pre-training, generative learning, instructional interventions, and peer assessment, exploring design approaches to reduce cognitive load and maximize the educational value of immersive technology. Third, it addresses systemic educational transformation enabled by immersive technology. Studies examine the strategic deployment, application scenarios, and teachers' technological readiness of VR and related technologies in K-12 and higher education, analyzing organizational barriers and standardization challenges in scaling immersive technology. Research emphasizes the need for support systems that guide teachers from technology adoption to instructional innovation, driving improvements in teaching effectiveness through technology-supported pedagogical innovation.

Driven by immersive interactive technology, learning models are evolving from technology-mediated perception of the world toward collaborative human–technology exploration of the world. The integration of GenAI further enables immersive interactive technology to more dynamically reshape learners' cognitive structures. At the level of learning mechanisms, immersion and interactivity are no longer merely technical features; they deeply engage in learning processes by stimulating interest, sustaining motivation, and facilitating embodied experience, fundamentally reshaping learners' cognitive processing and emotional engagement patterns. At the level of teaching practice, instructional strategies for regulating cognitive load and mitigating novelty effects have become a core research focus. The coordinated application of pre-training, generative learning, and diversified assessment is driving immersive learning to advance from enhanced perception to optimized learning, with educational effectiveness increasingly relying on refined instructional design rather than mere technological investment. At the level of education systems, XR-based emerging technologies are gradually integrated into teaching across all educational stages, driving systemic changes in curriculum structures, teaching models, and teacher roles, while imposing higher requirements for technical standards, organizational coordination, and teacher professional development.

In this research area, the top 3 countries by core paper output are China, Denmark, and the USA; countries with high citation counts include Denmark, China, and Germany; the top 3 countries by average citations per paper are Germany, Liechtenstein, and Norway. Among major core-producing countries, Germany, Liechtenstein, and Norway show extensive international collaboration. Leading institutions include University of Copenhagen and University of California Santa Barbara; the top 3 institutions by average citations per paper are University of Agder, University of Duisburg-Essen, and University of Liechtenstein. Among major core-producing institutions, University of Agder, University of Duisburg-Essen, and University of Liechtenstein collaborate most. Countries ranking top 3 in citing core papers are China, the USA, and Germany; institutions ranking top 3 are National Taiwan University of Science and Technology, National Taiwan Normal University, and The Chinese University of Hong Kong.

Table 35 Major countries producing core papers on immersive interactive technology reshapes future learning

Order	Country	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	China	6	28.57	1,154	192.33	2022.0
2	Denmark	4	19.05	1,361	340.25	2021.5
2	USA	4	19.05	676	169.00	2022.0
4	Republic of Korea	2	9.52	307	153.50	2022.0
4	Spain	2	9.52	266	133.00	2023.0
6	Germany	1	4.76	1,027	1,027.00	2020.0
6	Liechtenstein	1	4.76	1,027	1,027.00	2020.0
6	Norway	1	4.76	1,027	1,027.00	2020.0
6	Italy	1	4.76	292	292.00	2020.0
6	Cyprus	1	4.76	228	228.00	2023.0

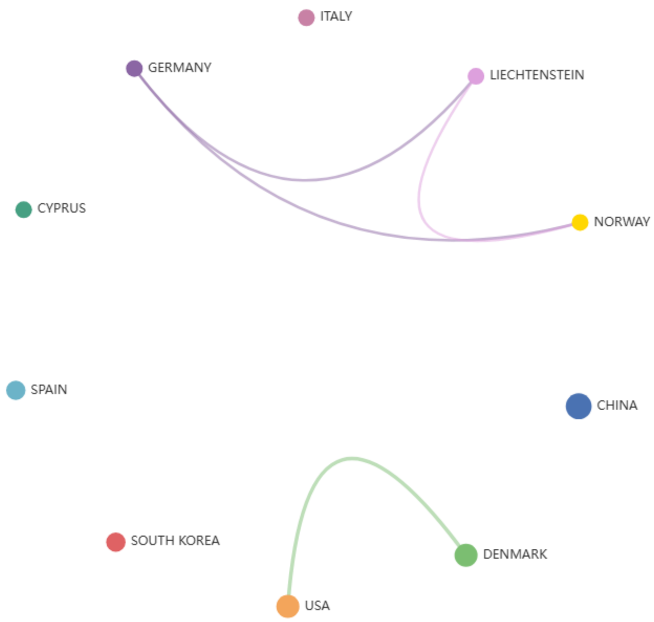

Figure 32 Collaboration network among major core-producing countries on immersive interactive technology reshapes future learning paradigms

Table 36 Major institutions producing core papers on immersive interactive technology reshapes future learning paradigms

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
1	University of Copenhagen	4	19.05	1,361	340.25	2021.5
1	University of California Santa Barbara	4	19.05	676	169.00	2022.0
3	University of Agder	1	4.76	1,027	1,027.00	2020.0
3	University of Duisburg Essen	1	4.76	1,027	1,027.00	2020.0
3	University of Liechtenstein	1	4.76	1,027	1,027.00	2020.0
3	East China Normal University	1	4.76	350	350.00	2020.0
3	Catholic University of the Sacred Heart	1	4.76	292	292.00	2020.0
3	University of Milano-Bicocca	1	4.76	292	292.00	2020.0
3	Wenzhou University	1	4.76	287	287.00	2022.0
3	The Chinese University of Hong Kong	1	4.76	270	270.00	2020.0

Order	Institution	Number of core papers	Percentage of core papers /%	Total citations	Average citations per paper	Mean publication year
3	National Taiwan University of Science and Technology	1	4.76	270	270.00	2,020.0

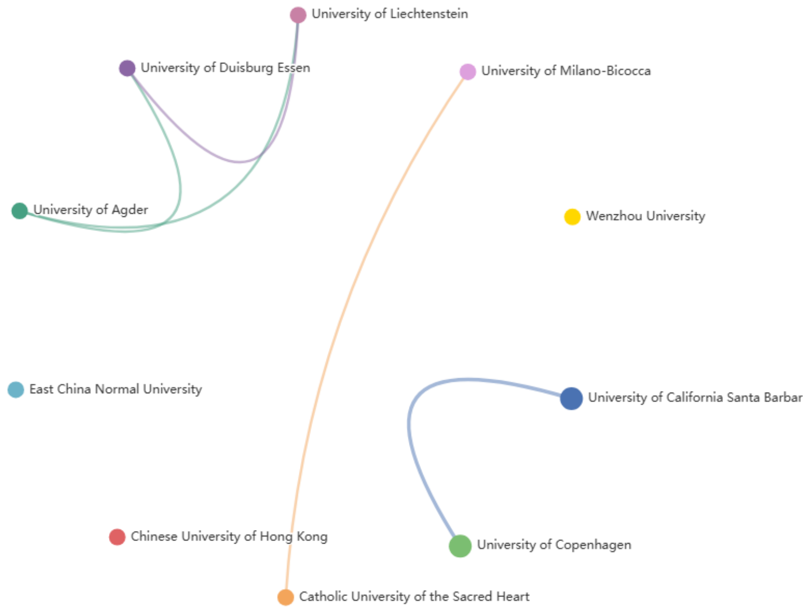

Figure 33 Collaboration network among major core-producing institutions on immersive interactive technology reshapes future learning paradigms

Table 37 Major countries citing core papers on immersive interactive technology reshapes future learning paradigms

Order	Country	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	China	1,115	28.19	2024.1
2	USA	575	14.54	2023.8
3	Germany	273	6.90	2023.9
4	UK	222	5.61	2023.7
5	Spain	189	4.78	2023.8
6	Republic of Korea	182	4.60	2024.1
7	Australia	178	4.50	2023.7
8	Italy	156	3.94	2024.0
9	Malaysia	138	3.49	2024.2
10	India	122	3.08	2024.3

Table 38 Major institutions citing core papers on immersive interactive technology reshapes future learning paradigms

Order	Institution	Number of citing papers	Percentage of citing papers /%	Mean citing year
1	National Taiwan University of Science and Technology	56	1.42	2024.2
2	National Taiwan Normal University	50	1.26	2023.6
3	The Chinese University of Hong Kong	49	1.24	2023.2
4	The Hong Kong Polytechnic University	47	1.19	2024.0
5	Central China Normal University	44	1.11	2024.2
6	National Taichung University of Education	41	1.04	2024.6
7	University of Copenhagen	40	1.01	2023.0
8	The University of Hong Kong	36	0.91	2024.0
9	The Education University of Hong Kong	35	0.88	2023.9
10	Yuan Ze University	33	0.83	2024.9

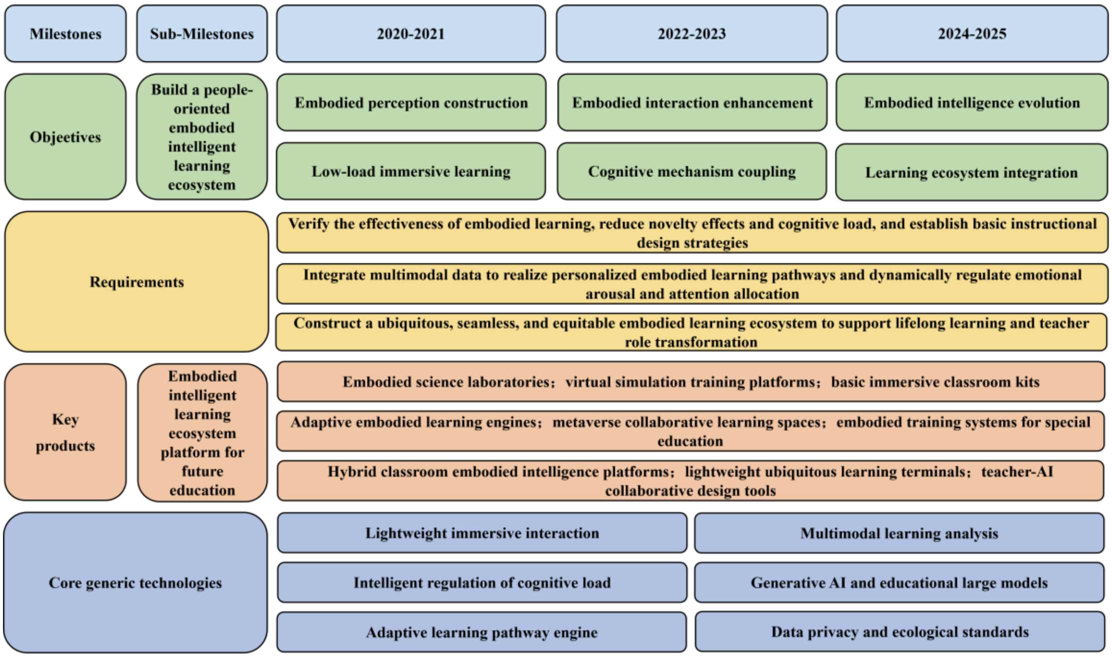

Figure 34 Development roadmap for immersive interactive technology reshapes future learning paradigms

Figure 34 illustrates the development roadmap for immersive interactive technology in reshaping future learning paradigms. Before 2020, immersive applications in education remained fragmented, centered on basic VR or AR experiences. Constrained by novelty effects and excessive cognitive load, research had not formed systematic embodied teaching frameworks.

From 2020 to 2021, research entered a perceptual awakening phase, focusing technically on addressing the issue of insufficient embodied presence. Motion tracking and basic gesture recognition were used to create a low-latency sense of presence, though embodied experiences remained script-driven.

From 2022 to 2023, research advanced into an interactive emergence phase. Pose estimation and behavior sequence modeling were adopted to interpret movement intentions and deliver contextually responsive feedback. Interactive platforms evolved from merely recording user actions to interpreting interactive processes, significantly reducing user operational burdens.

From 2024 to 2025, research entered an intelligent generation phase. With the application of embodied AI models and neural rendering technologies, systems can generate prompts based on learners' physical movements. Natural actions like walking, bending, or pointing dynamically adjust learning narratives and task difficulty, achieving deep integration of cognition, body, and learning environments.

The embodied learning paradigm is evolving rapidly from perceptual interaction to intelligent collaboration, yet multiple challenges persist. First, current research relies heavily on short-term interventions, lacking longitudinal evidence from real classroom settings to validate long-term effectiveness. Second, high immersion often leads to cognitive overload, and balancing immersive experience with learning efficiency remains a key challenge. Third, insufficient teacher readiness and limited human–AI collaboration capacity create structural bottlenecks, while high equipment costs and regional disparities risk widening the digital divide. Fourth, ethical governance and assessment frameworks are underdeveloped: large-scale collection of behavioral and physiological data raises privacy concerns, and evaluation systems for embodied learning outcomes are still in early stages. Future research must shift from short-term effectiveness validation to long-term dynamic tracking, advancing teacher capacity development, low-cost implementation models, instructional design optimization, ethical governance improvement, and assessment standardization to support large-scale, sustainable adoption of embodied learning.

3.2.10 Self-directed learning ability Reflects Essential Characteristics of Digital Education

As digital technologies are deeply integrated into teaching scenarios and GenAI rapidly reshapes learning approaches, the classic question of "how learners learn" has returned to the center of research from a new perspective. This issue is significant in two dimensions. First, from the perspective of learner development, the core requirement for talent in the smart era is maintaining clear judgment, setting goals proactively, and adjusting strategies flexibly in ongoing collaboration with technological tools. Understanding how learners sustain autonomous motivation and effectively apply self-regulation strategies with technological support is fundamental to nurturing a new generation of learners who master, rather than being driven by, smart tools. Second, from the perspective of research on self-directed learning, emerging technologies represented by GenAI provide a new experimental field for research that has long relied on manual intervention or fixed system support. With high flexibility, technological tools quickly respond to learners' personalized needs, opening new pathways for self-directed learning.

Research in this field exhibits three key characteristics. First, research is shifting from online and blended learning toward learning support with deep GenAI integration. Current studies on online engagement and blended learning show that technology integration does not directly lead to high-quality academic outcomes. The key factors remain learners' autonomy, sense of competence, and whether their connection with AI can be effectively sustained. Second, the theoretical frameworks of relevant research have converged significantly. Self-determination theory has become a common framework for explaining learner engagement, self-regulation, and emotional experience. Combined with the unified theory of acceptance and use of technology and metacognitive theory, research focus has shifted from “whether technology is effective” to “under what conditions technology is effective”. Third, application scenarios are concentrated on language learning, indicating that language learning—due to its high reliance on interaction, feedback, and expression—has gradually become a key field for examining the relationship among AI, motivation, and self-regulation.

Research on learners’ motivation and self-regulated learning strategies under technological support has gained increasing attention in digital education in recent years. Early intelligent tutoring systems were designed around system control, reducing learners to passive responders within precise automated workflows. With the popularization of GenAI, passive learning has evolved into over-reliance on AI, significantly increasing learning risks. Meanwhile, the openness and flexibility of GenAI enable personalized deep learning. However, GenAI’s inherent “hallucination” characteristic objectively pushes researchers to reduce system automation and return responsibility for critical judgment and active verification to learners. Thus, how learners maintain autonomous motivation and effectively apply self-regulation strategies when collaborating with technological tools has become a research issue of practical urgency and theoretical value.

Current research in this field centers on three main aspects. First, the impact of learners' motivation and self-regulation strategies on technology interaction processes. By analyzing behavioral patterns of learner–technology interaction, research reveals how motivation and self-regulation strategies influence interaction quality and learning outcomes. Second, the impact of AI literacy on learning outcomes. It examines how AI literacy shapes the depth and quality of learner–AI collaboration, thereby affecting long-term learning outcomes. Third, the impact of AI-assisted instructional design on learners' motivation and AI literacy development. It explores how sound instructional design fosters positive motivation and stable self-regulation strategies, while promoting long-term development of learners' AI literacy.

Research in this field continues to advance in depth. It no longer merely confirms that AI and self-regulated learning improve academic performance, but explores underlying mechanisms. For example, in nursing training, mobile chatbots enhance learning outcomes and self-efficacy not only by providing more information, but by engaging learners in ongoing judgment and response through case-based interaction. In blended learning, AI with guidance mechanisms adds value not only by providing answers, but by reducing interruptions in self-regulation and facilitating knowledge construction through timely responses, question logging, and convergent information. Correspondingly, online and blended learning research shows that digital support matters only when it fosters autonomy and competence. Without emotional connection, resource support, or competence, learner engagement declines rapidly. With AI integrated into language learning, research progresses from “whether to use AI” to “how to use AI effectively”. AI literacy influences learning performance via self-efficacy, anxiety, and flow, while metacognitive awareness and critical AI literacy become new thresholds to avoid over-reliance and enable deep learning.

In this research area, the top 3 countries by core paper output are China, Malaysia, and Iran; countries with high citation counts include China, Malaysia, and Spain; the top 3 countries by average citations per paper are Spain, Switzerland, and Malaysia. Among major core-producing countries, Malaysia, Pakistan, Russia, and Saudi Arabia demonstrate extensive international collaboration. Leading core-producing institutions include The Chinese University of Hong Kong, National Cheng Kung University, and National Yunlin University of Science and Technology; the top 3 institutions by average citations per paper are Universiti Malaya, Universidad Autónoma de Madrid, and Universitat Oberta de Catalunya. Among major core-producing institutions, National Cheng Kung University and National Yunlin University of Science and Technology show extensive collaboration. Countries ranking top 3 in citing core papers are China, the USA, and Malaysia; institutions ranking top 3 are The

Chinese University of Hong Kong, The Education University of Hong Kong, and Beijing Normal University.

Table 39 Major countries producing core papers on self-directed learning ability reflects essential characteristics of digital education

Order	Country	Number of core papers	Percentage of core papers/%	Total citations	Average citations per paper	Mean publication year
1	China	13	65.00	2,049	157.62	2023.5
2	Malaysia	2	10.00	702	351.00	2022.0
2	Iran	2	10.00	147	73.50	2024.5
4	Spain	1	5.00	449	449.00	2020.0
4	Switzerland	1	5.00	383	383.00	2024.0
4	Pakistan	1	5.00	114	114.00	2024.0
4	Russia	1	5.00	114	114.00	2024.0
4	Saudi Arabia	1	5.00	114	114.00	2024.0
4	Canada	1	5.00	43	43.00	2025.0
4	USA	1	5.00	43	43.00	2025.0

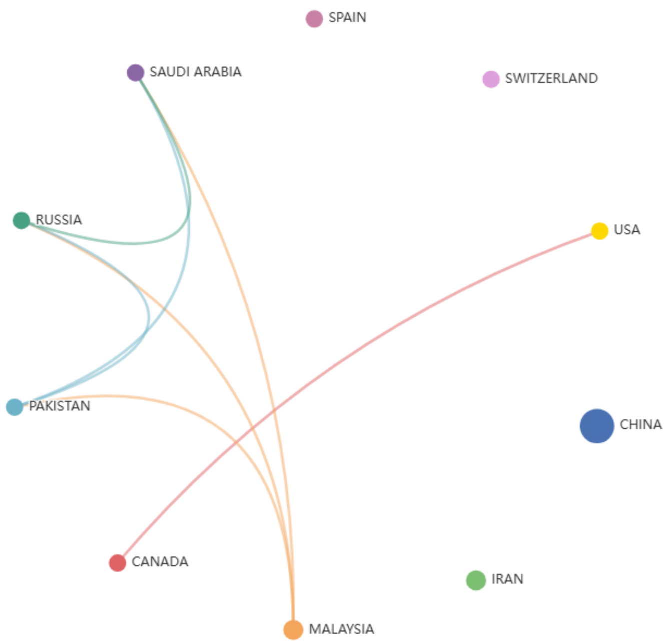

Figure 35 Collaboration network among major core-producing countries on self-directed learning ability reflects essential characteristics of digital education

Table 40 Major institutions producing core papers on self-directed learning ability reflects essential characteristics of digital education

Order	Institution	Number of core papers	Percentage of core papers/%	Total citations	Average citations per paper	Mean publication year
1	The Chinese University of Hong Kong	3	15	844	281.33	2022.0
2	National Cheng Kung University	2	10	288	144.00	2024.0
2	National Yunlin University Science and Technology	2	10	288	144.00	2024.0
2	Xi'an Jiaotong University	2	10	198	99.00	2024.0
2	Golestan University	2	10	147	73.50	2024.5
6	Universiti Malaya	1	5	588	588.00	2020.0
6	Autonomous University of Madrid	1	5	449	449.00	2020.0
6	UOC Universitat Oberta de Catalunya	1	5	449	449.00	2020.0
6	Central South University	1	5	280	280.00	2023.0
6	North Minzu University	1	5	280	280.00	2023.0

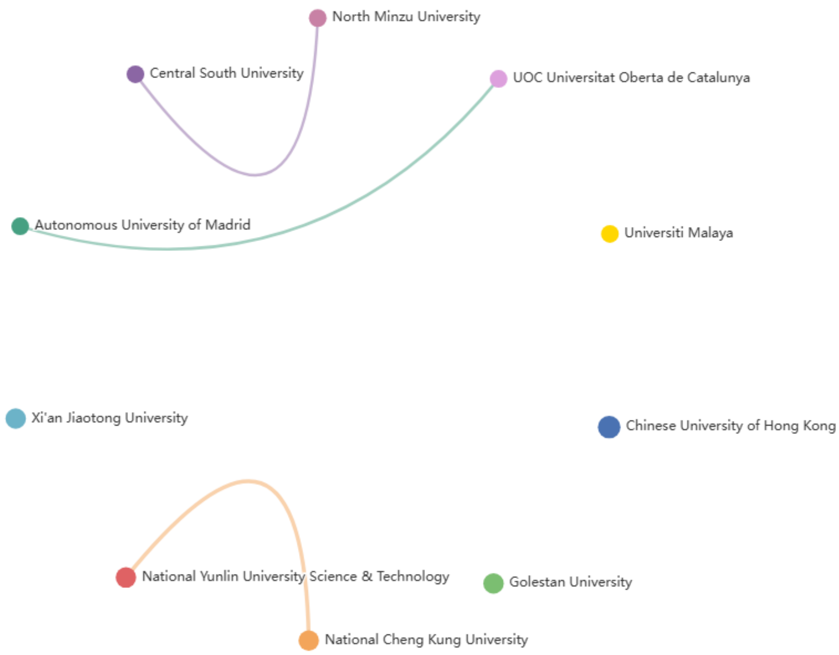

Figure 36 Collaboration network among major core-producing institutions on self-directed learning ability reflects essential characteristics of digital education

Table 41 Major countries citing core papers on self-directed learning ability reflects essential characteristics of digital education

Order	Country	Number of citing papers	Percentage of citing papers/%	Mean citing year
1	China	1,234	38.48	2024.6
2	USA	357	11.13	2024.0
3	Malaysia	171	5.33	2024.3
4	UK	160	4.99	2024.1
5	Saudi Arabia	152	4.74	2024.0
6	Türkiye	138	4.30	2024.9
7	Spain	132	4.12	2023.5
8	Australia	123	3.84	2023.7
9	Indonesia	93	2.90	2024.1
10	India	86	2.68	2023.9

Table 42 Major institutions citing core papers on self-directed learning ability reflects essential characteristics of digital education

Order	Institution	Number of citing papers	Percentage of citing papers/%	Mean citing year
1	Chinese University of Hong Kong	89	2.78	2024.1
2	Education University of Hong Kong	65	2.03	2024.4
3	Beijing Normal University	52	1.62	2024.4
4	Central China Normal University	44	1.37	2024.5
4	Zhejiang University	44	1.37	2025.0
6	University of Hong Kong	42	1.31	2024.5
7	Hong Kong Polytechnic University	35	1.09	2024.3
8	North China University of Water Resources and Electric Power	31	0.97	2025.0
9	Nanjing Normal University	30	0.94	2024.6
9	Universiti Sains Malaysia	30	0.94	2024.5

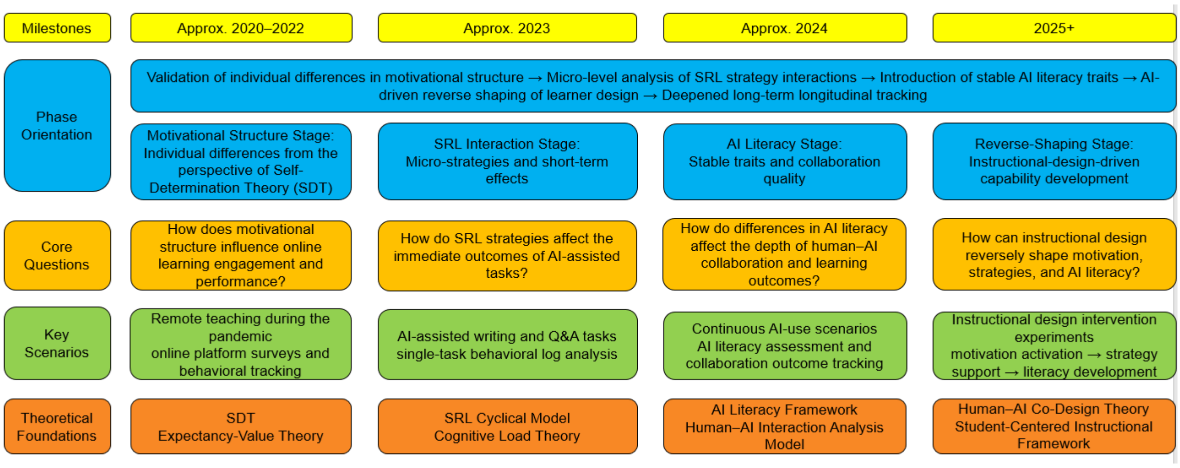

Figure 37 Development roadmap for self-directed learning ability reflects essential characteristics of digital education

Figure 37 illustrates the development roadmap for research in this field, which can be divided into four phases.

Phase I (2020–2022): Focused on motivational structures from the perspective of self-determination theory, examining how intrinsic motivation, autonomy, competence, and relatedness influence online engagement and academic performance. Against a backdrop of reduced in-person support, research centered on online participation, digital support strategies, and self-regulation difficulties in blended learning. A key conclusion emerged: technology itself does not improve learning quality; outcomes depend on whether learners' self-regulation supports higher autonomy.

Phase II (2023): With GenAI integrated into teaching, research shifted to how self-regulated learning strategies shape short-term AI-assisted learning effects at the micro-interaction level. It focused on how goal-setting, monitoring, questioning, revision, and reflection in single or short tasks impact outcomes. AI evolved from a resource provider to an interactive scaffold. Research emphasized guidance mechanisms, task scaffolding, and real-time feedback in sustaining learning continuity, examining whether self-regulation, higher-order thinking, and knowledge construction improve simultaneously. The focus shifted from "whether learners use technology" to "how learners organize learning through AI interaction".

Phase III (2024): AI literacy was introduced as a stable individual trait, examining learners' understanding of AI, critical use, prompt design, ethical awareness, and the depth and quality of long-term collaboration and learning outcomes. Research sought to explain why some learners benefit from AI as a learning tool. It concentrated on high-interaction, high-feedback scenarios, with relationships among AI literacy, motivation, and usage behavior analyzed in detail.

Phase IV (2025 onward): Research explores how GenAI combined with targeted instructional design shapes learners' motivation, self-regulation strategies, and long-term AI literacy development. Beyond outcomes, it focuses on fostering stable flow, metacognitive awareness, critical AI literacy, and classroom engagement resilience. Four trends emerge: research subjects shift from online learners to AI-collaborating learners; variables expand from motivation and engagement to self-regulation, AI literacy, emotional experience, and ethical judgment; research scales move from short-term validation to long-term competence development; goals shift from "improving grades" to "cultivating responsible AI users".

Looking ahead, research may enter a phase of in-depth longitudinal tracking, focusing on four key directions: longitudinal tracking of changes in learners' motivation, self-regulation strategies, and AI literacy across semesters and courses; identification of real regulation paths in human–machine collaboration using process learning analytics; exploration of how metacognitive scaffolding, task design, platform interaction design, and agent design shape high-quality AI use; integration of critical AI literacy, ethical judgment, and learning transfer into a unified framework, addressing whether learners learn with AI or rely on AI to complete tasks.

Appendix A Project Team Structure

I. Guiding Organization

China Education Publishing & Media Group

II. PublishingOrganization

Frontiers of Digital Education

III. Supporting Organizations

Peking University

Clarivate

IV. Project Team Members

(1) Advisory Committee

Feng Yunsheng, Xu Zhongbo, Song Yidong

(2) Working Group

Group Leaders:

Tan Fangzheng, Yang Zongkai, Li Yongzhi

Chief Expert:

Wang Qiong

Members (in alphabetical order by surname):

Hu Xiangen, Huang Ronghuai, Wu Di, Wu Fei, Xu Xiaofei

(3) General Coordination Group

Jiang Wenbo, Guo Tingting, Zhao Xiaoyang, Wang Jin, Li Runjie

(4) Data Support Group

He Wei, Wang Na, Lv Ning, Liu Shihua, Anastassia Obolenskaia, Le Huixiao, Gao Xinyan, Li Nan, Qingmeilazha

(5) Fronts Interpretation Group (in alphabetical order by surname)

Chen Qian, Deng Yuhuan, Du Yanan, Fan Yizhou, Feng Ruyi, Gao Chanmengni, Gao Xinyan, Huang Xingyun, Le Huixiao, Li Nan, Li Xin, Li Xinya, Liu Min, Liu Chenchen, Ouyang Jiayu, Qingmeilazha, Shen Yuan, Song Xiaowei, Wang Qiong, Wang Ying, Xia Mengyu, Xu Mingxue, Yu Qingqing, Yu Xingxing, Zhang Huilun, Zhang Yao, Zhang Yi, Zhong Jiaxin, Zhu Zhen

Appendix B Terminology

This appendix delineates the analytical indicators employed in this report, along with their precise definitions.

Publication year: The year in which a scholarly work was formally published.

Core papers: Refers to highly cited publications positioned within the top 1% of citation frequency globally.

Number of papers: Denotes the total count of scholarly outputs indexed in the Web of Science™ Core Collection—including SCIE, SSCI, and eight supplementary indices—between 2020 and 2025, restricted to the document types Article, Review, and Proceedings Paper.

Number of core papers: The total number of core papers contributing substantively to a specific research hotspot.

Mean publication year: The arithmetic mean of publication years for all core papers associated with a defined research hotspot.

Paper percentage: Represents the relative contribution of a country or institution to the corpus of core papers, expressed as a percentage of the global total. Within a particular hotspot, it denotes the share of core papers attributable to a given country or institution.

Total citations: The aggregate number of citations a publication has received from other documents indexed within the Web of Science™ Core Collection.

High-impact papers: Publications ranked within the top 10% of citation counts in their respective disciplines, calibrated by publication year and document type.

Highly cited Papers: Designated by the Essential Science Indicators (ESI) as publications ranking in the top 1% by citation frequency within their subject area and year of publication, based on a rolling ten-year citation window.

ESI research fronts: A proprietary classification within the ESI framework. When a cluster of highly cited papers exhibits strong co-citation relationships and thematic coherence, it is algorithmically identified as a “research front”—an indicator of emergent and converging scholarly trajectories.

Category Normalized Citation Impact (CNCI): A normalized bibliometric indicator derived by dividing a paper’s citation count by the average citation count of all publications within the same subject category, publication year, and document type. For multidisciplinary papers, the CNCI represents the mean value across all relevant subject areas.

Percentage of internationally collaborative papers: The proportion of publications co-authored by contributors affiliated with institutions in different countries, expressed as a percentage of the total dataset. This metric reflects the extent of cross-border academic engagement and international research integration.

Number of citing papers: The cumulative number of publications that have cited any of the identified core papers.

Percentage of citing papers: The share of citing publications originating from a specific country or institution, measured against the global total. Within a defined research hotspot, it reflects the proportion of citations received by core papers from a particular entity, relative to the total number of citing publications within that thematic area.