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Mapping a Decade of Research on Artificial Intelligence and Augmented Reality in Physics Education: A Bibliometric Analysis (2016–2025)

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Abstract

This study presents a Scopus-based bibliometric mapping of a decade of research on Artificial Intelligence (AI) and Augmented Reality (AR) in physics education, spanning the period from 2016 to 2025. The dataset was retrieved from Scopus on August 2, 2025, and, following PRISMA-style screening and filtering, comprised 1,038 English-language journal articles at the final publication stage. Bibliometric analyses were conducted using Bibliometrix (Biblioshiny), VOSviewer, and Microsoft Excel to examine publication growth, leading sources and authors, geographic and institutional contributions, collaboration patterns, and conceptual structures through keyword co-occurrence, thematic mapping, and thematic evolution. The results indicate accelerated publication growth after 2019 and an interdisciplinary dissemination pattern across education- and technology-facing outlets. Conceptual mapping suggests that AI-related themes (e.g., adaptive and data-informed learning support) and AR-related themes (e.g., interactive visualization and representational learning) constitute the dominant pillars of the field, while physics-education-specific learning mechanisms (e.g., conceptual change, multi-representational reasoning, and inquiry/laboratory enactment) are unevenly foregrounded across clusters. Because this is a bibliometric study, the findings provide a structured overview of research patterns and thematic orientations rather than causal evidence of learning effectiveness, thereby informing future empirical and design-based studies that connect AI/AR developments to physics-education-specific learning mechanisms and implementation contexts.

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INTRODUCTION

Over the past decade, educational technology research has increasingly converged on two powerful trajectories: Artificial Intelligence (AI) as a driver of adaptive, data-informed learning support, and Augmented Reality (AR) as a driver of immersive and interactive representational experiences. Such a phenomenon has particular importance for physics education, where students' conceptual understanding depends on their ability to integrate various representations (such as diagrams, graphs, and equations), to reconcile abstract models with concrete data, and to engage with inquiry-based and experimental reasoning (Kökver et al., 2025). In principle, artificial

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intelligence could offer scaffolding support for problem solving and conceptual change, while augmented reality could make abstract physical phenomena visible through interactive visualization. However, in spite of growing enthusiasm and a rapid increase in the volume of publications, the field is still in need of a more solidly established knowledge base about what has been studied, how it is structurally organized, and what has been achieved in terms of maturity or fragmentation in research approaches.

Artificial intelligence is defined as computational methods that mimic certain aspects of human cognition, such as learning, reasoning, and decision-making, particularly in the form of data-driven algorithms for prediction, personalization, and support. (Benvenuti et al., 2023; Dong et al., 2020; Siemens et al., 2022). These capabilities are often translated into learning analytics, intelligent tutoring, automated feedback, and adaptive systems that can support instructional decisions in educational contexts (Mohamadou et al., 2020; Sarker, 2022). Augmented Reality (AR), on the other hand, involves the superimposition of digital information over physical environments, allowing the learner to engage with virtual representations within a real-world context; AR has been typically linked to improved visualization, increased engagement, and contextualized learning experiences (Al-Ansi et al., 2023; Cabero-Almenara et al., 2019). However, such general claims take on specific relevance to education only when related to specific learning mechanisms (Alzahrani, 2020; Papanastasiou et al., 2019). In physics education, we are not simply dealing with a form of STEM learning; we are dealing with a representationally intensive subject area characterized by the presence of misconceptions, difficulty with conceptual change, and the requirement for successful problem solving to be translated between symbolic and conceptual representations (Buchner, 2025; Buchner et al., 2022). Therefore, the key question is not whether AI and AR are "promising," but whether and how the literature connects AI/AR affordances to physics-education-specific challenges such as representational reasoning, model-based thinking, inquiry enactment, and valid assessment of understanding (Kabudi et al., 2021; Sajja et al., 2024).

Although empirical studies have increasingly examined AI-enabled supports for learning and instruction (Kortemeyer, 2023; Krenn et al., 2022; Wink & Bonivento, 2023) and AR-based visualization for improving conceptual access to abstract physics phenomena (Fidan & Tuncel, 2019; Karim et al., 2024; Rahmat et al., 2023), the accumulated evidence base remains difficult to interpret at the field level. Current syntheses often treat AI and AR as separate streams, which obscures how they co-develop and how complementary affordances are framed within physics education. Meanwhile, many bibliometric mappings either analyze general educational technology trends or group AR primarily with VR/mixed reality, producing a broad landscape that does not isolate physics-education-relevant discourse or the specific intersection of AI and AR (Angra et al., 2025; Gusteti et al., 2025; Prahani et al., 2022; Rojas-Sánchez et al., 2023; Soegoto et al., 2025; Zhao et al., 2023). As a consequence, the field risks two forms of conceptual drift: first, adopting generic educational technology narratives that under-specify physics learning mechanisms; and second, scattering physics-education-relevant AI/AR scholarship across interdisciplinary venues without a clear map of central themes, collaboration structures, and emerging opportunity spaces (Donthu et al., 2021; Mukherjee et al., 2022).

There are serious repercussions from this lack of consolidation. Without mapping, for instance, one might make similar prototypes without overcoming learning obstacles, rely on generalizations from particular cases, or mistakenly identify "hot topics" as being essential to learning when, in reality, they are not essential to the underlying physics learning mechanisms (Herrera-Franco et al., 2020). Moreover, effective consideration of factors such as teacher readiness, infrastructure, equity, transparency, and academic integrity cannot be effectively addressed without an awareness of which sub-communities are working on such issues and how connected they are to the underlying conceptual framework of the field (Amiruddin et al., 2025). Bibliometric mapping offers a defensible solution at this stage: it can systematically profile publication growth, identify influential sources and contributors, reveal collaboration patterns, and clarify conceptual structures and their evolution. Crucially, bibliometric evidence does not establish causal learning impact; instead, it clarifies how the literature is organized and how pedagogical contributions are framed, thereby strengthening the foundation for subsequent empirical and design-based investigations.

The current study performs a Scopus-based bibliometric mapping of AI and AR research in physics education from 2016 to 2025 in order to close the aforementioned gap. The study makes three contributions. First, it provides a performance profile of the field, including publication growth and leading sources, authors, countries, affiliations, and citation indicators. In order to determine how research communities are formed and where collaboration is still fragmented, it also examines collaboration structures using co-authorship patterns. Third, it uses keyword co-occurrence, thematic mapping, and temporal overlay interpretation to map conceptual structures and identify areas of weak integration, emerging directions, and dominant themes. Lastly, the study provides an interpretive synthesis of how AI and AR are framed as pedagogical supports for physics education, explicitly treating such framings as discourse patterns rather than proof of efficacy, building on these mappings. This mapping can direct future empirical research that tests mechanisms (such as conceptual change and representational reasoning) and assesses the viability of implementation in real-world physics classrooms and laboratory settings by revealing the structure of the field.

As such, it is necessary to create a mapping of bibliometric patterns across a decade of publication to move the discourse beyond singularized implementations and technology-centric narratives. Through such an identification of dominant themes and conceptual centers of collaboration, this study seeks to clarify what has been consolidated, what has remained in a state of fragmentation, and where opportunities for innovation in physics education can be found. With this in mind, it is possible to assert that the following research questions are pertinent to this study.

RQ1 : What are the publication growth patterns and key performance characteristics (sources, authors, countries, affiliations, and citations) of AI–AR research in physics education (2016–2025)?

RQ2 : What are the dominant themes and their evolution in AI–AR research related to physics education?

RQ3 : What keyword co-occurrence structures and overlay trends characterize the conceptual landscape of AI–AR scholarship in physics education?

RQ4 : How does the literature frame the pedagogical affordances and reported contributions of AI and AR for physics education (as an interpretive synthesis rather than an impact evaluation)?

METHOD

Study Design

This study employs a bibliometric approach to map the research landscape on Artificial Intelligence (AI) and Augmented Reality (AR) in physics education over the last decade (2016–2025). Bibliometric analysis is widely used to examine the growth, intellectual structure, and thematic development of research fields through quantitative indicators and science-mapping techniques (Van Eck & Waltman, 2017; Zupic & Čater, 2015). Following established bibliometric review principles, the present study focuses on performance analysis (e.g., productivity and citation patterns) and science mapping (e.g., collaboration networks and conceptual structures) to provide an evidence-based overview of the field's evolution and emerging directions (Donthu et al., 2021; Mukherjee et al., 2022).

Data Source and Search Strategy

Scopus was selected as the primary database because it provides standardized bibliographic metadata suitable for bibliometric mapping and reproducible retrieval. The search was executed on 2 August 2025 using the following refined Boolean query: Seek TITLE-ABS KEY ("Artificial Intelligence" OR AI) & ("Augmented Reality" OR AR) & ("Physics Education" OR "Teaching Physics" OR "Physics Learning"). Export the search result data as a CSV & RIS file so you have the necessary metadata fields (e.g., Author(s), Affiliation(s), Title(s), Abstract(s), Keyword(s), Source(s), Reference/Citation links, etc.) to perform processing and network analysis on them.

Table 1. Inclusion and Exclusion Criteria

Inclusion	Exclusion
Must be published in 2016-2025*	Articles published before 2016 or after 2025*
Document type must be article	Documents other than articles, such as reviews, conference papers, book chapters, etc.
Publication stage must be final	Articles that are still in press or early access
Source tye must be journal	Sources other than journals, such as book series, conference proceedings, and trade journals
Language must be English	Articles written in languages other than English, such as Chinese, Spanish, Russian, Italian, Turkish, etc.

* = August 2, 2025

Eligibility Criteria (Inclusion and Exclusion)

The study utilized a set of explicit eligibility criteria to ensure transparency and replicability. Inclusion criteria for articles were: (1) dated between 2016 and 2025; (2) an article type publication; (3) a final published article; (4) a journal source; and (5) were in English. Exclusion criteria were: (1) records published outside the specified time frame; (2) all document types except Articles (Reviews, Conference Papers, Book Chapters/Edited Collections, Editorials, Notes, and Corrections/Errata); (3) non-final publications (In-Press/Early Access); (4) all sources except Journals (Conference Proceedings/Book Series/Trade Journals); (5) non-English records. Because the retrieval was conducted during 2025 (2 August 2025), year-2025 outputs should be interpreted cautiously due to potential indexing dynamics within the year.

Selection Process (PRISMA-Style)

The selection followed a PRISMA-style procedure (Page et al., 2021). The Scopus search initially identified 4,616 records. Before screening, 285 records outside the 2016–2025 time window were removed, leaving 4,331 records screened. Document-type filtering excluded 1,197 non-article records, yielding 3,134 journal-article records. Next, 38 records were excluded because they were not at the final publication stage (e.g., in press/early access), leaving 1,159 records assessed for eligibility. Finally, 121 records were excluded due to source type not being a journal (n = 27) or language not being English (n = 94). The final dataset comprised 1,038 Scopus-indexed journal articles included for bibliometric analysis (see Figure 1).

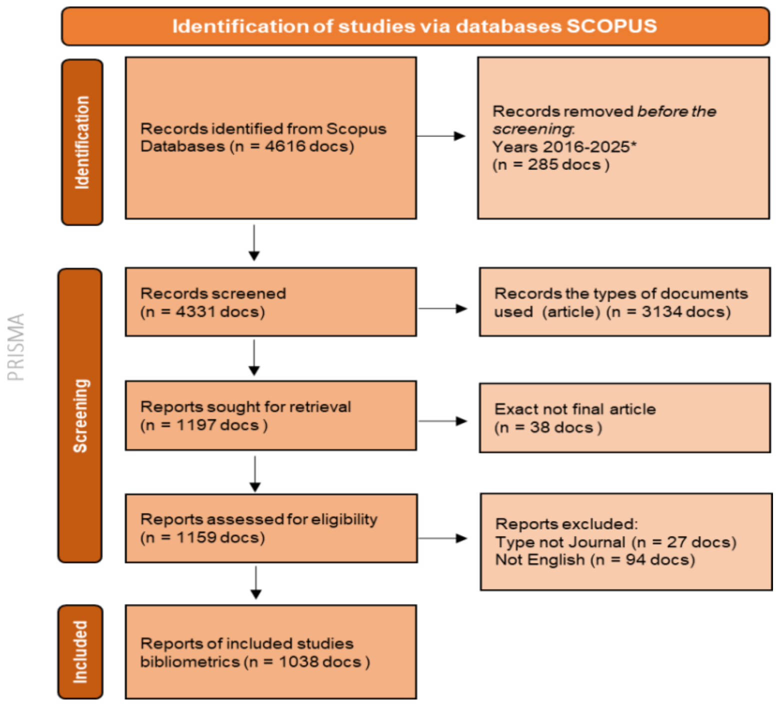

Figure 1. Article Selection Process

Data Cleaning and Preprocessing

Before analysis, the dataset underwent preprocessing to enhance metadata integrity and consistency in mapping. First, duplication checking was conducted using DOI and title matching within Bibliometrix, followed by manual verification for cases that were ambiguous. Second, records were checked for completeness of essential bibliographic fields required for mapping (e.g., authors, affiliations, keywords, and citation links). Third, keyword harmonization was applied to reduce terminological fragmentation by unifying synonymous expressions (e.g., "AI" and "artificial intelligence") and standardizing variants through a thesaurus/keyword normalization list to support consistent co-occurrence mapping.

Data Analysis and Tools

Analyses were conducted using a combination of Bibliometrix (via the Biblioshiny interface), VOSviewer, and Microsoft Excel to support triangulation and replicability. Biblioshiny (Bibliometrix) was used for performance analysis and thematic analytics (e.g., annual publication trends, leading sources/authors/countries/affiliations, citation indicators, thematic mapping, and thematic evolution) (Aria & Cuccurullo, 2017). VOSviewer was employed for science mapping and visualization of networks, including keyword co-occurrence and co-authorship structures, using distance-based mapping suitable for large bibliographic datasets (van Eck & Waltman, 2010). Excel was used for data organization and for generating customized descriptive figures where needed.

Analytical Procedures

The analysis followed four complementary procedures:

1) Productivity and distribution analysis: Annual publication counts and leading contributors (sources, authors, countries, affiliations) were generated to describe growth patterns across 2016–2025.
2) Collaboration patterns: Co-authorship networks were mapped to examine collaboration structures. Where applicable, basic network indicators were reported to strengthen interpretability (e.g., number of nodes and edges, network density, and average degree).
3) Research impact: Citation-based indicators (e.g., total citations and citations per year) were used to identify influential sources and publications, while acknowledging the time-sensitivity of citation accumulation.
4) Conceptual structures: Keyword co-occurrence networks and overlay visualization were used to identify thematic clusters and their temporal trends. Keyword selection for co-occurrence followed a clearly stated minimum-occurrence threshold in VOSviewer, applied consistently after keyword cleaning.

RESULTS AND DISCUSSION

Publication growth and temporal pattern

The year-wise distribution demonstrates a clear decade-scale expansion in AI–AR research within physics education-related outputs. In 2016 and 2017, as can be seen from Figure 2, there was little or no publication activity (no entries for both years). Starting in 2018, there was a slight increase in publication activity (6), and this trend has clearly accelerated on a continuous basis from 2019 (39) through 2021 (92) (Rapanta et al., 2021). The strongest growth occurred after 2021, reaching 145 (2022) and 182 (2023), and peaking in 2024 (289). The count for the year 2025 (192) should be interpreted with caution, as Scopus was retrieved on 2 August 2025, resulting in a partial year of indexation rather than an entire year of indexation. Overall, the trajectory of the AI-AR agenda for physics education has clearly moved from occasional activity to quickly evolving into a significant research stream, mirroring the global trend toward adaptive and immersive learning technologies (Lee & Haupt, 2021; Mohrman et al., 2008).

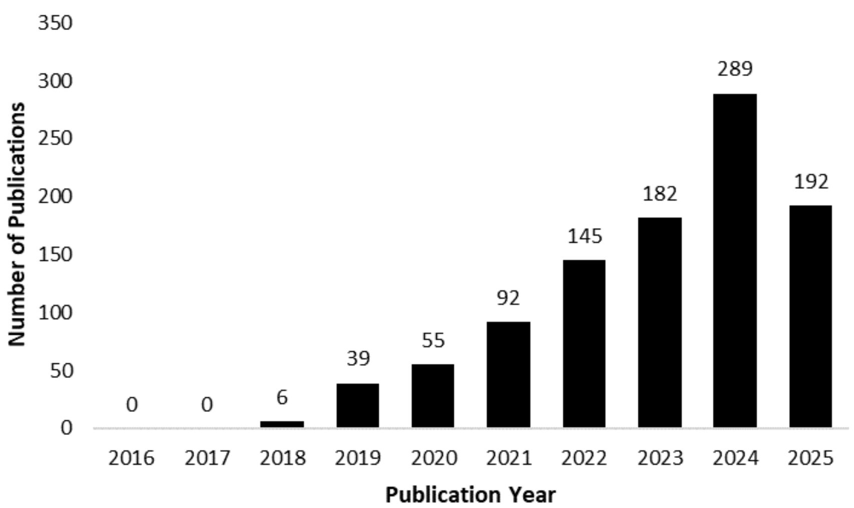

Figure 2. Year-wise Distribution of Publications (2016–2025).

Influential contributors, sources, and citation anchors

The bibliometric profile indicates that scholarly influence is shaped by both productivity and citation visibility (Hutson et al., 2024; Sedkaoui & Benaichouba, 2024; Soliman et al., 2024). Table 2 (Top 10 Researchers' Impact) lists the top researchers based on their article citation ability, indicating that while it is still possible to publish many papers, having papers with a high number of citations reflects more on a researcher's impact than simply the total number of published papers. In interdisciplinary fields of education/technology starting in 2019, the methodologies used and tools created for reusability can provide individuals with far more significant interdisciplinary impact.

Table 2. Top 10 Authors' Impact

Author	H_index	G_index	M_index	TC	NP	PSY
Kumar A	7	7	1.75	166	7	2022
Chen X	6	7	0.857	112	7	2019
Liu Y	6	12	0.857	*753	12	2019
Singh R	6	6	1.5	225	6	2022
Wang X	6	9	1.2	131	9	2021
Zhang S	6	7	1.2	532	7	2021
Amparore D	5	6	1.25	86	6	2022
Checcucci E	5	6	1.25	86	6	2022
De Cillis S	5	6	1.25	86	6	2022
Fiori C	5	6	1.25	86	6	2022

* = Highest; TC = Total citations NP = Number of publications; PSY = Publication start Year

As seen in Table 3 (Top 10 Influential Journals), the delivery of AI-AR physics education research appears to be accomplished through educational technology and applied sciences across multiple disciplines. This pattern is important because venue diversity can amplify reach, Costas and Bordons, (2007); Hodge and Lacasse (2011); Roldan-Valadez et al. (2019) yet it can also introduce heterogeneity in evaluation norms (e.g., variations in learning-outcome operationalization, design reporting, or rigor standards), which must be considered when interpreting aggregated trends (Kelly et al., 2014; Knight & Steinbach, 2008; Templier & Pare, 2018).

Table 3. Top 10 Influential Journals

Sources	Articles	SJR 2024	H-index
IEEE Access	32	0.85	290
Applied Sciences	21	0.52	162
Sustainability	12	0.68	207
Sensors	11	0.74	273
Buildings	9	0.65	71
Analysis and Metaphysics	8	0.15	19
Electronics	8	0.15	110
IEEE Internet of Things Journal	8	2.48	208
Journal of Medical Internet Research	6	1.99	214
IEEE Transactions on Visualization and Computer Graphics	6	1.05	175

Finally, Table 4 (Top 10 cited publication) highlights the intellectual anchors of the corpus: a small set of highly cited studies functions as reference points shaping methodological choices and dominant conceptual framings (Kelly et al., 2014). While citation accumulation is time-dependent, these most-cited publications still provide a pragmatic indicator of which studies the field most frequently mobilizes to justify new developments or position novelty (Donthu et al., 2021; Horta & Santos, 2016; Ravenscroft et al., 2017).

Table 4. Top 10 Cited Publication

Paper	Total Citations	TC per Year	Normalized TC
(Dwivedi et al., 2021)	1285	257.00	20.28
(Park & Kim, 2022)	1243	310.75	25.15
(Buhalis et al., 2019)	737	105.29	11.37
(Hoyer et al., 2020)	652	108.67	8.61
(Mihai et al., 2022)	600	150.00	12.14
(Minerva et al., 2020)	559	93.17	7.38
(Hwang & Chien, 2022)	519	129.75	10.50
(Shi et al., 2021)	483	96.60	7.62
(Liu et al., 2022)	434	108.50	8.78
(Yang et al., 2020)	419	69.83	5.53

Cross-field linkages among countries, keywords, and authors

The three-field Sankey diagram (Figure 3) provides a structural overview of how production, concepts, and contributors connect (Chong et al., 2021). The most visible country-level contributors include China and the United States, followed by other active producers such as Turkey and India, indicating that the field's output is globally distributed but led by a small set of high-throughput countries. On the conceptual axis, the dominant terms include "augmented reality," "artificial intelligence," "virtual reality," "machine learning," and "deep learning," showing that AI–AR physics education scholarship is linguistically anchored not only in pedagogy but also in the broader technical vocabulary of intelligent and immersive systems(Wang et al., 2023). The right-side author field shows that multiple author groups connect into these dominant conceptual streams rather than clustering around narrowly specialized terminology, implying that the field is converging around a common conceptual core.

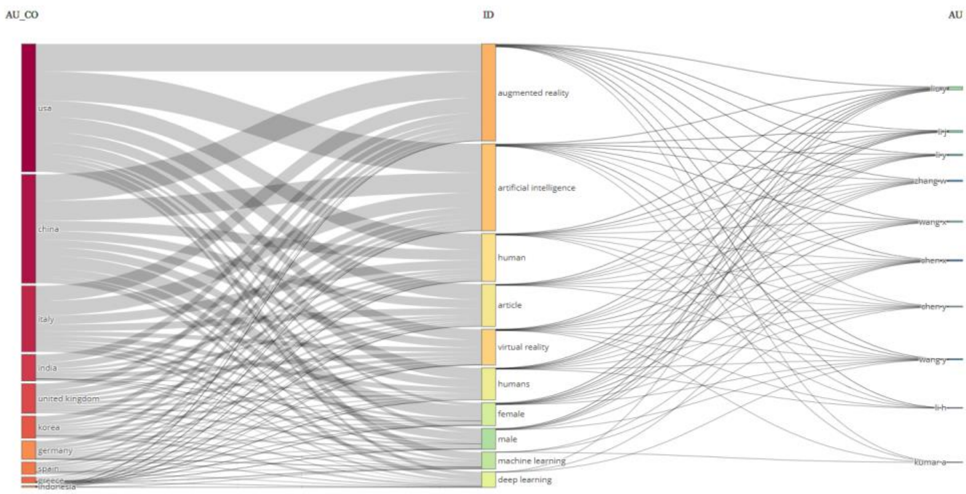

Figure 3. Three Field Plots using the Sankey Diagram

Thematic structure and maturity

The thematic development map (Figure 4) positions themes by centrality (relevance/connectedness) and density (development/specialization). The most prominent Basic Themes cluster is composed of augmented reality, artificial intelligence, virtual reality, and machine learning, indicating that these concepts function as the field's foundational "common language" rather than specialized niches. This is consistent with a rapidly expanding domain in which technology-driven constructs are used primarily to organize a variety of educational applications.

One notable feature of Figure 4 is that a new, more specialized cluster is apparent, which is related to more general indexing terms such as 'human/humans/article,' and this is generally evident in Scopus metadata from more general applied science or health/engineering education-related sources. (Amiruddin et al., 2025; Mortazavi et al., 2025). The presence of such a cluster also points to the fact that, even when it comes to query terms related to physics education, the literaturesphere is an integrating space, one that can incorporate new methodologies and technological developments from neighboring applied disciplines (Amiruddin et al., 2025; Fergnani, 2019; Kapoor et al., 2018). From an interpretive perspective, this duality indicates that (i) physics education research includes studies that have roots in a much broader technology ecosystem than just physics, (ii) careful review and contextualization are critical to make sure that conclusions made are tied specifically to physics education and not just to "educational technology" in general.

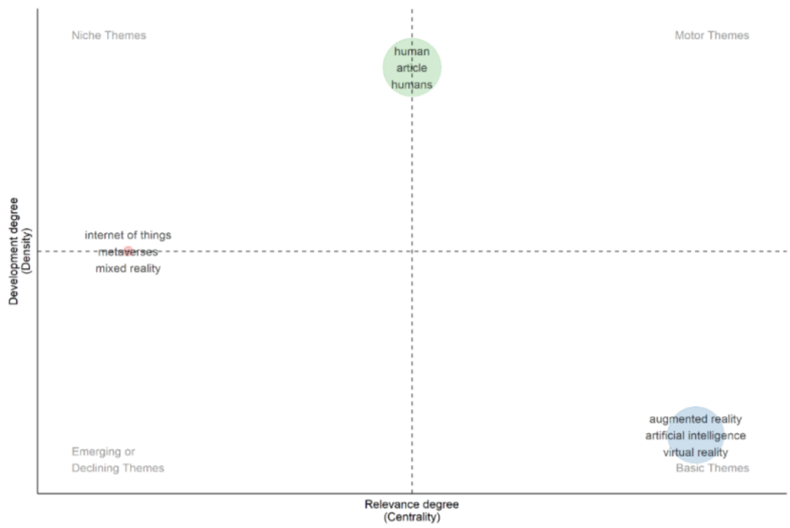

Figure 4. Thematic Development Map

Note. Themes are mapped by centrality (relevance) and density (development), distinguishing Motor, Basic, Niche, and Emerging/Declining themes.

Thematic evolution across time slices

The thematic evolution map (Figure 5) shows a clear development of the conceptual repertoire of the field. In the initial period (2018-2022), the structure is characterized by a dominance of the core terms of artificial intelligence and augmented reality, which suggests a process of foundational development and conceptual consolidation (Al Faruq et al., 2023; Chandran et al., 2025; Wolniak & Stecuła, 2024). In 2023, there is a more differentiated structure of the field, which includes intermediate terms of augmented reality systems, decision making, Internet of Things, etc., which suggests a shift from "technology adoption" to "technology integration" and a systems approach. In 2024, there is a re-consolidation of the field around the dominant poles of AI and AR, while in 2025, there is a diversification of the field into a larger set of applied terms, which is consistent with a rapid expansion of the field and cross-domain conceptual borrowing (Chithra & Bhambri, 2024; Huda, 2019; Lescrauwaet et al., 2022). It is also important to see that there is a co-development of the field rather than a replacement effect, where augmented reality remains a persistent dimension of the field as a representational and interactive pillar, while AI expands the scope of the field to include adaptivity, analytics-informed support, intelligent systems design, etc.

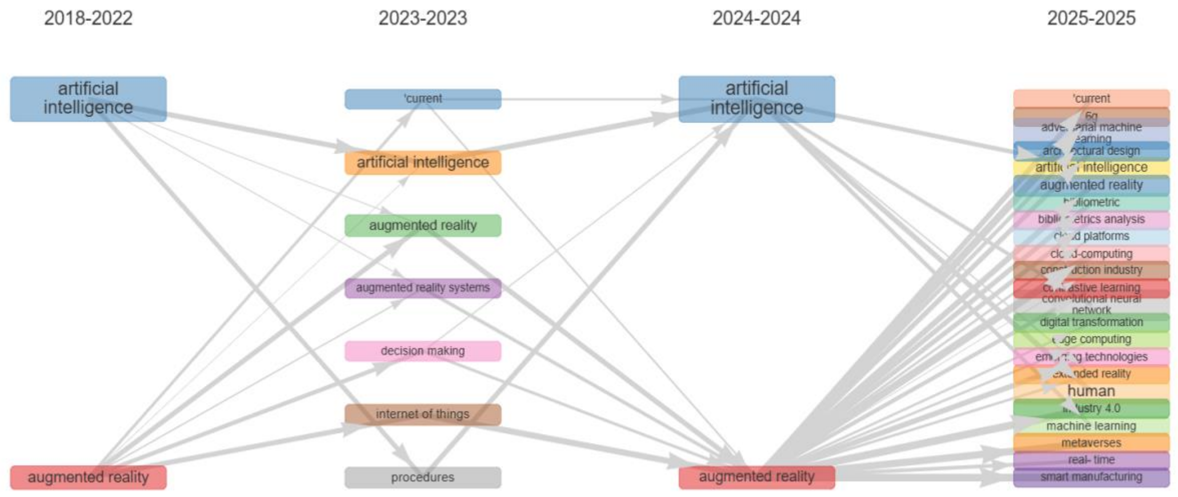

Figure 5. Thematic Evaluation Map

Note. The map traces how themes evolve and connect across defined time slices based on keyword co-occurrence structures.

Keyword prominence and topical emphasis

The visualization of these trends in keywords (Figure 6) further supports the field's principal conceptual framework in that augmented reality and virtual reality are seen as dominant and salient keywords, while artificial intelligence, deep learning, machine learning, mixed reality, Internet of Things, metaverse, and robotics are seen as important adjacent conceptual fields (Golle et al., 2004; Stubbs, 2010). This supports an interpretation of the research discourse in terms of a blended vocabulary of immersive media technologies (augmented, virtual, and mixed reality) and intelligent systems technologies (artificial intelligence, machine learning, and deep learning), with emergent frames such as metaverse and robotics that often indicate new application directions or technology platforms (Kalantari et al., 2017; Maltseva & Batagelj, 2020; Weismayer & Pezenka, 2017). Substantively, this supports an interpretation of the field in terms of an increasingly integrated position of physics education research within an ecosystem of intelligent immersive technologies, in which learning design questions are addressed in concert with rapid innovation in these technologies (Kumar et al., 2024; McAllister et al., 2022; Orduña-Malea & Costas, 2021).

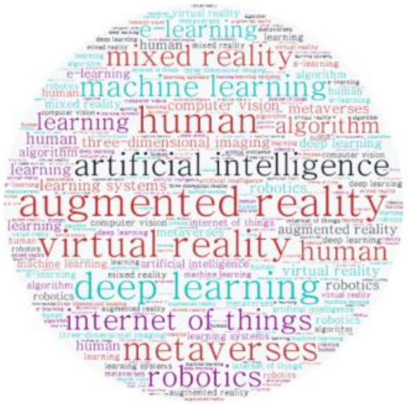

Figure 6. Keywords Trend

Note. The keyword trend summarizes the most salient terms in the corpus, highlighting dominant and emerging concepts.

Conceptual network dynamics and recency signals

The overlay network visualization (Figure 7) places artificial intelligence, augmented reality, and virtual reality at the center of the conceptual network, confirming their role as the primary hubs linking many subtopics (Fergnani, 2019; Kirby, 2023; Marchiori et al., 2021). The overlay scale (average publication year) indicates that more recent attention gravitates toward AI-associated and system-level terms (e.g., those connected to analytics, advanced computation, or applied integrations), while earlier layers remain strongly tied to immersive visualization and exploratory AR/VR implementations (Mejia et al., 2021; Skute et al., 2019; Zawacki-Richter & Naidu, 2016). The network also shows that the corpus includes cross-domain terms extending beyond traditional school physics contexts, which likely reflects interdisciplinary spillover and the broad adoption of AR/AI approaches across applied training environments. For physics education interpretation, this implies that future synthesis work should distinguish "physics education proper" from neighboring applied-physics and technology-training contexts to prevent conceptual dilution, while still benefiting from methodological innovation that transfers into physics learning research (Alqahtani & Wafula., 2025; Ejjami., 2024; Llorente de Pedro et al., 2025).

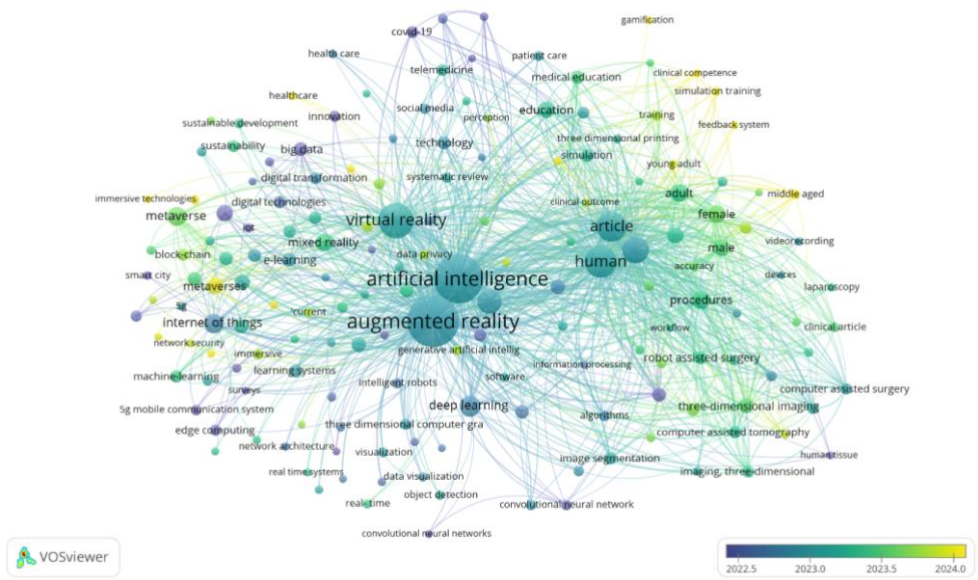

Figure 7. Network Overlay Visualization

Note. Node size indicates keyword prominence, links indicate co-occurrence relationships, and overlay color reflects average publication year (recency).

Evidence synthesis of pedagogical contributions

To complement the macro-level mapping, Tables 5 and 6 provide an interpretive review of representative studies to clarify how AI and AR are framed as contributing to physics education. This synthesis is presented as a thematic interpretation rather than a causal effectiveness evaluation (Donthu et al., 2021).

AI-focused contributions

Across the reviewed AI-focused studies (Table 5), AI is predominantly framed as an instructional support layer enabling (i) adaptive feedback and personalization, (ii) diagnostic inference of learner misconceptions or learning difficulties, and (iii) analytics-informed scaffolding for problem solving and conceptual development. This discovery is consistent with the larger bibliometric study and suggests that discourse around AI is beginning to function as a mechanism for moving from visualization-based innovations towards a more data-driven approach for guidance and support. In terms of physics education, the most credible approach for AI contribution is one that ties AI functionality to relevant learning mechanisms such as multi-representational reasoning, conceptual change, and problem strategy development, as opposed to a more generic approach.

Table 5. Review 10 Articles AI Contributes to Physics Education

Author	Focus of Study	Contribution to Physics Education
Yehya et al. (2025)	AI integration & physics teacher self-efficacy	The article discusses the readiness of physics teachers to introduce AI into classrooms. It mentions that teachers generally have a positive attitude towards AI. However, there are some obstacles to consider, such as teachers' lack of preparation, infrastructure, and understanding of AI.
Guerrero-Zambrano et al. (2025)	ChatGPT in physics teacher training	It also discusses how AI can help physics teachers make abstract concepts more concrete and increase students' engagement. Nevertheless, to achieve this, there is a need to improve infrastructure, teachers' preparation, and supportive policies
Agyare et al. (2025)	Student perceptions of AI chatbots in physics	The study also mentions how AI chatbots can assist students at university to improve their understanding, problem-solving skills, and engagement. Nevertheless, there are some ethical and systemic issues to consider.
Jang (2025)	Limited AI in collaborative physics problem solving	The basic idea is simple: giving students controlled access to AI can improve how well students problem-solve together, learn concepts, and think about their own thinking in physics.
Jang and Choi (2025)	Teachers' views on ChatGPT in physics classrooms	It also examines the pros and cons of using ChatGPT in physics education—how it can and should integrate with a course, what teachers need to know, ethical considerations, and what it takes to make it work well.
Polverini et al. (2025)	ChatGPT on physics visual representation tasks	In terms of visualization, ChatGPT has its pros and cons. It can assist in AI-assisted teaching, inclusive design, and ensuring integrity in physics education, although its cons must also be considered.
Bessas et al. (2025)	ChatGPT use in junior high physics learning	Essentially, ChatGPT can be used as a tool to assist in teaching, improve student understanding, tailor education to individual students, and assist teachers in developing materials, as long as it is properly supervised.
Werdhiana et al. (2025)	ChatGPT reasoning on static fluid concepts	The study also examines the application of AI reasoning in static fluids, including areas of student conceptual difficulties and areas where AI can assist or confuse in physics education.
Kregear et al. (2025)	LLM support in introductory physics labs	It demonstrates how AI can assist in lab learning through feedback and theoretical guidance, although it also acknowledges that inaccuracies can sometimes arise.
Tschisgale et al. (2023)	AI-based qualitative analysis in PER	It also presents AI-supported computational grounded theory to enhance qualitative analyses of student reasoning to improve physics education.

AR-focused contributions

The review of augmented reality (AR) (Table 6) shows that there is a strong pedagogical perspective in this area, where AR is seen as being used in support of interactive visualization, multimodal representation, and inquiry or laboratory learning. There are several reviews of AR in terms of connecting abstract representations of physics with more concrete or contextual representations. For example, ethnoscience simulation, when linked with AR and inquiry learning, can be seen as having motivational and creative effects (Rizki et al., 2025). The proposals for pre-service teachers emphasize the promise of augmented reality to improve experiments and identify students' preferences for virtual and augmented experiments in basic domains like optics and electricity (Park, 2025). AR-HMD implementations for convex lens image formation are framed as supporting real-time overlay of ray diagrams on physical experiments, targeting misconceptions through direct representational coupling (Park, 2025b). AR glasses in university laboratories show that instructional design quality may matter more than device novelty for learning outcomes (Laumann et al., 2024). Other studies report improvements in achievement, motivation, self-efficacy, attitudes, and conceptual understanding across topics including nuclear physics, mechanical waves, and electricity (Arymbekov et al., 2024; Cai et al., 2021; Fidan & Tuncel, 2019; Nasir & Fakhruddin, 2023; Ropawandi et al., 2022). Collectively, these studies support a coherent interpretation: AR is most educationally meaningful when embedded in a structured pedagogy (e.g., inquiry, PBL, guided experimentation) and when it directly strengthens representational reasoning rather than operating as a standalone novelty.

Table 6. Review 10 Articles AR Contributes to Physics Education

Author	Focus of Study	Contribution to Physics Education
Rizki et al. (2025)	Ethnoscience-based virtual simulation & AR in inquiry physics learning	Introduces the ESIL model integrating ethnoscience-based virtual simulation and AR in inquiry learning, shown to enhance students' creativity, motivation, and conceptual understanding through contextual and interactive approaches.
Park (2025)	Pre-service teachers' use of AR to improve physics experiments	Identifies how pre-service teachers propose using AR to improve elementary physics experiments, highlighting key topics and the role of virtual–real integration for better conceptual understanding.
Park (2025b)	AR-HMD for teaching image formation in optics	Develops AR-HMD content that overlays ray diagrams onto real experiments, helping reduce misconceptions and improve understanding of image formation through immersive multi-representational learning.
Laumann et al. (2024)	AR glasses use in university physics laboratory learning	Examines AR glasses in university physics labs, showing that learning impact depends more on instructional design than on technology alone.
Arymbekov et al. (2024)	AR-supported teaching in high school nuclear physics	Demonstrates that AR-supported teaching improves high school students' academic achievement and motivation in learning complex physics topics.
Karim et al. (2024)	AR learning kit integrating social cognitive theory in physics	Shows that AR-integrated interactive learning kits enhance engagement, motivation, and understanding of complex physics concepts through active learning strategies.
Nasir and Fakhruddin (2023)	AR-based mobile multimedia learning in physics	Develops AR-based mobile multimedia learning that improves students' engagement and achievement in understanding complex physics concepts.
Ropawandi et al. (2022)	AR-based physics learning during online/COVID learning	Shows that AR enhances conceptual understanding, engagement, and analytical skills in online physics learning, especially for abstract topics.
Fidan and Tuncel (2019)	AR integrated with problem-based learning in physics	Demonstrates that integrating AR with problem-based learning improves students' achievement, attitudes, and understanding of abstract physics concepts.
Sung et al.	Real-time AR physics	Develops a real-time AR physics simulator that supports

Author	Focus of Study	Contribution to Physics Education
(2019)	simulation system for education	interactive visualization and increases student engagement and perceived learning effectiveness.
Cai et al. (2021)	AR-based physics learning and student self-efficacy	Shows that AR-based physics learning enhances students' self-efficacy, motivation, and higher-level conceptions of learning.

Integrated implications for the field

Synthesizing the bibliometric maps (Figures 2–7) with the interpretive review (Tables 5–6) yields three field-level implications:

1) A technology-centric conceptual backbone is now established, but physics-learning mechanisms must be made explicit.
   The dominance of AI/AR/VR/ML as Basic Themes (Figure 4) and central network hubs (Figure 7) indicates conceptual consolidation around technology terms. The next maturation step is to more consistently foreground physics-education mechanisms (e.g., multi-representation, conceptual change, inquiry enactment) so the field's claims are anchored to domain learning rather than generic engagement narratives.
2) AR and AI appear as complementary, not competing, contribution pathways.
   The thematic evolution (Figure 5) and review synthesis suggest AR's strength lies in representational and experiential scaffolding, while AI's strength lies in adaptivity and analytics-informed guidance. The most promising research agenda is therefore integrative: AR-rich representational experiences paired with AI-driven diagnostic feedback and personalization, designed explicitly around physics learning targets.
3) Interdisciplinary spillover is a strength but requires careful interpretive boundaries.
   The presence of general indexing terms (Figure 4) and cross-domain sub-terms (Figure 7) implies a fluid boundary between physics education and related applied disciplines. While fluid boundaries can facilitate innovation through cross-disciplinary sharing, they can also result in conceptual ambiguity if experiments are not properly contextualized within physics education and stratified accordingly.

In summary, there has been rapid expansion (Figure 2), consolidation around conceptual hubs of AI/AR/VR/ML (Figures 4, 6, 7), and thematic diversification (Figure 5). Some of these papers illustrate credible paths for pedagogical contributions, particularly where immersive media are part of well-thought-out learning strategies that are congruent with the laws of physics (Cai et al., 2021; Fidan & Tuncel, 2019b; Laumann et al., 2024; Park, 2025; Park, 2025b; Rizki et al., 2025; Ropawandi et al., 2022).

LIMITATIONS

Several limitations should be considered when interpreting the findings of this bibliometric mapping. First, the study relies exclusively on the Scopus database and includes only English-language journal articles at the final publication stage (see Table 1). Although these criteria strengthen metadata consistency and replicability, they may also introduce coverage bias by excluding relevant studies indexed in other databases (e.g., Web of Science, ERIC, IEEE Xplore) and scholarship published in non-English outlets. Consequently, contributions from regions where physics education research is frequently disseminated through local-language journals or non-Scopus venues may be underrepresented.

Second, bibliometric results are inherently sensitive to the construction and indexing of search queries. The Boolean query was intentionally designed to capture AI, AR, and physics education-related terms; however, relevant studies may use alternative terminology (e.g., "intelligent tutoring," "learning analytics," "extended reality," "mixed reality," "immersive simulation," or domain-specific physics topic labels) and therefore may not have been fully retrieved. In addition, Scopus metadata quality and indexing conventions (e.g., author keywords vs. indexed keywords, or inconsistencies in affiliation fields) may affect the precision of productivity counts and network structures despite preprocessing.

Third, the 2025 publication counts should be interpreted cautiously because the retrieval was conducted on 2 August 2025, meaning that the year-2025 distribution reflects partial-year indexing rather than a complete annual total. This limitation may influence apparent year-to-year comparisons, particularly near the end of the time window.

Fourth, the study uses science-mapping techniques (e.g., keyword co-occurrence, thematic development/evolution, and overlay visualization). While these techniques are effective for identifying conceptual structure and thematic shifts, they reflect patterns of discourse and co-labeling rather than the substantive depth or methodological rigor of individual studies. For example, prominent keywords may represent fashionable terminology rather than theoretically grounded constructs, and network centrality does not necessarily indicate pedagogical effectiveness or instructional validity.

Fifth, the interpretive synthesis of pedagogical contributions in Tables 5 and 6 is illustrative rather than exhaustive. Although representative articles were reviewed to contextualize the bibliometric patterns, the synthesis does not constitute a systematic qualitative review with formal quality appraisal, nor does it establish causal claims about learning outcomes beyond what each original study reported. As such, the contribution mapping should be read as an informed thematic interpretation aligned with the bibliometric evidence, not as an effectiveness meta-analysis.

Finally, bibliometric mapping cannot determine causal impacts on students' learning, teachers' practice, or curriculum outcomes. The present study identifies growth patterns, influential sources, conceptual hubs, and thematic trajectories, but it does not test intervention effects, implementation feasibility, or long-term learning gains. Future work should therefore complement the mapping with empirical and design-based research that examines how AI and AR interventions operate in authentic physics classrooms and laboratories, including attention to assessment validity, equity, and responsible AI use.

CONCLUSION

This study provides a Scopus-based bibliometric mapping of a decade of research (2016–2025) on Artificial Intelligence (AI) and Augmented Reality (AR) in physics education. The year-wise distribution indicates a clear expansion of the field, with publication output accelerating markedly after 2021 and reaching its highest level in 2024, while the 2025 count should be interpreted cautiously due to partial-year indexing at the time of retrieval (2 August 2025). Across performance indicators and source patterns, the corpus demonstrates an interdisciplinary publication ecology in which influential contributors and journals shape a rapidly consolidating knowledge base.

Science mapping results show that the conceptual framework of the literature is largely centered around technology-related themes such as augmented reality, artificial intelligence, virtual reality, and machine learning. These themes are identified as foundational in the thematic development map and are key hubs in the keyword co-occurrence network. The thematic evolution analysis results show that there is co-development and no replacement of one technology by another. AR remains as one of the major pillars in interactive visualization and representational learning, while AI emerges as an important aspect of current discourse in the field in terms of adaptivity, analytics-based support, and integration of intelligent systems. From the perspective of reviewing and synthesizing the literature, it can be seen that while AI is described in terms of providing diagnostic and adaptive support in instructional contexts, AR is described in terms of providing support in visualization, inquiry, and multi-representational learning.

Taken together, these results suggest a clear direction forward for AI–AR in physics education: more alignment of what the technology is capable of doing with what students are learning about physics—conceptual change, reasoning about multiple representations, and the nature of inquiry and lab work. Future studies should therefore move beyond technology adoption narratives by developing mechanism-explicit interventions and conducting rigorous classroom- and laboratory-grounded evaluations, including attention to assessment validity, implementation constraints, equity, and responsible AI use. By clarifying growth trajectories, conceptual hubs, and emerging thematic directions, this bibliometric mapping offers an evidence-based foundation for more cumulative and physics-education-grounded research agendas.

AUTHOR CONTRIBUTIONS

ZZ contributed to conceptualization, methodology, formal analysis, and writing of the original draft, as well as review and editing of the manuscript. Mi was responsible for data curation, investigation, visualization, writing of the original draft, and review and editing. QQ contributed to data collection, formal analysis, methodology, and writing of the original draft. MZBA contributed to conceptualization, provision of resources, supervision, and review and editing of the manuscript. Ma was involved in conceptualization, project administration, funding acquisition, and review and editing. NFAR contributed to resources, methodology, supervision, and review and editing of the manuscript.

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