Jurnal Pendidikan dan Ilmu Fisika (JPIF)
Fakultas Pendidikan Islam dan Keguruan
Universitas Garut
p-ISSN: 2798-9488 e-ISSN: 2798-334X

Artificial Intelligence and Internet of Things (AI-IoT) in Physics Education: A Bibliometric Analysis and Future Research Directions

Anderias Henukh[1*], Amzal Heri[2], Tutik Yuliatun[3], Momna Khattak[4]

[1,2,3]Program Studi Pendidikan Fisika, Fakultas Keguruan dan Ilmu Pendidikan, Universitas Musamus, Indonesia
Jl. Kamizaun, Mopah Lama, Merauke

[4]COMSATS University Islamabad (CUI), Attock Campus, Pakistan
Kamra Road, dekat Officers Colony / Farooq-e-Azam Colony, Attock, 43600, Punjab, Pakistan

*e-mail: henukh_fkip@unmus.ac.id

DOI: https://doi.org/10.52434/jpif.v6i2.44450

Accepted: October 12, 2026 Approved: November 4, 2026 Published: November 5, 2026

ABSTRACT

This study maps the research landscape of Artificial Intelligence and Internet of Things (AI-IoT) in physics education and identifies directions for future research. A bibliometric design combining performance analysis and science mapping was applied to 1,566 Scopus-indexed journal articles published between 2016 and 2026, selected following the PRISMA 2020 procedure. Five research questions guided the analysis: dataset profile and growth, country productivity and collaboration, intellectual base, conceptual structure, and thematic evolution. The corpus is young and growing quickly (annual growth rate 83.38%, computed over a window that includes the partial year 2026; average document age 1.44 years) and dispersed across 549 sources. China is the most productive country (286 articles), followed by Saudi Arabia, Indonesia, and the USA, while international co-authorship is only 28.67%. Co-citation analysis reveals two intellectual bases, namely AI in education and generative AI, and technology acceptance and survey methodology. Keyword mapping and thematic evolution show a shift from computer-aided instruction and machine learning toward learning systems, ChatGPT, and generative AI, whereas physics-specific and IoT terms remain peripheral. The findings point to the need for physics-grounded, pedagogically validated AI-IoT studies, particularly on sensor-based experiments, learning outcomes, generative AI, and data privacy, supported by broader international collaboration.

Keywords: artificial intelligence; bibliometric analysis; Internet of Things; physics education; science mapping

Kecerdasan Buatan dan Internet of Things (AI-IoT) dalam Pendidikan Fisika: Analisis Bibliometrik dan Arah Penelitian Masa Depan

ABSTRAK

Penelitian ini memetakan lanskap penelitian mengenai Kecerdasan Buatan dan Internet of Things (AI-IoT) dalam pendidikan fisika serta mengidentifikasi arah penelitian di masa

mendatang. Desain bibliometrik yang menggabungkan analisis kinerja (performance analysis) dan pemetaan ilmu pengetahuan (science mapping) diterapkan terhadap 1.566 artikel jurnal terindeks Scopus yang diterbitkan antara tahun 2016 dan 2026, dengan seleksi berdasarkan prosedur PRISMA 2020. Analisis ini dipandu oleh lima pertanyaan penelitian, yaitu profil dan pertumbuhan dataset, produktivitas dan kolaborasi antarnegara, landasan intelektual, struktur konseptual, serta evolusi tematik. Korpus penelitian ini tergolong relatif baru dan berkembang dengan sangat cepat (tingkat pertumbuhan tahunan sebesar 83,38%, dihitung berdasarkan rentang waktu yang mencakup tahun 2026 yang belum sepenuhnya berjalan; dengan rata-rata usia dokumen 1,44 tahun) serta tersebar dalam 549 sumber publikasi. Tiongkok merupakan negara dengan produktivitas publikasi tertinggi (286 artikel), diikuti oleh Arab Saudi, Indonesia, dan Amerika Serikat, sementara tingkat kolaborasi kepenulisan internasional hanya mencapai 28,67%. Analisis ko-sitasi mengungkapkan dua landasan intelektual utama, yaitu kecerdasan buatan dalam pendidikan dan AI generatif, serta penerimaan teknologi dan metodologi survei. Pemetaan kata kunci dan evolusi tematik menunjukkan adanya pergeseran fokus penelitian dari pembelajaran berbantuan komputer dan machine learning menuju sistem pembelajaran, ChatGPT, dan AI generatif. Sementara itu, istilah-istilah yang secara khusus berkaitan dengan fisika dan Internet of Things masih menempati posisi periferal. Temuan ini menunjukkan perlunya penelitian AI-IoT yang lebih berlandaskan pada karakteristik keilmuan fisika dan tervalidasi secara pedagogis, khususnya dalam bidang eksperimen berbasis sensor, hasil belajar, AI generatif, dan privasi data, yang didukung oleh kolaborasi internasional yang lebih luas.

Kata kunci: kecerdasan buatan; analisis bibliometrik; Internet of Things; pendidikan fisika; pemetaan ilmu pengetahuan.

INTRODUCTION

Physics is a discipline that requires students to connect abstract concepts, mathematical representations, and empirical phenomena at the same time. Decades of physics education research show that effective learning requires active engagement, timely feedback, and authentic experimental experiences rather than one-way transmission of information (Bao & Koenig, 2019; Freeman et al., 2014; Hake, 1998; Wieman, 2007). Persistent misconceptions, difficulty in translating data into models, and weak science process skills remain recurring problems at many educational levels. Addressing these problems therefore calls for instructional approaches that make the link between theory and measurement explicit and testable.

In many institutions, efforts to provide active, experiment-based learning are constrained by practical limitations. Expensive laboratory equipment, large class sizes, limited practical session time, and instructor workload make individual feedback difficult to provide. These constraints are even more pronounced in resource-limited contexts, and become more evident when instruction must be delivered online or remotely. This situation motivates the search for technologies that can widen access to experiments while improving the quality of feedback.

One relevant technology is the Internet of Things (IoT), a network of physical objects equipped with sensors, software, and connectivity that can collect and exchange data over a network (Al-

Fuqaha et al., 2015; Atzori et al., 2010; Gubbi et al., 2013; Sethi & Sarangi, 2017). Architecturally, IoT systems typically comprise sensing, communication, and processing/application functions. This makes IoT closely aligned with the nature of physics as a science of measurement, because quantities such as temperature, acceleration, voltage, and light intensity can be acquired and transmitted automatically. Because these data streams can be logged continuously, they also let students analyze real phenomena rather than idealized textbook examples.

In physics education, IoT and related sensor technologies enable real-time acquisition of experimental data, long-duration observation of phenomena, and the conduct of practical work from different locations. Reviews of IoT in education describe both pedagogical opportunities and implementation challenges, including privacy, security, scalability, and human factors (Kassab et al., 2020). Studies comparing hands-on, simulated, and remote laboratories have examined the strengths and limitations of each laboratory mode (Ma & Nickerson, 2006). In addition, smartphones equipped with built-in sensors and software such as phyphox have made physics experiments cheaper and more portable (Staacks et al., 2018). These developments pave the way for connected, data-driven physics laboratories.

The second technology is Artificial Intelligence (AI). Systematic reviews show that AI has been used in higher education for student profiling and performance prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems (Zawacki-Richter et al., 2019). Other reviews have mapped the roles, challenges, and research issues of AI in education (Chen et al., 2020; Hwang et al., 2020; Roll & Wylie, 2016; Zhai et al., 2021), while more recent work describes the state of the field in higher education (Crompton & Burke, 2023). However, these reviews also note that educator involvement and pedagogical grounding in AI research still need to be strengthened (Holmes et al., 2019).

In science education specifically, *machine learning* has been used to support innovative assessment practices, such as automatically scoring constructed responses and scientific models created by students (Zhai, 2021; Zhai et al., 2022). These findings suggest that AI can analyze complex learning products at scale, something that is difficult for instructors to do manually. The same potential could be applied to physics experimental data, for example to recognize patterns in sensor data, detect measurement errors, or infer misconceptions from how students interpret graphs. Such capability is particularly valuable in physics, where students' reasoning is often expressed through graphs, equations, and short explanations.

The convergence of AI and IoT (AI-IoT) offers the idea of an intelligent physics learning environment. In a simple conceptual pipeline, IoT sensors generate experimental data, the network transmits the data, and AI models analyze it to produce adaptive feedback for students and diagnostic information for instructors. AI-IoT thus not only automates data collection but also has the potential to change how experimental data are interpreted and used as a basis for pedagogical decisions. Realizing this potential, however, depends on whether such systems are grounded in sound learning objectives and validated against student outcomes.

Despite this potential, the literature on AI-IoT in physics education appears to be scattered across fields such as physics, engineering, computer science, and education, with varied terminology

and objectives. Existing reviews generally address AI in education or IoT in education broadly, and have not specifically mapped the intersection of the two in the context of physics quantitatively. As a result, it is unclear who the key actors are, which themes dominate, how those themes have evolved, and which gaps remain open. This gap makes it difficult for researchers and curriculum developers to set priorities.

Bibliometric analysis offers an objective, systematic, and replicable approach to mapping the intellectual structure and dynamics of a research field, particularly when the volume of literature is too large or too dispersed to be reviewed narratively (Donthu et al., 2021; Zupic & Čater, 2015). Through performance analysis and science mapping techniques, this approach can reveal publication trends, collaboration, thematic clusters, and emerging research fronts (Cobo et al., 2011; Moral-Muñoz et al., 2020). Co-citation analysis uses the joint citation of works to indicate intellectual relationships, while keyword co-occurrence helps describe conceptual associations in a corpus (Small, 1973).

This study aims to map the development of AI-IoT research in physics education and learning in Scopus-indexed journal articles from 2016 to 2026, and to formulate directions for future research. The expected contributions include a quantitative map of the field, the identification of the countries, intellectual foundations, and thematic clusters that shape it, and an evidence-based research agenda. The analysis proceeds from the general to the specific: it first profiles the dataset, then examines the geography of production and collaboration, the intellectual base, the conceptual structure, and finally the evolution of themes over time, from which research gaps are derived. To achieve these aims, the study addresses five research questions:

RQ1. What is the overall profile and growth of AI-IoT research in physics education in Scopus-indexed journal articles from 2016 to 2026?
RQ2. Which countries lead the production of this literature, and how do they collaborate?
RQ3. Which authors form the intellectual base of the field, as revealed by co-citation patterns?
RQ4. What is the conceptual structure of the field, in terms of dominant keywords and thematic clusters?
RQ5. How have the research themes evolved over time, and what research gaps and future directions emerge?

METHOD

2.1 Research Design

This study employs a quantitative bibliometric design combining performance analysis and science mapping, as recommended in guidelines for bibliometric analysis (Donthu et al., 2021; Cobo et al., 2011; Moral-Muñoz et al., 2020). Performance analysis addresses how productive and influential authors, institutions, countries, or journals are, whereas science mapping addresses how these elements are related to one another intellectually, socially, and conceptually. Network visualization and clustering depend on methodological choices and parameters, so maps should be interpreted as analytical representations rather than definitive taxonomies (van Eck & Waltman, 2010; Waltman & van Eck, 2013). To make document selection transparent and auditable, reporting follows the PRISMA 2020 statement (Page et al., 2021).

2.2 Search Strategy and Document Selection

The search string was built from three concept blocks joined with the AND operator: an artificial intelligence block, an IoT block, and a physics or physics learning block. Each block contains synonyms joined with OR and was searched in the title, abstract, and keywords (TITLE-ABS-KEY). Results were limited to the article document type and publication years 2016 to 2026. The lower bound of 2016 was chosen because it marks the period in which applications of AI and IoT in education began to appear in meaningful volume, whereas earlier output combining them with physics was negligible, so that an earlier start would add little to the corpus; the upper bound of 2026 reflects the date of data retrieval (28 September 2026), so the final year is incomplete (see Section 3.1). Search reporting should make the databases, complete search strings, limits, and selection process reproducible, consistent with guidance on transparent systematic-review searches (Rethlefsen et al., 2021). The full string is as follows: TITLE-ABS-KEY (("artificial intelligence" OR AI) AND (IoT OR "Internet of Things") AND (physics OR "physical science" OR "physics education" OR "physics learning" OR "learning physics") AND NOT "physical education") AND LIMIT-TO (DOCTYPE, "ar") AND PUBYEAR > 2015 AND PUBYEAR < 2027. The abbreviation “AI” was retained alongside “artificial intelligence” to capture papers that use only the acronym, and records on physical education were excluded at the search-design stage with a NOT clause rather than flagged after retrieval.

The inclusion criteria were (a) journal articles, (b) published between 2016 and 2026, (c) addressing AI, IoT, and a physics or physics education context in the title, abstract, or keywords, and (d) written in English. The exclusion criteria comprised conference proceedings, book chapters, conference reviews, editorials, and articles that, after title and abstract screening, were not relevant to physics education or learning, for example articles that use physics terms only for purely engineering applications. Restricting the dataset to journal articles ensures that all records have undergone peer review, although this choice also affects coverage (see Limitations). Borderline cases were flagged and discussed by both raters before a final decision was made. Because document selection in this bibliometric study rested on explicit, rule-based criteria applied to bibliographic metadata (document type, language, publication year, and the presence of the three concept blocks in the title, abstract, or keywords), and every borderline decision was settled by consensus between the two raters, a chance-corrected agreement statistic such as Cohen’s kappa was not computed; the screening procedure is documented in full so that it can be audited and repeated.

Selection was carried out in three stages following the PRISMA 2020 flow (Figure 1). In the identification stage, 3,655 journal articles were retrieved from Scopus with the search string above. In the screening stage, 11 records published outside 2016–2026 and 53 non-English papers were removed, leaving 3,591 records, and 2,025 records were then excluded after title and abstract screening and eligibility assessment because they were not relevant to physics education or learning. In the eligibility stage, the remaining records were checked against all inclusion and exclusion criteria, which yielded the final dataset of 1,566 journal articles for analysis. In Figure 1, each box now states unambiguously whether the number shown is the count of records removed

or retained at that stage, and the counts reconcile from the initial retrieval to the final dataset (records at the previous stage minus records removed equals records at the next stage).

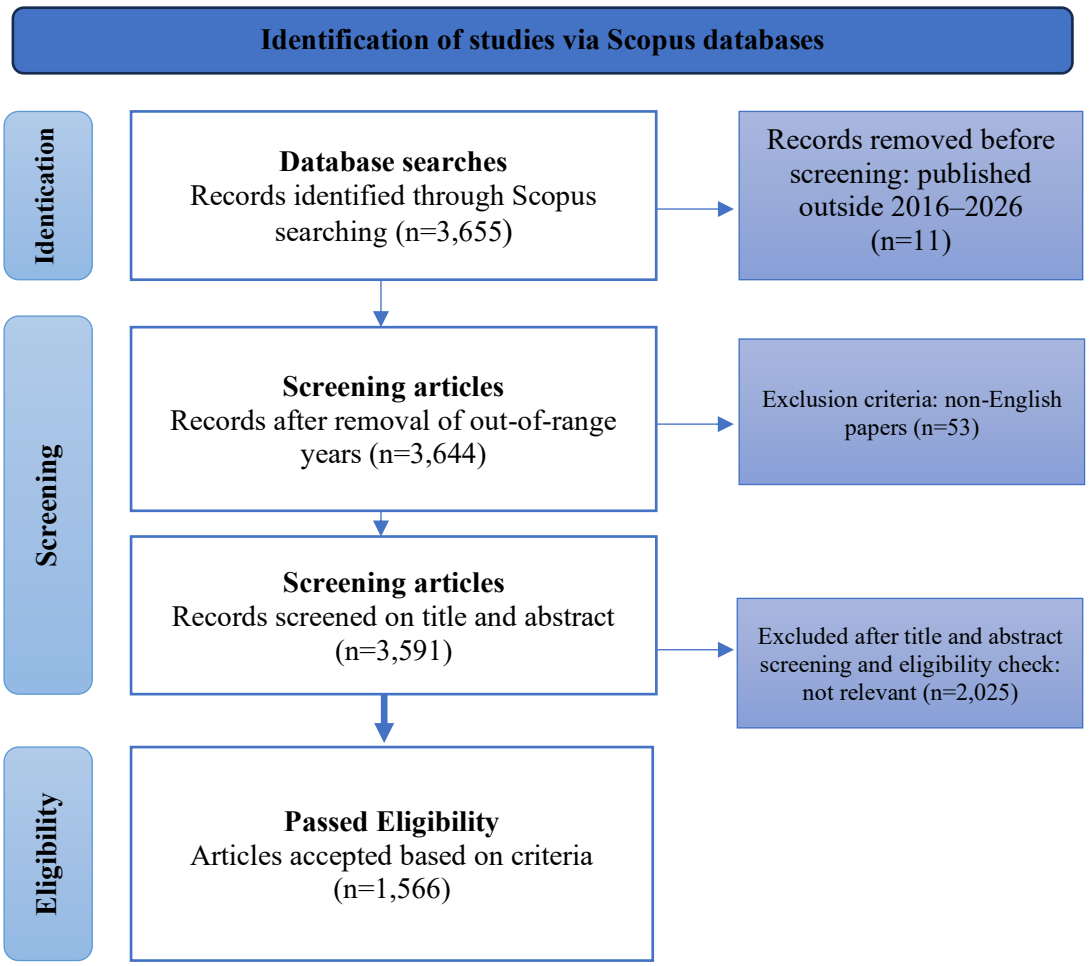


Figure 1. PRISMA flow diagram of the document identification, screening, and eligibility process

2.3 Data Analysis

The analyses were organized around the five research questions, as summarized in Table 1. Performance analysis was used to describe the dataset (RQ1) and the productivity and collaboration of countries (RQ2). Science mapping was used to examine the intellectual base through co-citation analysis (RQ3), the conceptual structure through keyword frequency and keyword co-occurrence analysis (RQ4), and the evolution of themes through thematic evolution analysis across four periods: 2016–2019, 2020–2022, 2023–2024, and 2025–2026 (RQ5). Country production was attributed by the corresponding author's country and divided into single-country publications (SCP) and multiple-country publications (MCP); the MCP ratio, defined as the share of MCP in a country's output, served as an indicator of international collaboration. Bibliometric indicators and maps were generated with the bibliometrix R package and its Biblioshiny interface (Aria & Cuccurullo, 2017) and with VOSviewer (van Eck & Waltman, 2010). Clusters and themes were labeled interpretively from the terms they contain.

Table 1. Alignment of research questions, analyses, and results

Research question	Analysis	Results shown in
RQ1	Performance analysis: main information about the dataset	Figure 2
RQ2	Performance analysis: corresponding-author countries and SCP/MCP collaboration	Figures 3 and 4
RQ3	Science mapping: co-citation network	Figure 5
RQ4	Science mapping: keyword frequency and keyword co-occurrence network	Figures 6 and 7
RQ5	Science mapping: thematic evolution; gap analysis based on RQ1–RQ4	Figure 8 and Section 3.6

RESULT AND DISCUSSION

3.1 Dataset Profile and Growth (RQ1)

Figure 2 summarizes the main information of the dataset. The corpus consists of 1,566 journal articles published between 2016 and 2026 in 549 sources, written by 5,155 authors, and citing 219,028 references. The annual growth rate of 83.38% and the average document age of only 1.44 years indicate that the field is very young and that most of the literature has appeared in the last few years. The growth rate is calculated between the first and last year of the window, and the final year is incomplete: the data were retrieved on 28 September 2026, so 2026 covers only the part of the year up to that date. An incomplete final year systematically understates the most recent output and distorts the apparent acceleration. The reported 83.38% should therefore be read as a directional signal of rapid expansion rather than as a precise rate. The average of 28.82 citations per document is relatively high for such a recent corpus, which is consistent with the strong presence of highly visible generative AI studies in the intellectual base discussed in Section 3.3.

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2016:2026
Sources (Journals, Books, etc)	549
Documents	1566
Annual Growth Rate %	83.38
Document Average Age	1.44
Average citations per doc	28.82
References	219028
DOCUMENT CONTENTS	
Keywords Plus (ID)	5156
Author's Keywords (DE)	4319
AUTHORS	
Authors	5155
Authors of single-authored docs	198
AUTHORS COLLABORATION	
Single-authored docs	213
Co-Authors per Doc	3.79
International co-authorships %	28.67
DOCUMENT TYPES	
article	1566

Figure 2. Main information about the AI-IoT in physics education dataset (2016–2026)

Authorship and vocabulary indicators point to a collaborative but fragmented field. Documents have 3.79 co-authors on average, and single-authored documents are a minority (213 documents, about 13.6%). International co-authorship accounts for 28.67% of the articles, so most collaboration occurs within national boundaries. At the same time, the 1,566 articles are spread across 549 sources (about 2.9 articles per source) and described by 4,319 author keywords and 5,156 Keywords Plus terms. This dispersion across venues and vocabularies supports the observation in the Introduction that the literature is scattered across disciplines with varied terminology, and it anticipates the heterogeneous thematic structure reported in Section 3.4.

3.2 Country Productivity and Collaboration (RQ2)

Figure 3 lists the ten most productive countries by corresponding-author affiliation, and Figure 4 shows the 20 most productive countries with their split between single-country publications (SCP) and multiple-country publications (MCP). China is by far the most productive country with 286 articles (18.26% of the corpus), almost four times the output of Saudi Arabia (75), which ranks next among the countries with an identified affiliation. Indonesia (66), the USA (65), India (60), Malaysia (51), Turkey (42), the United Kingdom (42), and Australia (39) complete the top ten. The row without a country name in Figure 3 (157 articles, 10.03%) corresponds to records whose corresponding-author country is not available in the exported data; it is not shown in Figure 4.

Country	Articles	SCP	MCP	Freq	MCP_Ratio
CHINA	286	236	50	0.1826309067688378	0.1748251748251748
	157	129	28	0.1002554278416347	0.178343949044586
SAUDI ARABIA	75	46	29	0.04789272030651341	0.3866666666666667
INDONESIA	66	43	23	0.0421455938697318	0.3484848484848485
USA	65	49	16	0.04150702426564495	0.2461538461538462
INDIA	60	42	18	0.03831417624521073	0.3
MALAYSIA	51	21	30	0.03256704980842912	0.5882352941176471
TURKEY	42	35	7	0.02681992337164751	0.1666666666666667
UNITED KINGDOM	42	23	19	0.02681992337164751	0.4523809523809524
AUSTRALIA	39	24	15	0.02490421455938697	0.3846153846153846

Figure 3. Top ten countries by corresponding-author affiliation, with SCP, MCP, and MCP ratio

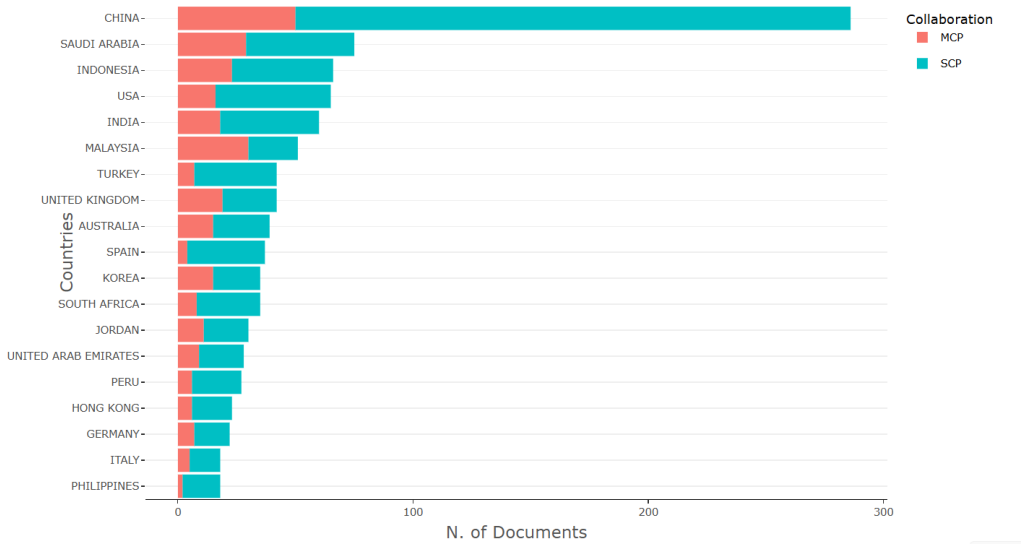


Figure 4. Most productive countries and their collaboration pattern (SCP and MCP)

Collaboration patterns differ markedly among the leading countries. Malaysia has the highest MCP ratio (0.588), followed by the United Kingdom (0.452), Saudi Arabia (0.387), Australia (0.385), and Indonesia (0.348). In contrast, China (0.175) and Turkey (0.167) publish mostly without international partners, and Spain, visible in Figure 4, shows a similar single-country pattern. Productivity and international orientation are therefore not the same thing: China's volume is driven mainly by domestic research, whereas mid-sized producers such as Malaysia, Saudi Arabia, and Indonesia are more outward-looking.

For the context of this study, Indonesia's position as the third most productive country with an identified affiliation is notable. It indicates a growing national base of AI-related education research in a setting where constraints on laboratory provision are a central motivation for AI-IoT approaches (see Introduction). Overall, production is concentrated in Asia and the Middle East, and the low overall international co-authorship (28.67%) suggests untapped potential for cross-country collaboration.

The 157 records without country information (10.03% of the corpus) should be treated as a potential source of bias rather than as a footnote. Because the corresponding-author country field is empty in the exported data, these records cannot be attributed to any country and are excluded from the SCP and MCP ratios. Because the missing records cannot be assumed to be missing at random, the direction of the bias is uncertain, but two possibilities should be acknowledged. If the records come disproportionately from journals with poor affiliation metadata, the countries that publish in such venues would be underestimated and the concentration of production in a few leading countries overstated. Conversely, if they are concentrated in one large producer, that country’s output would be understated. A simple bound shows which results are robust: China leads the second-ranked country by 211 articles, so even if all 157 missing records belonged to Saudi Arabia, China’s first position would be unchanged (286 versus 232). By contrast, the differences among countries ranked second to tenth are small (75 to 39 articles), so their order, and their SCP/MCP ratios, should be read as indicative only.

3.3 Intellectual Base of the Field (RQ3)

Figure 5 presents the co-citation network, which shows which authors are most frequently cited together and therefore which works form the foundation of the field. The network splits into two distinct groups. The blue group is centered on Venkatesh, Ringle, Sarstedt, Henseler, Morris, Hult, Podsakoff, and Bagozzi, among others. These names are associated with technology acceptance theory (e.g., Venkatesh et al., 2003) and with the methodology of partial least squares structural equation modeling and survey research. The red group is centered on Dwivedi, Kuchemann, Dementieva, Baidoo-Anu, Zawacki-Richter, Cukurova, Crompton, Hwang, and Chan, among others. These are largely authors of reviews and perspectives on AI in education

and of studies on ChatGPT and generative AI (e.g., Zawacki-Richter et al., 2019; Crompton & Burke, 2023; Kasneci et al., 2023).

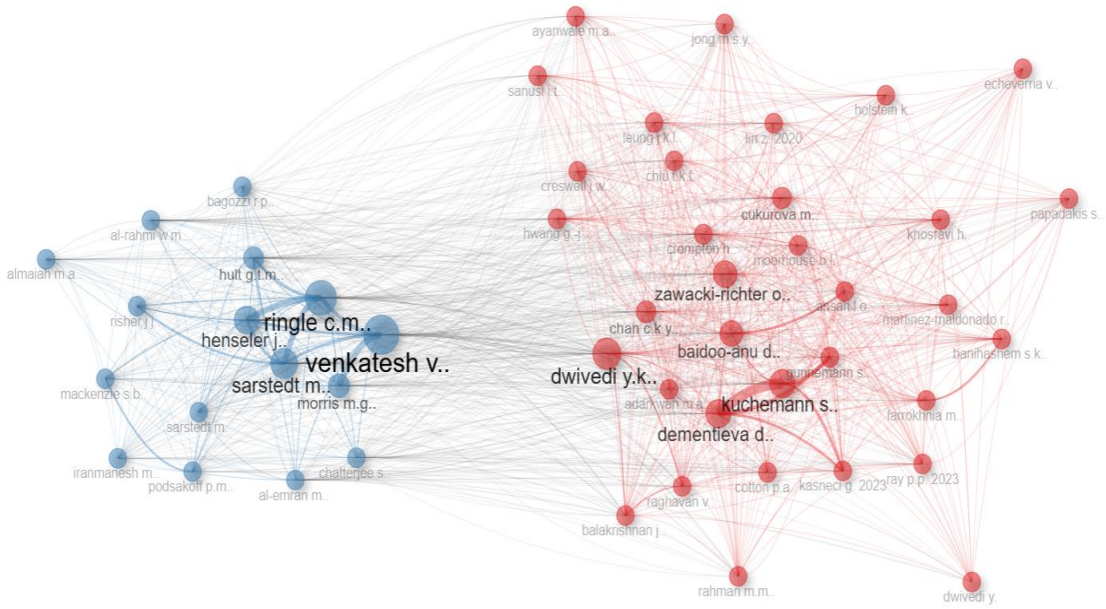


Figure 5. Co-citation network showing two intellectual groups

The two-group structure raises a question about pedagogical validity. Neither group is centered on the physics education research (PER) tradition: the central authors named above are specialists in information systems, survey methodology, and general AI in education, and none of them belongs to the PER literature on which the Introduction draws (e.g., Hake, 1998; Wieman, 2007). The corpus therefore appears to rest on intellectual foundations from outside PER. The red group draws on general AI-in-education reviews, and the blue group on a technology-acceptance logic, a tradition grounded in models of perceived usefulness, perceived ease of use, and behavioral intention (Davis, 1989; Venkatesh et al., 2003). Studies built on such a base typically report perceptions and intentions, whereas the means by which PER establishes that a technology improves physics understanding, such as concept inventories (Hestenes et al., 1992), research on student difficulties with graphs (McDermott et al., 1987), and syntheses of discipline-based education research (Docktor & Mestre, 2014), are absent from the central citation structure. This pattern is consistent with a field driven mainly by computer scientists, engineers, and general educational technologists who do not engage closely with the PER literature, and it means that claims of effectiveness in this corpus cannot be assumed to be pedagogically validated for physics. Whether physics educators publish in different venues and cite different networks cannot be determined from a co-citation network of the whole corpus; testing it would require a venue-level analysis (for example, source co-citation or bibliographic coupling restricted to physics education journals), which is proposed as future work.

3.4 Conceptual Structure: Keywords and Thematic Clusters (RQ4)

Figure 6 shows the most frequent keywords. Artificial intelligence is the dominant term (452 occurrences, 11% of the keywords shown), followed by students (311), teaching (246), learning

systems (180), engineering education (150), deep learning (143), education computing (142), e-learning (127), and human (122). Generative AI terms such as generative artificial intelligence (67), large language model (58), and ChatGPT (56) occupy the middle range, together with technical terms such as contrastive learning (64), adversarial machine learning (60), and federated learning (59). Internet of things appears only 43 times (1%), and no physics-specific term appears among the keywords displayed. The vocabulary therefore confirms that the literature is dominated by AI applied to teaching and learning in general, with engineering education as the most visible disciplinary context, whereas the IoT and physics components that define the scope of this study occupy a marginal position.

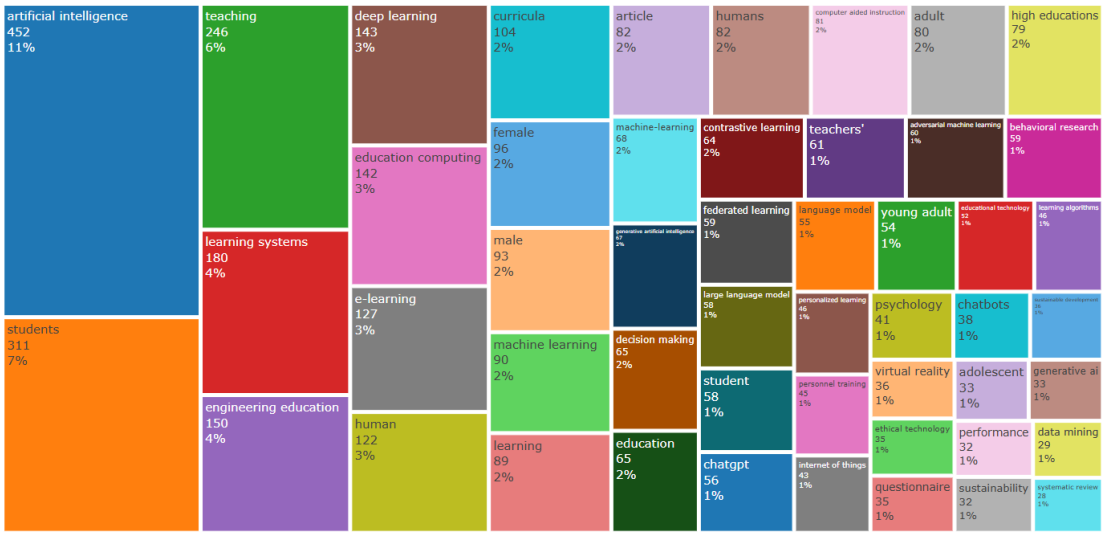


Figure 6. Treemap of the most frequent keywords

Figure 7 maps the co-occurrence of keywords and reveals six main clusters. The red cluster is a technical learning-systems cluster (learning systems, teaching, deep learning, machine learning, learning analytics, educational data mining, federated learning, personalized learning, and recommender systems). The green cluster concerns AI in education and educational technology, with virtual reality, ethical technology, and the IoT terms. The purple cluster represents generative AI and language technologies (ChatGPT, language model, natural language processing, GPT-4) together with ethical concerns. The yellow cluster covers higher education, chatbots, technology adoption, and student perceptions. The blue cluster represents empirical, human-subject studies (student, psychology, questionnaires, structural equation modeling, adult, adolescent). The

smallest, cyan cluster is formed around intelligent tutoring systems, network security, cloud computing, and feature selection.

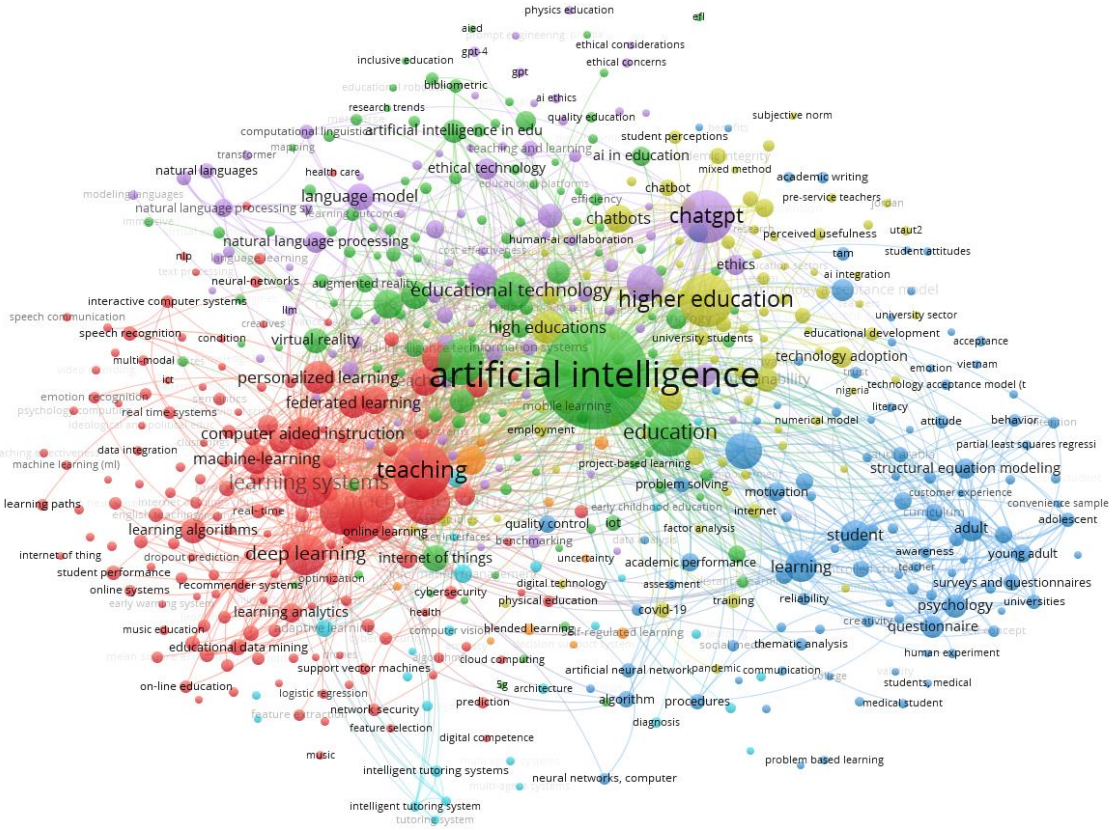


Figure 7. Keyword co-occurrence network and thematic clusters

These clusters correspond closely to the intellectual groups in Figure 5: the blue and yellow clusters reflect the technology acceptance and survey tradition, whereas the red, green, and purple clusters reflect the technical, educational, and generative AI streams. Notably, the IoT terms (internet of things, iot) appear as small nodes away from the center of the map, and sensor-based or laboratory-related terms are not prominent. Physics education itself appears only as a small, peripheral node.

3.5 Thematic Evolution (RQ5)

Figure 8 shows how the main themes flow across four periods. In 2016–2019, research was small and technical, concentrated on computer-aided instruction, artificial intelligence, and machine learning. In 2020–2022, the landscape diversified into many themes: artificial intelligence, students, e-learning, learning algorithms, convolutional neural networks, intelligent systems, sustainable development, and sustainability, alongside behavioral intention and UTAUT themes, English teaching, virtual reality, and network security. The appearance of e-learning and behavioral intention is consistent with the expansion of online learning and the interest in technology acceptance in this period. In 2023–2024, the themes consolidated around learning

systems, ChatGPT, adversarial machine learning, students, artificial intelligence, human, and higher education; ChatGPT emerged as a new and large theme, marking the arrival of generative AI. In 2025–2026, the flows converge on two themes, artificial intelligence and human.

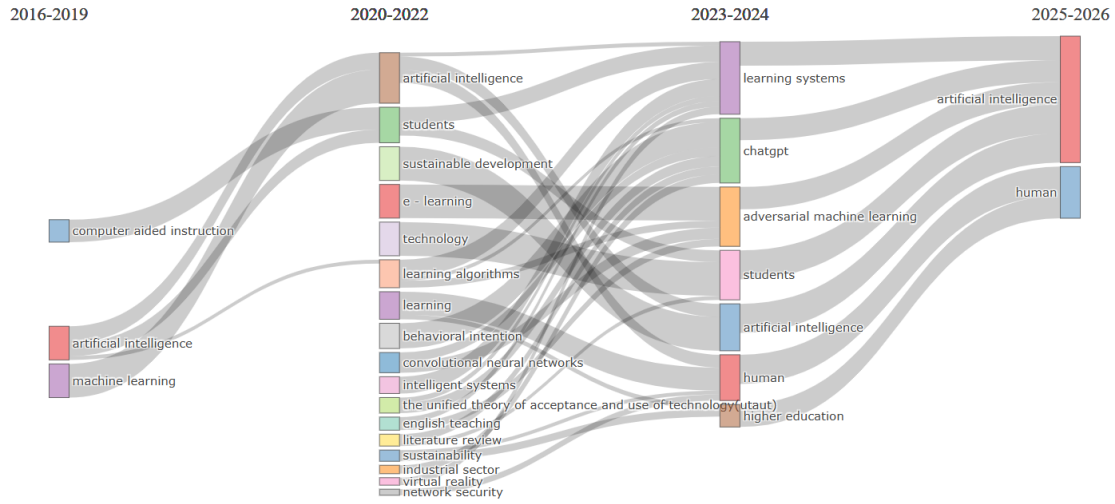


Figure 8. Thematic evolution of AI-IoT research in physics education, 2016–2026

The convergence reflects a shift from algorithm-centered themes to AI as an overarching educational topic. Because human and humans are also database indexing terms (Figure 6), the human theme should be read partly as an indexing effect that marks human-subject studies rather than as a distinct conceptual direction. Importantly, no physics-specific theme and no IoT theme appears as a stand-alone node in any period; the closest technical themes, such as network security, appear only as minor themes in 2020–2022. The evolution of the field has thus been driven by developments in AI in general, not by developments in physics teaching or sensor-based laboratory work.

3.6 Research Gaps and Future Directions (RQ5)

Combining the results for RQ1 to RQ4 with the thematic evolution, six gaps and corresponding directions for future research can be formulated.

Physics-grounded studies. Physics and IoT are marginal in the keyword structure, the intellectual base, and the thematic evolution. Future studies should place physics concepts, such as kinematics, thermodynamics, and electricity, at the center of AI-IoT designs rather than treating physics as one subject among many. Such designs should build on established PER findings, for example the persistent conceptual difficulties in mechanics and electricity documented with concept inventories (Hestenes et al., 1992) and the syntheses of discipline-based research on physics learning (Docktor & Mestre, 2014), so that AI-IoT systems address documented learning problems rather than technical novelty.

AI-IoT physics experiments. The conceptual pipeline in which sensors generate data, a network transmits it, and AI analyzes it to give adaptive feedback is rarely visible in the mapped literature. Research is needed on smartphone-based and remote laboratories (Ma & Nickerson, 2006; Staacks et al., 2018) in which machine learning detects measurement errors, recognizes patterns

in sensor data, and diagnoses misconceptions from students' graphs. Misconception diagnosis is a concrete starting point: PER work on students' difficulties in connecting graphs and physical situations (McDermott et al., 1987) provides a catalogue of errors that classifiers applied to sensor-derived graphs could be designed to detect, and the scientific-abilities framework (Etkina et al., 2006) offers criteria for evaluating experimental design, data analysis, and the treatment of measurement uncertainty in AI-supported laboratories.

From acceptance to learning outcomes. The blue clusters in Figures 5 and 7 show that many studies address perceptions and behavioral intention. Experimental and quasi-experimental studies are needed to test the effect of AI-IoT environments on conceptual understanding, representational skills, and science process skills. Learning gains should be measured with validated physics instruments, such as concept inventories (Hestenes et al., 1992) or rubric-based assessment of scientific abilities (Etkina et al., 2006), rather than perception surveys alone, and compared with interactive-engagement baselines (Hake, 1998).

Generative AI and ethics in physics learning. ChatGPT and large language models are the fastest-growing themes. Reviews of early educational use identify potential support for explanation, feedback, and learning activities, alongside risks involving reliability, bias, academic integrity, and overreliance (Lo, 2023; Tlili et al., 2023). International guidance also emphasizes a human-centred approach, data privacy, and institutional validation when using generative AI in education (Miao & Holmes, 2023). Their reliability in physics problem solving, their handling of graphs and equations, their use in automated assessment (Zhai, 2021; Zhai et al., 2022), and issues of academic integrity deserve systematic study in physics classrooms. Early physics-specific work has begun to test whether chatbots can solve and explain introductory physics problems (Kortemeyer, 2023), and machine-learning-based assessment of student responses in science has been reviewed more broadly (Zhai et al., 2020); extending this work to the interpretation of graphs and sensor data is an open task.

Privacy and security of educational IoT data. Federated learning, adversarial machine learning, and network security appear as technical terms but are rarely connected to classroom practice. Studies should examine how continuous sensor and learner data can be protected while still supporting personalized feedback.

Broader collaboration and complementary reviews. With only 28.67% international co-authorship and a strong concentration of production in a few countries, cross-country collaboration, including partnerships with and within the Global South, would diversify contexts. Complementary systematic reviews of the physics-specific subset of the literature, across more than one database, would verify and deepen the patterns reported here.

CONCLUSION

This study mapped 1,566 Scopus-indexed journal articles published between 2016 and 2026 to examine how AI-IoT research relates to physics education. The central finding is a mismatch between the label and the literature: the corpus is large, young, and geographically concentrated, but it rests on general AI-in-education and technology-acceptance foundations, while the physics

and IoT components that define its scope remain peripheral in the keyword structure, the intellectual base, and the thematic evolution alike.

AI-IoT in physics education is therefore better described as an emerging intersection than as a consolidated field, and the implications differ by audience. For journal editors and reviewers in physics education, submissions in this area will often come from authors outside PER; asking for validated physics learning measures and engagement with the PER literature would help ensure that AI-IoT claims rest on evidence of learning rather than on perceived usefulness. For curriculum developers and teacher educators, the evidence base for adopting AI-IoT tools in physics classrooms is thinner than the volume of publications suggests, so adoption should favor tools tied to documented learning problems and piloted with concept-level assessment before scale-up. For researchers deciding where to invest effort, the most under-explored opportunities are physics-grounded, sensor-based experiments with AI-supported feedback, measured learning outcomes, and physics-specific evaluation of generative AI; for research groups and funders, the limited international co-authorship suggests that partnerships linking PER groups with AI and IoT engineers, including partners in the Global South, are likely to add the most value. Given the limitations below, these implications are directional rather than definitive and should be tested in complementary physics-specific reviews.

LIMITATIONS

Several limitations should be considered when interpreting the findings. First, data were drawn only from Scopus and limited to English-language journal articles; conference papers, book chapters, and other databases such as Web of Science and ERIC were excluded, so coverage is incomplete. Second, the search string combined the abbreviation “AI” and broad physics terms in the title, abstract, and keywords, and relevance screening relied on titles and abstracts without a chance-corrected agreement statistic (Section 2.2). The resulting corpus is dominated by general AI-in-education studies, and some records may be only loosely related to physics learning. Third, bibliometric indicators describe volume, structure, and visibility, not the quality, rigor, or effectiveness of studies; citation-based measures also favor older works, and recent publications, including those of 2026, which were retrieved on 28 September 2026 and are incomplete, have had little time to be cited. Fourth, country analysis relies on the corresponding author's country, which does not capture all contributing countries, and 157 records lack country information, which may bias the country ranking in a direction that cannot be determined (Section 3.2). Fifth, the labels of clusters and themes are interpretive, and the groupings depend on software settings and thresholds, so different parameters could yield different structures. Finally, this study reports growth in aggregate and does not examine annual production and citation trends in detail, which could be addressed in future work.

REFERENCES

Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., & Ayyash, M. (2015). Internet of Things: A survey on enabling technologies, protocols, and applications. IEEE Communications Surveys & Tutorials, 17(4), 2347–2376. https://doi.org/10.1109/COMST.2015.2444095

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. Journal of Informetrics, 11(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. Computer Networks, 54(15), 2787–2805. https://doi.org/10.1016/j.comnet.2010.05.010

Bao, L., & Koenig, K. (2019). Physics education research for 21st century learning. Disciplinary and Interdisciplinary Science Education Research, 1, Article 2. https://doi.org/10.1186/s43031-019-0007-8

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. IEEE Access, 8, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2011). Science mapping software tools: Review, analysis, and cooperative study among tools. Journal of the American Society for Information Science and Technology, 62(7), 1382–1402. https://doi.org/10.1002/asi.21525

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. International Journal of Educational Technology in Higher Education, 20, Article 22. https://doi.org/10.1186/s41239-023-00392-8

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Docktor, J. L., & Mestre, J. P. (2014). Synthesis of discipline-based education research in physics. Physical Review Special Topics - Physics Education Research, 10(2), 020119. https://doi.org/10.1103/PhysRevSTPER.10.020119

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research, 133, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

Etkina, E., Van Heuvelen, A., White-Brahmia, S., Brookes, D. T., Gentile, M., Murthy, S., Rosengrant, D., & Warren, A. (2006). Scientific abilities and their assessment. Physical Review Special Topics - Physics Education Research, 2(2), 020103. https://doi.org/10.1103/PhysRevSTPER.2.020103

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. Proceedings of the National Academy of Sciences, 111(23), 8410–8415. https://doi.org/10.1073/pnas.1319030111

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. Future Generation Computer Systems, 29(7), 1645–1660. https://doi.org/10.1016/j.future.2013.01.010

Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. American Journal of Physics, 66(1), 64–74. https://doi.org/10.1119/1.18809

Hestenes, D., Wells, M., & Swackhamer, G. (1992). Force concept inventory. The Physics Teacher, 30(3), 141–158. https://doi.org/10.1119/1.2343497

Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.

Hwang, G.-J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of artificial intelligence in education. Computers and Education: Artificial Intelligence, 1, 100001. https://doi.org/10.1016/j.caeai.2020.100001

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kassab, M., DeFranco, J., & Laplante, P. (2020). A systematic literature review on Internet of things in education: Benefits and challenges. Journal of Computer Assisted Learning, 36(2), 115–127. https://doi.org/10.1111/jcal.12383

Kortemeyer, G. (2023). Could an artificial-intelligence agent pass an introductory physics course? Physical Review Physics Education Research, 19(1), 010132. https://doi.org/10.1103/PhysRevPhysEducRes.19.010132

Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. Education Sciences, 13(4), Article 410. https://doi.org/10.3390/educsci13040410

Ma, J., & Nickerson, J. V. (2006). Hands-on, simulated, and remote laboratories: A comparative literature review. ACM Computing Surveys, 38(3), Article 7. https://doi.org/10.1145/1132960.1132961

McDermott, L. C., Rosenquist, M. L., & van Zee, E. H. (1987). Student difficulties in connecting graphs and physics: Examples from kinematics. American Journal of Physics, 55(6), 503–513. https://doi.org/10.1119/1.15104

Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000386693

Moral-Muñoz, J. A., Herrera-Viedma, E., Santisteban-Espejo, A., & Cobo, M. J. (2020). Software tools for conducting bibliometric analysis in science: An up-to-date review. Profesional de la Información, 29(1), Article e290103. https://doi.org/10.3145/epi.2020.ene.03

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Rethlefsen, M. L., Kirtley, S., Waffenschmidt, S., Ayala, A. P., Moher, D., Page, M. J., & Koffel, J. B. (2021). PRISMA-S: An extension to the PRISMA statement for reporting literature searches in systematic reviews. Systematic Reviews, 10, Article 39. https://doi.org/10.1186/s13643-020-01542-z

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. International Journal of Artificial Intelligence in Education, 26, 582–599. https://doi.org/10.1007/s40593-016-0110-3

Sethi, P., & Sarangi, S. R. (2017). Internet of Things: Architectures, protocols, and applications. Journal of Electrical and Computer Engineering, 2017, Article 9324035. https://doi.org/10.1155/2017/9324035

Small, H. (1973). Co-citation in the scientific literature: A new measure of the relationship between two documents. Journal of the American Society for Information Science, 24(4), 265–269. https://doi.org/10.1002/asi.4630240406

Staacks, S., Hütz, S., Heinke, H., & Stampfer, C. (2018). Advanced tools for smartphone-based experiments: phyphox. Physics Education, 53(4), 045009. https://doi.org/10.1088/1361-6552/aac05e

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. Smart Learning Environments, 10, Article 15. https://doi.org/10.1186/s40561-023-00237-x

van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics, 84(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Waltman, L., & van Eck, N. J. (2013). A smart local moving algorithm for large-scale modularity-based community detection. The European Physical Journal B, 86, Article 471. https://doi.org/10.1140/epjb/e2013-40829-0

Wieman, C. (2007). Why not try a scientific approach to science education? Change: The Magazine of Higher Learning, 39(5), 9–15. https://doi.org/10.3200/CHNG.39.5.9-15

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? International Journal of Educational Technology in Higher Education, 16, Article 39. https://doi.org/10.1186/s41239-019-0171-0

Zhai, X. (2021). Practices and theories: How can machine learning assist in innovative assessment practices in science education. Journal of Science Education and Technology, 30(2), 139–149. https://doi.org/10.1007/s10956-021-09901-8

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. Complexity, 2021, Article 8812542. https://doi.org/10.1155/2021/8812542

Zhai, X., He, P., & Krajcik, J. (2022). Applying machine learning to automatically assess scientific models. Journal of Research in Science Teaching, 59(10), 1765–1794. https://doi.org/10.1002/tea.21773

Zhai, X., Yin, Y., Pellegrino, J. W., Haudek, K. C., & Shi, L. (2020). Applying machine learning in science assessment: A systematic review. Studies in Science Education, 56(1), 111–151. https://doi.org/10.1080/03057267.2020.1735757

Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization. Organizational Research Methods, 18(3), 429–472. https://doi.org/10.1177/1094428114562629