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Mapping Problem-Based Learning, Computational Methods, and AI in Physics-Related Education: A Bibliometric Analysis

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Abstract

This study maps the development, collaboration patterns, and conceptual structure of research connecting Problem-Based Learning (PBL), computational methods, and artificial intelligence (AI) in physics-related education. A descriptive bibliometric design was applied to 251 English-language journal articles and conference papers indexed in Scopus between 2016 and 2025. The dataset was retrieved on January 16, 2026, and analyzed using Microsoft Excel and VOSviewer 1.6.20 through performance analysis, country-level collaboration mapping, keyword co-occurrence analysis, and temporal overlay visualization. Publication output showed an overall upward trend with annual fluctuations, increasing from 10 documents in 2016 and reaching a peak of 36 documents in 2023. The reported citation counts also increased across the study period. The United States led in publication output, citation count, and collaboration strength, followed by China in productivity, while Indonesia ranked third in publication output. Of 2,330 identified keywords, 96 met the minimum occurrence threshold and formed four clusters. Problem-based learning was the most prominent keyword, with 143 occurrences and a total link strength of 999, and was strongly connected with students, simulations, curriculum, and active learning. Artificial intelligence and machine learning each recorded 30 occurrences and comparatively recent average publication years, indicating their emerging position within the network. However, their connections with PBL remained weaker than those of established simulation-based themes. The presence of medical, engineering, and technology-enhanced education terms further indicates that the corpus was interdisciplinary rather than restricted exclusively to physics education. These findings provide a structured basis for future qualitative and empirical research on the effectiveness, design, and responsible implementation of AI-supported PBL environments.

Keywords: Artificial Intelligence; Bibliometric Analysis; Computational Methods; Physics-Related Education; Problem-Based Learning

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INTRODUCTION

Rapid advances in automation, computational technologies, and artificial intelligence have reshaped the competencies expected in science education. Computational thinking, data-informed reasoning, scientific modeling, and AI literacy are increasingly relevant to students' preparation for technology-intensive academic and professional environments. Workforce projections reported by Li (2024) indicate substantial growth in digitally oriented occupations alongside the displacement of some conventional roles through automation. Recent STEM education research likewise emphasizes the increasing importance of computational and communication technologies in preparing learners for changing scientific and technological contexts (Tassilova et al., 2025).

Physics education plays a foundational role in this transformation because physics develops mathematical reasoning, model construction, abstraction, and evidence-based explanation across many STEM domains (Develaki, 2020; Galili, 2018). Computational approaches and AI-related methods may further support conceptual representation, data analysis, and scientific reasoning in physics learning (Tschisgale et al., 2023; Mahligawati et al., 2023). Consequently, physics education requires pedagogical approaches that engage students actively in applying concepts, evaluating evidence, and solving authentic problems rather than relying primarily on procedural or teacher-centered instruction.

Problem-Based Learning (PBL) provides one such learner-centered framework. PBL organizes learning around meaningful problems that require students to identify relevant information, develop explanations, evaluate possible solutions, and reflect on their reasoning. In physics education, PBL has been associated with the development of problem-solving and critical-thinking skills (Samadun & Dwikoranto, 2022). Its emphasis on inquiry, collaboration, and independent learning also aligns with the reasoning processes involved in scientific investigation. AI-supported systems may complement this framework by providing adaptive assistance, personalized feedback, and information about learner progress (Demartini et al., 2024; Ouyang et al., 2023).

Implementing PBL in physics nevertheless presents distinct pedagogical challenges. Topics such as quantum mechanics and electromagnetism require learners to coordinate abstract concepts, mathematical representations, and physical interpretations. Processing such complex and highly interconnected information can place substantial demands on working memory, particularly when learners receive insufficient instructional or representational support (Skulmowski & Xu, 2022; Szulewski et al., 2021). Computational modeling and simulations can help learners visualize processes, manipulate variables, test assumptions, and examine relationships that are difficult to observe directly (Magana et al., 2022; Pang et al., 2024; Singh-Pillay, 2024). Interactive media, electronic modules, and digital learning resources have also been developed to support problem-solving and critical-thinking activities in science and physics education (Daryanes et al., 2023; Dwikoranto et al., 2023; Lintangesukmanjaya et al., 2024; Utaminingsih & Ellianawati, 2025).

The educational value of these technologies, however, depends on their pedagogical design and implementation. Evidence from active-learning and inquiry-oriented STEM settings shows that instructors may experience difficulty providing timely guidance, monitoring students' reasoning, and maintaining productive inquiry processes (Auerbach & Andrews, 2018; Andrews et al., 2019; Stanfield et al., 2022). Research on educational AI similarly identifies teacher competence, confidence, and critical evaluation of generated content as important conditions for effective implementation (Jang & Choi, 2025; Zou et al., 2025). Computational and AI-based tools should therefore be understood as potential forms of instructional support rather than as automatic solutions to conceptual difficulties. Their contribution depends on alignment with learning objectives, teacher guidance, feedback quality, and the structure of the problems presented to students.

As research on PBL, simulations, computational methods, and AI continues to expand, systematic mapping is needed to clarify how these themes are connected within physics-related education. Bibliometric analysis offers a quantitative approach for examining publication development, citation visibility, collaboration networks, and conceptual structures across a large body of literature (Donthu et al., 2021; Gan et al., 2022; Pessin et al., 2022). It can also identify established themes, comparatively recent topics, and areas in which research remains fragmented.

Previous studies have addressed individual components of this research area but have not comprehensively mapped their intersection. Research has examined generative AI in physics education (Moundridou et al., 2025), computational thinking in physics and maker-oriented learning (Hutchins et al., 2020; Yin et al., 2020), and AI-enhanced STEM education more broadly (Yang et al., 2025). Other publications provide conceptual, experimental, or methodological perspectives on AI, PBL, computational thinking, and bibliometric analysis without integrating these elements into a unified longitudinal map of physics-related education. Table 1 summarizes selected related studies and clarifies their relationship to the present investigation.

Table 1. Selected Related Studies and Their Methodological Scope

Author	Year	Focus	Design	Relevance or limitation
Moundridou et al.	2025	Generative AI in physics education	PRISMA-informed bibliometric review	Focused primarily on generative AI and higher education
Singh and Arora	2023	Research trends in *The TQM Journal*	Bibliometric analysis	Demonstrates bibliometric procedures but examines a single journal outside education
Yan and Zhiping	2023	Academic publishing trends	Science mapping	Provides a methodological comparison but uses a different disciplinary scope and database
Williamson	2024	AI in education	Conceptual review	Examines the social and educational implications of AI without bibliometric mapping
Erol et al.	2023	PBL- and STEAM-related learning outcomes	Experimental study	Evaluates learning outcomes in a specific sample without mapping the research field
Kafai and Proctor	2022	Computational thinking in K–12 education	Theoretical analysis	Develops a conceptual perspective without examining longitudinal publication trends

The studies summarized in Table 1 provide important conceptual and methodological foundations, but they address different disciplinary settings or examine PBL, computational thinking, and AI separately. Consequently, the development of research connecting these themes within physics-related education remains insufficiently mapped. In particular, limited evidence is available regarding the countries, sources, authors, and institutions shaping this literature; the collaboration networks through which it develops; the conceptual position of PBL relative to simulations and AI; and the temporal emergence of artificial intelligence and machine learning within the broader keyword structure.

The present study addresses this gap by integrating performance analysis and science mapping within a single bibliometric framework. Its contribution lies in four areas. First, it examines the intersection of PBL, computational methods, simulations, and AI in physics-related educational literature. Second, it evaluates productivity, citation visibility, and collaboration across countries, publication sources, authors, and institutions. Third, it maps the co-occurrence structure of the principal research concepts. Fourth, it uses temporal overlay visualization to distinguish comparatively established themes from more recent topics, including artificial intelligence, machine learning, and learning systems.

Accordingly, this study aims to map the intellectual and temporal structure of research connecting PBL, computational methods, and AI in physics-related education. Specifically, it seeks to: (1) examine annual publication output and citation patterns; (2) identify leading countries, sources, authors, and institutions and describe their collaboration networks; (3) analyze keyword co-occurrence clusters and the position of PBL within the conceptual network; and (4) identify comparatively recent themes based on average publication-year indicators.

The analysis covers 251 English-language journal articles and conference papers indexed in Scopus between 2016 and 2025. The period was selected to capture recent developments in simulation-supported, computational, and AI-related education, including the years preceding and following the rapid expansion of generative AI. The primary indicators include total publications, total citations, keyword occurrences, average publication year, and total link strength (Donthu et al., 2021; Pessin et al., 2022; Hassan & Duarte, 2024). Because the search strategy retrieved literature from adjacent educational fields, the resulting corpus is interpreted as an interdisciplinary body of physics-related and computationally supported educational research rather than as an exhaustive representation of physics education alone.

By clarifying publication trends, collaboration patterns, and conceptual relationships, this study provides an evidence-based overview of the development of the field. The findings can inform more focused qualitative reviews and empirical investigations of how PBL, simulations, computational methods, and AI are designed and evaluated in physics-learning environments.

METHOD

Research Design

This study employed a descriptive quantitative bibliometric design supported by systematic literature-search and screening procedures. The design was used to map publication performance, collaboration patterns, keyword relationships, and the temporal development of research integrating Problem-Based Learning (PBL), computational methods, and artificial intelligence (AI) within physics-related education. Bibliometric analysis enables the quantitative examination of a large body of publication metadata and supports the identification of knowledge structures, thematic developments, and research trajectories (Donthu et al., 2021; Jing et al., 2024).

The study should be understood as a bibliometric investigation with a systematic search and screening process rather than as a qualitative Systematic Literature Review. A PRISMA-informed workflow was applied to document the identification, screening, eligibility, and inclusion of records transparently (O'Dea et al., 2021; Batten & Brackett, 2022). The analytical design combined performance analysis and science mapping because these approaches capture complementary dimensions of scientific production, citation visibility, collaboration, and conceptual structure (Donthu et al., 2021; Bardakci et al., 2022; Jing et al., 2024).

Data Source and Retrieval

Publication metadata were retrieved exclusively from the Scopus database. Scopus was selected because it provides broad coverage of peer-reviewed journals and conference proceedings and supplies standardized metadata suitable for bibliometric analysis (Gerasimov et al., 2024). The study covered publications issued between 2016 and 2025. The dataset was retrieved on January 16, 2026, allowing additional time for documents published in 2025 to be indexed.

The initial search returned 655 records. The records were subsequently filtered according to publication year, subject area, document type, language, and relevance to the study scope. After all eligibility and screening procedures had been completed, 251 journal articles and conference papers were retained for analysis.

Search Strategy

The search strategy combined four conceptual components: PBL, physics-related subject matter, AI or computationally supported technologies, and educational contexts. The query was applied to publication titles, abstracts, and keywords using the Scopus TITLE-ABS-KEY field. To ensure reproducibility, the exact corrected query is presented as follow.

> *TITLE-ABS-KEY ("problem-based learn*" OR "PBL")AND TITLE-ABS-KEY ("physic*" OR "mechanic*" OR "thermodynamic*" OR "electric*" OR "optic*" OR "electromagnet*" OR "quantum*")AND TITLE-ABS-KEY ("artificial intelligen*" OR "machine learning" OR "deep learning" OR "neural network*" OR "generative AI" OR "ChatGPT" OR "virtual realit*" OR "augmented realit*" OR "mixed realit*" OR "gamif*" OR "game-based" OR "virtual lab*" OR "simulation*" OR "digital twin*")AND TITLE-ABS-KEY ("educat*" OR "teach*" OR "student*" OR "learn*" OR "instruct*" OR "pedagog*" OR "curricul*")*

The asterisk served as a wildcard operator that captured multiple forms of words with the same root. For example, learn* retrieved terms such as "learn," "learning," and "learner," while physic* retrieved variants such as "physics" and "physical." This procedure increased retrieval sensitivity while retaining the conceptual structure of the search.

The results were limited to English-language journal articles and conference papers published from 2016 to 2025. The 10-year period was selected to examine recent developments in computationally supported and AI-related learning while covering the period before and after the rapid expansion of generative AI. The search strategy was refined to balance sensitivity and specificity and to reduce the retrieval of records without an educational context (Donthu et al., 2021; MacFarlane et al., 2022; Nowakowska, 2025).

Eligibility Criteria

Explicit inclusion and exclusion criteria were established before the final analysis. These criteria are summarized in Table 2.

Table 2. Inclusion and Exclusion Criteria

Criterion	Description
Language	English
Document type	Journal articles and conference papers
Publication period	2016–2025
Subject scope	Physics, science, engineering, and technology-enhanced education
Inclusion criteria	Records addressing educational applications of PBL, computational or simulation-based methods, or AI in physics-related or adjacent STEM learning contexts
Exclusion criteria	(a) Purely technical physics modeling without an educational context; (b) medical or nursing studies without a relevant educational connection to PBL, simulation, computational methods, or AI; and (c) non-peer-reviewed, incomplete, or conceptually irrelevant records

The eligibility criteria were intended to retain studies with a recognizable educational dimension while excluding purely technical studies that did not address teaching or learning. Because PBL, simulation, and AI are also widely used in engineering, medical, nursing, and other professional-education contexts, the broad search terms retrieved some records from adjacent fields. Such records were retained when they met the predefined search dimensions and addressed relevant educational applications. This decision preserved the reproducibility of the screening process but also contributed to the interdisciplinary composition of the final corpus.

The resulting dataset should therefore be interpreted as literature at the intersection of PBL, physics-related or computationally supported education, simulation, and AI rather than as a corpus restricted exclusively to physics education. Rigorous screening was used to reduce, but could not entirely eliminate, cross-disciplinary records and purely technical literature (Fan et al., 2022; Kolaski et al., 2023; Mancin et al., 2024).

Screening and Selection Procedures

The selection process followed four PRISMA-informed stages: identification, screening, eligibility assessment, and inclusion. The database search initially identified 655 records. Applying the publication-year restriction reduced the dataset to 398 records. Subject-area filtering further reduced the number to 299, and restricting the dataset to journal articles and conference papers produced 262 records. Language filtering and manual assessment of titles and abstracts resulted in the final inclusion of 251 documents.

During manual screening, records were assessed for their alignment with the educational focus of the study. Records devoted exclusively to technical modeling, physical systems, or engineering computation without a teaching or learning component were excluded. Titles and abstracts were also examined to identify studies whose terminology matched the search query but whose substantive focus was unrelated to the integration of PBL, computational or simulation-based methods, and

AI in educational contexts. The complete record-selection process, including the number of documents retained at each stage, is presented in Figure 1.

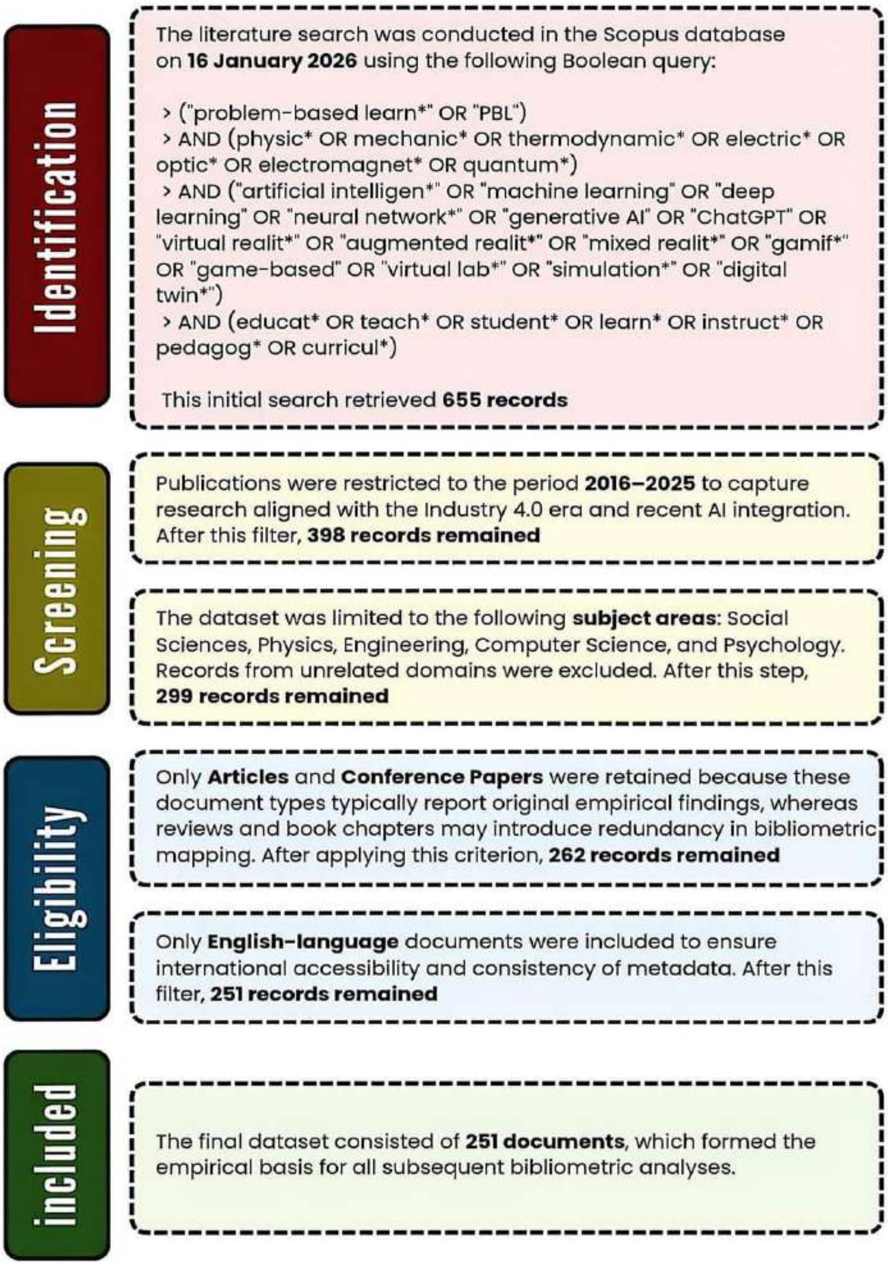

Figure 1. PRISMA-informed flow diagram of record identification, screening, eligibility assessment, and inclusion

Data Cleaning and Terminology Standardization

Before bibliometric mapping, the metadata were prepared to reduce inconsistencies in keyword terminology. A thesaurus file was applied in VOSviewer to merge spelling variants, abbreviations, and semantically equivalent terms. For example, "problem based learning," "PBL," and related variants were standardized as "problem-based learning." The terms "AI," "genAI," and "artificial intelligence" were consolidated under "artificial intelligence."

Terms related to "computational physics," "computational modeling," and "computational thinking" were standardized under "computational methods," whereas relevant simulation variants were grouped under "simulations." This preprocessing reduced the fragmentation of conceptually related terms and improved the interpretability of the co-occurrence network (Donthu et al., 2021; Nowakowska, 2025).

Terminology standardization was limited to the bibliographic metadata available in the original dataset. Consequently, variations in institutional names and affiliation units could remain in the analysis, as illustrated by entries that did not correspond clearly to a standardized institutional name.

Bibliometric Indicators

Three principal bibliometric indicators were used: total publications, total citations, and total link strength. Total publications (TP) represented the number of documents associated with a year, country, source, author, or institution. Total citations (TC) represented the citation count recorded in the Scopus metadata at the time of retrieval. For the annual trend analysis, TC referred to the citations received by the analyzed corpus during each calendar year, according to the annual aggregation used in the dataset.

Total link strength (TLS) was generated by VOSviewer and represented the cumulative strength of a unit's relationships with other units in a specified network. Depending on the analysis, TLS described collaboration links among countries, authors, or institutions or co-occurrence links among keywords. TP, TC, and TLS were interpreted separately because publication productivity, citation visibility, and network connectivity represent different dimensions of research activity (Donthu et al., 2021; Hassan & Duarte, 2024).

Bibliometric Analysis Procedures

The bibliometric analysis was performed using VOSviewer version 1.6.20 and Microsoft Excel. Excel was used to organize the metadata and calculate descriptive publication indicators, including annual publication output, annual citation counts, and distributions by country, source, author, and institution.

VOSviewer was used for science mapping. The analyses included country-level co-authorship mapping, collaboration indicators for authors and institutions, keyword co-occurrence analysis, cluster visualization, and overlay visualization. Co-citation analysis was not included because no co-citation findings were reported in the Results section.

Keyword co-occurrence analysis used the full-counting method, meaning that each occurrence of a keyword contributed equally to the analysis. A minimum threshold of five keyword occurrences was applied to reduce infrequent terms and improve the interpretability of the network. Of the 2,330 keywords identified in the complete dataset, 96 met the minimum occurrence threshold and were included in the final keyword map.

VOSviewer's association-strength method was used to normalize the co-occurrence relationships. The final keyword network consisted of four clusters, 1,826 links, and a combined total link strength of 7,450. Overlay visualization was based on the average publication year of each keyword and was used to examine the relative temporal position of established and more recent themes.

Visualization and Interpretation

The bibliometric maps were interpreted using node size, link thickness, spatial proximity, cluster membership, and overlay color. Node size represented the weight of an item, such as its number of occurrences or publications. Link thickness represented the strength of the relationship between two items, while spatial proximity indicated their relative relatedness within the network. Cluster colors represented groups of strongly associated items identified by the VOSviewer clustering algorithm. In the overlay visualization, colors represented the average publication year of each keyword.

The visualizations were interpreted as representations of frequency, association, collaboration, and temporal distribution within the analyzed corpus. They were not treated as evidence of causal relationships, research quality, or the pedagogical effectiveness of PBL, simulations, computational methods, or AI. Terms with recent average publication years were therefore described as comparatively recent or emerging within the dataset rather than as proof of a field-wide transformation (Pessin et al., 2022; Jing et al., 2024). Figure 2 summarizes the analytical stages conducted after record selection, including metadata preparation, performance analysis, science mapping, and interpretation.

Figure 2. Workflow for metadata preparation, performance analysis, science mapping, and interpretation

RESULTS AND DISCUSSION

Annual Publication and Citation Trends

Figure 3 presents the annual publication output and citation counts in the analyzed Scopus dataset from 2016 to 2025. A total of 251 documents were published during this period. The annual number of publications showed an overall upward trajectory with year-to-year fluctuations. Publication output increased from 10 documents in 2016 to 24 in 2017, decreased to 17 in 2018, and then increased to 26 in both 2019 and 2020. The number of publications declined slightly to 24 documents in 2021 and remained at the same level in 2022.

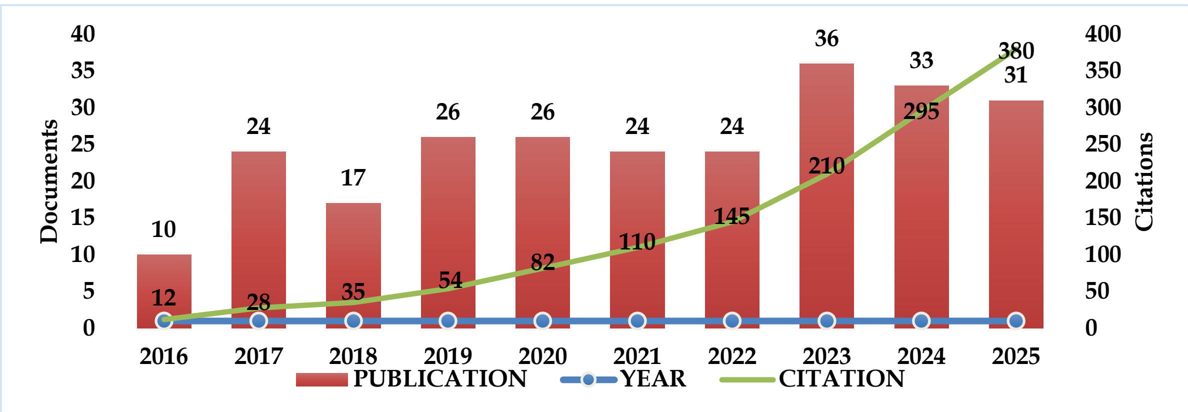

Figure 3. Annual publication output (TP) and citation counts (TC) associated with publications on PBL, computational methods, and AI in physics education (2016–2025)

The highest annual publication output was recorded in 2023, with 36 documents. This peak was followed by 33 documents in 2024 and 31 documents in 2025. Although publication output did not increase consistently every year, the annual total remained higher during 2020–2025 than at the beginning of the study period.

The citation counts associated with the analyzed publication years increased from 12 in 2016 to 380 in 2025. Unlike publication output, which fluctuated across the period, the reported citation counts increased in every successive year. The largest citation totals were recorded in 2023, 2024, and 2025, with 210, 295, and 380 citations, respectively.

Table 3. Annual Publication and Citation Data (2016–2025)

Year	Total Publications	Total Citations
2016	10	12
2017	24	28
2018	17	35
2019	26	54
2020	26	82
2021	24	110
2022	24	145
2023	36	210
2024	33	295
2025	31	380

Note. Total Publications refers to the number of documents published in each year. Total Citations refers to the citation count associated with each publication year in the analyzed dataset.

Table 3 provides the numerical values represented in Figure 3. The annual publication totals ranged from 10 to 36 documents, whereas the citation totals ranged from 12 to 380. Overall, the results show fluctuating publication output alongside a continuous increase in the reported citation counts during the study period.

Geographical Distribution and International Collaboration

Country Productivity and Citation Performance

Figure 4 presents the 10 countries with the highest publication output in the analyzed dataset. The United States ranked first with 56 publications, followed by China with 26 publications and Indonesia with 20 publications. Spain contributed 17 publications, Brazil contributed 15, and Germany contributed 13. India, Portugal, and the United Kingdom each produced 10 publications, whereas Australia contributed eight publications.

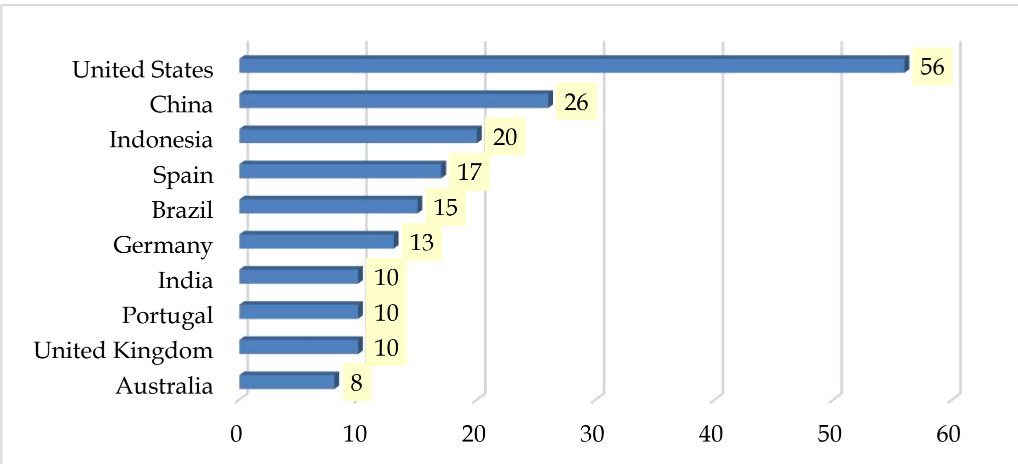

Figure 4. Top 10 contributing countries in research on PBL, computational methods, simulation, and AI in physics-related education

The results show that the United States contributed more than twice the publication output of China, which ranked second. Indonesia ranked third in publication productivity, followed by several European and Latin American countries.

Table 4. Top 10 Countries by Publications, Citations, and Total Link Strength

Country	Publications	Citations	Total Link Strength
United States	56	420	5
China	26	361	1
Indonesia	20	87	2
Spain	17	303	4
Brazil	15	108	4
Germany	13	94	4
India	10	77	0
United Kingdom	10	256	4
Portugal	10	27	3
Australia	8	74	1

Note. Total Link Strength represents the cumulative strength of a country’s collaboration links in the VOSviewer network.

Table 4 compares publication output, citation counts, and collaboration strength. The United States recorded the highest values for publications, citations, and total link strength, with 56 publications, 420 citations, and a total link strength of five. China ranked second in both publication output and citation count, with 26 publications and 361 citations.

Spain recorded 303 citations from 17 publications, while the United Kingdom recorded 256 citations from 10 publications. Indonesia ranked third in publication output but recorded 87 citations and a total link strength of two. Spain, Brazil, Germany, and the United Kingdom each had a total link strength of four. India had a total link strength of zero in the generated collaboration network.

International Co-authorship Network

Figure 5 displays the country-level co-authorship network generated from the analyzed records. In the visible network, the United States occupies a central position and is connected with countries in Europe and Latin America, including Germany, France, Spain, Brazil, and Colombia. Connections are also visible among several European countries, including Germany, France, Spain, Portugal, Greece, and Turkey.

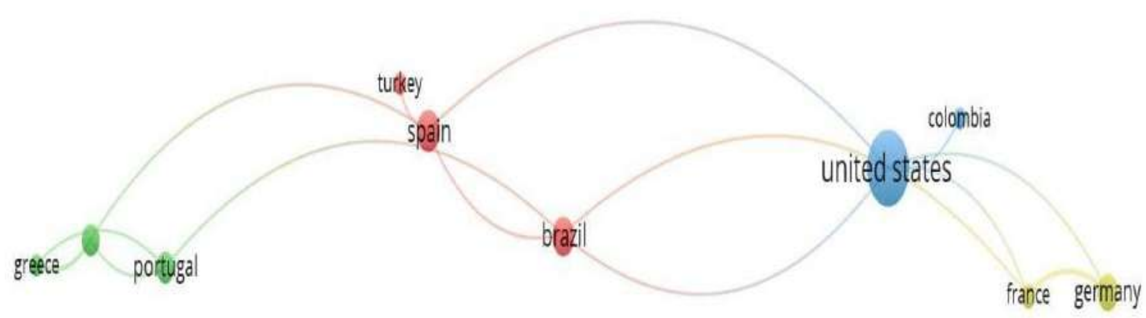

Figure 5. Network visualization of international collaboration between countries

The network further shows a direct connection between Spain and Brazil, while Portugal and Greece form a smaller regional connection. The size and position of the country nodes vary according to their contribution and connectivity within the network.

Table 5. Top International Collaboration Pairs Based on Link Strength

Country Pair	Total Link Strength
United States–Germany	5
United States–France	5
Spain–Brazil	4
United Kingdom–Spain	4
Germany–United Kingdom	4
Portugal–Greece	3
Indonesia–Malaysia	3
China–Australia	2
United States–Brazil	2
France–Germany	2

Table 5 lists the strongest international collaboration pairs identified in the complete country-level network. The United States–Germany and United States–France pairs recorded the highest total link strength, with a value of five for each pair. Spain–Brazil, United Kingdom–Spain, and Germany–United Kingdom each recorded a total link strength of four.

Portugal–Greece and Indonesia–Malaysia recorded a total link strength of three. China–Australia, United States–Brazil, and France–Germany each recorded a total link strength of two. The collaboration pairs reported in Table 5 represent results from the full network and therefore include countries that may not be clearly visible in the cropped visualization presented in Figure 5.

Leading Sources, Authors, and Institutions

Leading Publication Sources

The productivity and network positions of publication sources were assessed using total publications (TP), total citations (TC), and total link strength (TLS). Table 6 presents the 10 most productive sources in the analyzed dataset.

Table 6. Top 10 Sources by Publications, Citations, and Total Link Strength

No.	Source Title	TP	TC	TLS
1	ASEE Annual Conference and Exposition	11	27	9
2	BMC Medical Education	10	174	11
3	IEEE Global Engineering Education Conference	9	26	11
4	Journal of Physics: Conference Series	7	22	1
5	Proceedings—Frontiers in Education Conference	6	18	2
6	Nurse Education Today	5	148	0
7	Computer Applications in Engineering Education	5	44	16
8	Lecture Notes in Networks and Systems	5	36	20
9	IEEE Transactions on Education	4	90	5
10	Simulation in Healthcare	4	40	3

Note. TP = total publications; TC = total citations; TLS = total link strength generated by VOSviewer for the source network.

ASEE Annual Conference and Exposition ranked first in publication output, with 11 documents. BMC Medical Education ranked second with 10 documents, followed by the IEEE Global Engineering Education Conference with nine documents. Journal of Physics: Conference Series contributed seven documents, while Proceedings—Frontiers in Education Conference contributed six.

BMC Medical Education recorded the highest citation count among the listed sources, with 174 citations, followed by Nurse Education Today with 148 citations and IEEE Transactions on Education with 90 citations. Lecture Notes in Networks and Systems had the highest total link strength, with a value of 20, followed by Computer Applications in Engineering Education with a value of 16.

The source distribution includes conference proceedings and journals from engineering education, physics education, medical education, nursing education, and technology-enhanced learning.

Leading Authors

Jumadi, J. had the highest publication output, with seven documents, followed by Wang, X.; Kuswanto, H.; Wang, W.; and Maciel Barbosa, F. P., each with four documents. Wilujeng, I.; Valdez, M. T.; and Machado Ferreira, C. each contributed three documents.

Table 7. Top 10 Authors by Publications, Citations, and Total Link Strength

No.	Author	TP	TC	TLS
1	Jumadi, J.	7	33	20
2	Wang, X.	4	25	17
3	Kuswanto, H.	4	19	13
4	Wang, W.	4	10	26
5	Maciel Barbosa, F. P.	4	6	10
6	Wilujeng, I.	3	28	9
7	Valdez, M. T.	3	8	6
8	Machado Ferreira, C.	3	6	6
9	Zhang, J.	2	85	6
10	Nicholls, S. D.	2	24	17

Zhang, J. recorded the highest citation count among the listed authors, with 85 citations from two publications. Jumadi, J. recorded 33 citations, while Wilujeng, I. recorded 28 citations. Wang, W. had the highest total link strength, with a value of 26, followed by Jumadi, J. with 20 and Wang, X. and Nicholls, S. D. with 17 each.

The rankings differed across the three indicators. The author with the highest publication output was not the author with the highest citation count or total link strength.

Leading Institutions

Universitas Negeri Yogyakarta had the highest institutional publication output, with seven documents. The affiliation entry "Physics Education (Affiliation Unit)" ranked second with six documents, followed by California State University with four documents. Five institutions contributed three publications each, while Universidad de Los Andes and The Education University of Hong Kong contributed two publications each.

Table 8. Top 10 Institutions by Publications, Citations, and Total Link Strength

No.	Institution	TP	TC	TLS
1	Universitas Negeri Yogyakarta	7	35	2
2	Physics Education (Affiliation Unit)	6	10	3
3	California State University	4	14	3
4	Universidad del País Vasco	3	72	0
5	Universidade Federal de Santa Catarina	3	38	5
6	Instituto Politécnico de Coimbra	3	6	4
7	Universidade de São Paulo	3	5	0
8	Texas A&M University	3	2	4
9	Universidad de Los Andes	2	125	2
10	The Education University of Hong Kong	2	109	2

Note. Institution names are reproduced from the Scopus metadata. "Physics Education (Affiliation Unit)" is retained as an unstandardized affiliation entry in the source dataset.

Universidad de Los Andes recorded the highest citation count, with 125 citations, followed by The Education University of Hong Kong with 109 citations and Universidad del País Vasco with 72 citations. Universidade Federal de Santa Catarina recorded the highest total link strength, with a value of five. Instituto Politécnico de Coimbra and Texas A&M University each recorded a total link strength of four.

Keyword Co-occurrence Structure

Keyword Network and Cluster Formation

The keyword co-occurrence analysis identified 2,330 keywords in the complete dataset. After applying the minimum occurrence threshold, 96 keywords were retained in the final network. These keywords formed four clusters containing 1,826 links and a combined total link strength of 7,450.

Problem-based learning was the most frequently occurring keyword, with 143 occurrences and a total link strength of 999. The keyword "students" occurred 115 times and had a total link strength of 599. Other prominent terms included "simulation education," "curriculum," "medical education," "controlled study," "artificial intelligence," "machine learning," "learning systems," and "active learning."

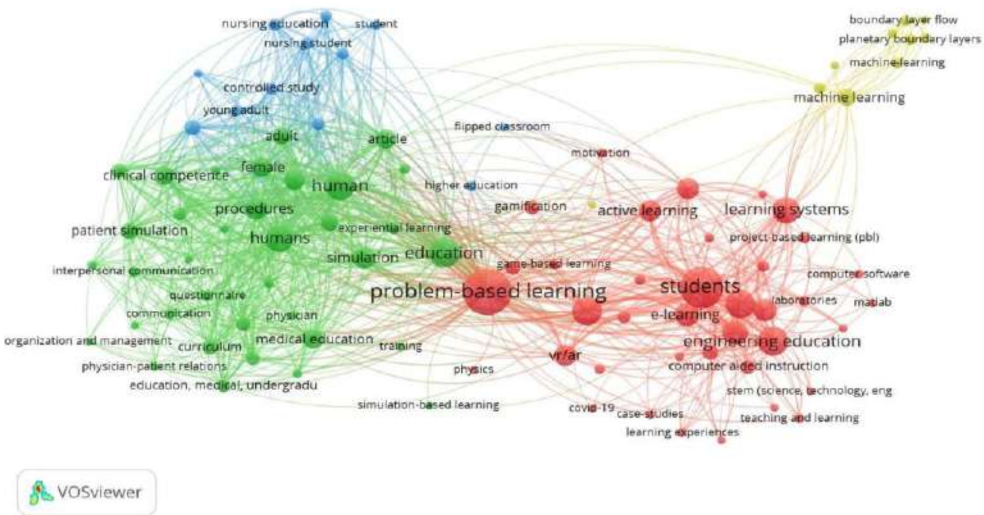

Figure 6. Network visualization of keyword co-occurrence clusters

The red cluster was centered on problem-based learning and students. The green cluster included simulation education and curriculum, while the blue cluster included medical education and controlled study. The yellow cluster contained artificial intelligence, machine learning, learning systems, and active learning.

Table 9. Keyword Cluster Analysis with Temporal Indicators

Cluster	Keyword	Occurrences	TLS	Average Publication Year
Red	problem-based learning	143	999	2021
Red	students	115	599	2022
Green	simulation education	57	310	2020
Green	curriculum	39	225	2020
Blue	medical education	26	317	2019
Blue	controlled study	24	342	2019
Yellow	artificial intelligence	30	197	2022
Yellow	machine learning	30	197	2023
Yellow	learning systems	28	180	2023
Yellow	active learning	35	210	2022

Note. Cluster colors correspond to the VOSviewer network visualization. TLS = total link strength.

The average publication years ranged from 2019 to 2023 among the keywords presented in Table 9. Medical education and controlled study had the earliest average publication year, at 2019. Simulation education and curriculum had an average publication year of 2020. Problem-based learning had an average publication year of 2021, while machine learning and learning systems had the most recent average publication year, at 2023.

Centrality of Problem-Based Learning

Figure 7 presents an enlarged view of the problem-based learning node and its surrounding connections. Problem-based learning has the largest node size in the local network and is connected with terms related to students, simulation, active learning, curriculum, and artificial intelligence.

The links between problem-based learning and established simulation- and student-related terms are more prominent than its links with artificial intelligence. The network also includes terms associated with medical education and controlled studies, reflecting the interdisciplinary composition of the retrieved dataset.

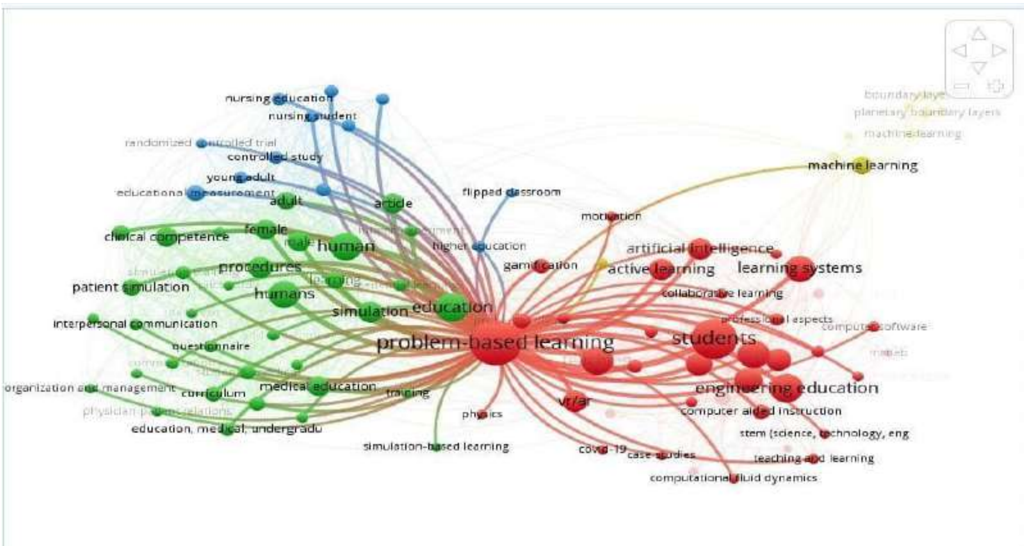

Figure 7. Zoomed-in visualization of the "problem-based learning" node

Temporal Evolution of Research Themes

Overlay Visualization of Keyword Development

Figure 8 presents the overlay visualization based on the average publication year of the keywords. In the visualization, keywords with earlier average publication years are represented by darker blue and green tones, whereas keywords with more recent average publication years are represented by yellow tones.

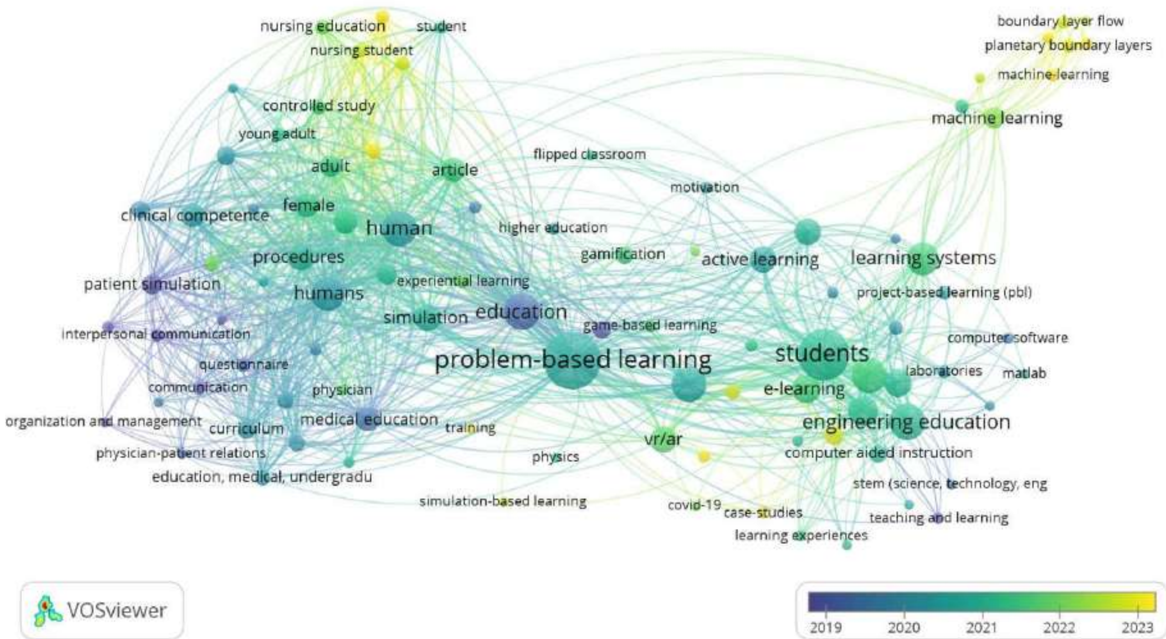

Figure 8. Overlay visualization showing the temporal evolution of research themes

Terms related to medical education, controlled studies, simulation education, and curriculum are positioned toward the earlier part of the temporal scale. In contrast, artificial intelligence, machine learning, learning systems, and active learning appear closer to the more recent end of the scale. Problem-based learning remains centrally positioned and is connected with keywords from both earlier and more recent publication periods.

Position of Artificial Intelligence in the Keyword Network

Figure 9 provides a detailed view of the artificial intelligence node and its immediate connections. Artificial intelligence recorded 30 occurrences and a total link strength of 197, with an average publication year of 2022. The node is connected with machine learning, learning systems, active learning, problem-based learning, and other computationally oriented terms.

Machine learning also recorded 30 occurrences and a total link strength of 197, but had a more recent average publication year of 2023. The artificial intelligence node was smaller and less strongly connected than the problem-based learning node, which recorded 143 occurrences and a total link strength of 999.

The network also contained peripheral disciplinary terms, including "boundary layer flow." In addition, keywords explicitly referring to ethics, data privacy, or algorithmic transparency did not appear among the terms that met the minimum occurrence threshold used in the analysis.

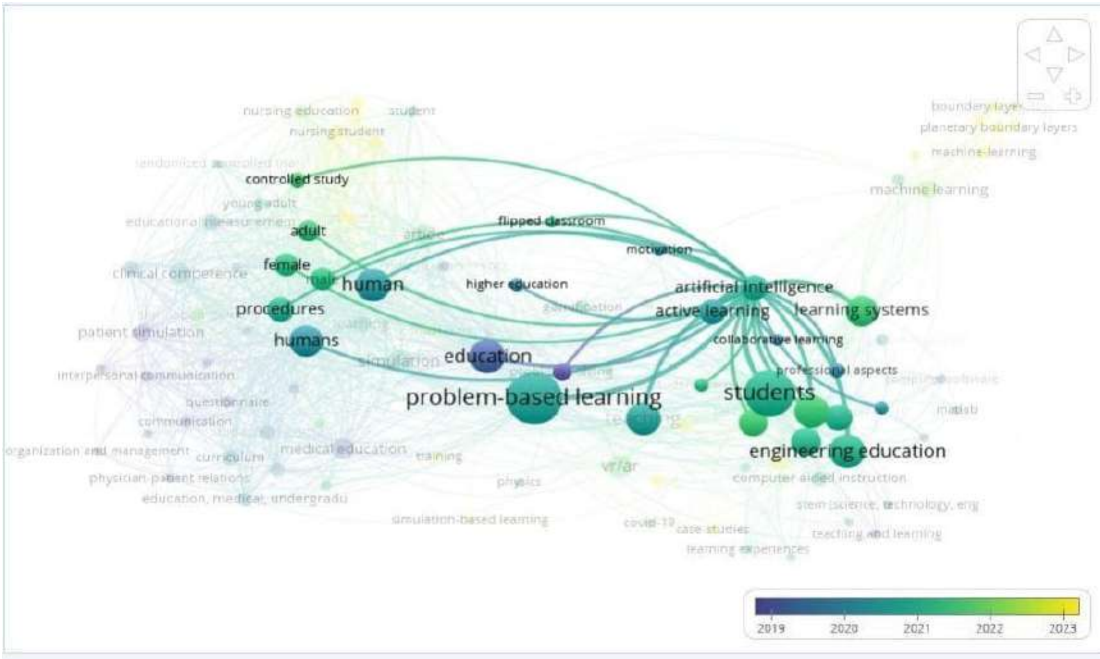

Figure 9. Zoomed-in visualization of the emerging “artificial intelligence” node

Discussion

Growth of Research Output and Citation Visibility

The annual publication pattern indicates an overall expansion of research at the intersection of problem-based learning, computational methods, artificial intelligence, and physics-related education. Although publication output fluctuated across the study period, the number of documents remained generally higher after 2020 and reached its maximum in 2023. This pattern suggests increasing scholarly attention to technology-supported and learner-centered approaches rather than continuous year-to-year growth. The fluctuations observed in 2018, 2021, 2022, 2024, and 2025 also demonstrate that the development of this research domain has not followed a strictly linear trajectory.

The increase in reported citation counts indicates that the analyzed body of literature has gained greater visibility within the Scopus-indexed research landscape. However, these citation values should be interpreted as corpus-level citation activity reported by year rather than as age-normalized measures of the influence of individual publication cohorts. Citation patterns can be affected by several factors, including document type, publication age, database coverage, disciplinary citation practices, and indexing delays. Therefore, the observed increase should not be attributed directly to a single technological development, including the emergence of generative artificial intelligence. Instead, it more cautiously reflects the cumulative growth and increasing visibility of interdisciplinary research involving active learning, simulations, computational technologies, and AI-supported education.

The publication trend is consistent with the broader expansion of AI-enhanced STEM education and computationally supported learning environments reported in recent literature (Yang et al., 2025). Computational approaches have increasingly been used to connect abstract scientific concepts with modeling, visualization, and interactive problem-solving activities (Hutchins et al., 2020; Mahligawati et al., 2023). Nevertheless, the bibliometric results indicate research attention and citation visibility rather than the educational effectiveness of these approaches. Claims about their effects on learning outcomes require evidence from empirical and experimental studies.

Geographical Concentration and International Collaboration

The country-level results reveal an uneven geographical distribution of research productivity. The United States led the dataset in publication output, citation count, and total link strength, indicating a prominent position in both knowledge production and international collaboration. China ranked second in publication output and citation count but had a comparatively low total link strength. This difference illustrates that national productivity, citation visibility, and international connectivity represent distinct dimensions of research performance and should not be treated as interchangeable indicators.

Indonesia's position as the third most productive country is notable because it demonstrates substantial publication activity from a developing-country context. However, its citation count and total link strength remained lower than those of several countries with fewer publications, including Spain and the United Kingdom. These differences should not be interpreted as direct evidence of differences in research quality. Citation counts may be influenced by publication venue, language, international visibility, document age, field-specific citation practices, and the size of the collaboration network. Bibliometric performance is therefore more accurately understood by examining publication output, citation counts, and network indicators together rather than relying on a single metric (Donthu et al., 2021; Hassan & Duarte, 2024).

The co-authorship network further shows that international collaboration was concentrated primarily among countries in North America and Europe. The strongest links involved the United States, Germany, France, Spain, and the United Kingdom. The Spain–Brazil connection also demonstrates collaboration between European and Latin American research communities. At the same time, the Indonesia–Malaysia and China–Australia links indicate the presence of regional and cross-regional partnerships involving Asian countries. These patterns suggest that the collaboration structure is becoming more geographically diverse, although the strongest network positions remain concentrated among countries with established research infrastructures.

International collaboration can facilitate the exchange of methodological expertise, technological resources, and context-specific educational knowledge. It can also support the development of interdisciplinary projects that require expertise in physics education, learning sciences, computing, and artificial intelligence. However, total link strength measures network connectivity rather than the quality or effectiveness of collaboration. Consequently, the collaboration results should be interpreted as indicators of relational structure within the analyzed corpus, not as direct measures of scientific excellence. Broader and more balanced partnerships may nevertheless strengthen knowledge flows and improve the representation of educational contexts that remain underrepresented in internationally indexed research (Nan & Huang, 2025; Newman, 2024).

Patterns of Knowledge Production Across Sources, Authors, and Institutions

The distribution of leading publication sources demonstrates the interdisciplinary nature of the retrieved literature. Conference proceedings, particularly those associated with engineering and technology education, accounted for a substantial share of the most productive sources. The prominent positions of the ASEE Annual Conference and Exposition, the IEEE Global Engineering Education Conference, and the Frontiers in Education Conference indicate that conference venues play an important role in disseminating developments in computational and technology-enhanced education. Such venues may facilitate the rapid circulation of emerging applications, instructional designs, and technological prototypes.

Publication productivity did not correspond directly with citation totals. For example, BMC Medical Education and Nurse Education Today produced fewer documents than the leading conference sources but accumulated substantially higher citation counts. Similarly, IEEE Transactions on Education showed comparatively high citation visibility despite a smaller number of documents. These differences reinforce the need to distinguish between productivity and citation impact when evaluating publication sources. They may also reflect variations in audience size, publication format, disciplinary citation practices, and the maturity of the research communities represented by each source.

The presence of medical and nursing education journals requires particular attention. Terms such as "medical education," "controlled study," and "simulation in healthcare" also appeared prominently in the keyword network. These findings indicate that the search strategy retrieved a broader interdisciplinary corpus rather than a dataset restricted entirely to physics education. Problem-based learning and simulation are widely used in medical, nursing, and professional education, which may explain the inclusion of these records. The broad educational and technological terms used in the search query increased retrieval sensitivity but also introduced studies from adjacent disciplinary contexts. This trade-off between comprehensiveness and specificity is common in bibliometric searches and should be considered when interpreting the findings (MacFarlane et al., 2022; Donthu et al., 2021).

The author-level analysis shows that publication productivity, citation visibility, and collaboration connectivity were distributed unevenly. Jumadi, J. recorded the highest publication output, Zhang, J. recorded the highest citation count, and Wang, W. had the highest total link strength. This variation confirms that the most productive author is not necessarily the most cited or the most extensively connected. The three indicators represent different forms of scholarly contribution: TP describes output, TC describes citation visibility, and TLS describes relational position within the analyzed network.

A similar pattern was observed among institutions. Universitas Negeri Yogyakarta led in publication output, whereas Universidad de Los Andes and The Education University of Hong Kong recorded higher citation totals. Universidade Federal de Santa Catarina had the highest total link strength among the listed institutions. These results show that institutional productivity, visibility, and collaboration intensity do not follow identical rankings. They also indicate that institutions from Asia, Europe, North America, and Latin America contribute to the development of this interdisciplinary domain.

The affiliation entry "Physics Education (Affiliation Unit)" illustrates a metadata-standardization issue. Because this entry does not clearly identify a formal institution, its ranking should be interpreted cautiously. Variations in institutional names, departmental labels, abbreviations, and author affiliations can fragment or incorrectly aggregate institutional records. Although the thesaurus procedure standardized keyword variations, affiliation-name cleaning remains an important consideration for future bibliometric analyses.

Intellectual Structure of Problem-Based Learning and Simulation

The keyword network positions problem-based learning as the principal conceptual hub of the analyzed literature. Its high occurrence frequency and total link strength indicate that PBL connects multiple themes, including students, simulation, curriculum, active learning, artificial intelligence, and learning systems. This centrality suggests that PBL functions as a major pedagogical framework through which computational and technology-supported approaches are discussed across the retrieved studies.

The strong relationship between problem-based learning and student-related terms is consistent with the learner-centered orientation of PBL. The model organizes learning around authentic or complex problems and requires students to identify information needs, formulate explanations, evaluate possible solutions, and participate actively in the learning process. Empirical research has associated PBL with the development of critical thinking and problem-solving skills in physics learning contexts (Samadun & Dwikoranto, 2022). However, the bibliometric network itself cannot establish whether PBL consistently improves these outcomes. It only demonstrates that these concepts frequently occur together in the analyzed literature.

Simulation-related terms also occupy an established position in the network. Their earlier average publication years and strong connections with problem-based learning indicate that simulations have served as a relatively mature technological support for inquiry and problem-solving activities. In physics education, simulations can assist learners in visualizing phenomena that are difficult to observe directly, manipulating variables, and examining relationships between mathematical representations and physical behavior. Previous studies have reported that simulation-based learning can support visualization, cognitive engagement, and conceptual exploration in complex scientific contexts (Magana et al., 2022; Pang et al., 2024; Singh-Pillay, 2024).

The relationship between PBL and simulation is particularly relevant to abstract physics topics, where students must coordinate conceptual, mathematical, and representational forms of reasoning. Simulations may provide a manageable environment in which learners can test hypotheses and observe the consequences of different assumptions. Nevertheless, the effectiveness of simulation-supported PBL depends on instructional design, teacher guidance, task structure, feedback quality, and the alignment between the simulation and the intended learning objectives. The prominence of simulation in the network should therefore be interpreted as evidence of sustained research attention rather than proof of uniform pedagogical effectiveness.

The blue cluster containing medical education and controlled-study terminology also affects the interpretation of the intellectual structure. Rather than representing a purely physics-education cluster, it reflects the broader use of PBL and simulation across professional and health-related education. Accordingly, conclusions drawn from the network should refer to the analyzed interdisciplinary corpus or to physics-related education within that corpus, rather than to the entire field of physics education without qualification.

Emergence of Artificial Intelligence and Machine Learning

The overlay visualization indicates that artificial intelligence, machine learning, and learning systems have more recent average publication years than simulation education, curriculum, medical education, and controlled-study terminology. This temporal pattern suggests that AI-related concepts have become more visible in the later years of the analyzed period. However, their lower occurrence frequencies and total link strengths relative to problem-based learning indicate that they remain emerging components rather than dominant foundations of the research structure.

Artificial intelligence appears to connect established pedagogical concepts with newer computational themes. Its links with problem-based learning, active learning, machine learning, and learning systems suggest growing interest in the use of intelligent technologies to support student-centered learning. AI-supported systems may provide adaptive feedback, analyze learner interactions, recommend learning resources, or assist instructors in monitoring students' progress (Ouyang et al., 2023; Demartini et al., 2024). In physics-related learning environments, these functions could complement simulations and computational modeling by providing more responsive forms of scaffolding.

Nevertheless, the network does not demonstrate that AI has already transformed physics education or that AI-supported PBL is more effective than established instructional approaches. The comparatively weaker connection between artificial intelligence and problem-based learning indicates that their integration is still developing. Existing research also identifies practical concerns related to teachers' pedagogical competence, the reliability of AI-generated information, and the appropriate role of generative AI in science teaching (Jang & Choi, 2025). Future empirical studies should therefore examine not only whether AI is used, but also how it is incorporated into problem formulation, inquiry, feedback, assessment, and collaborative reasoning.

Machine learning had the most recent average publication year among the principal keywords reported in Table 9. This finding suggests a growing interest in data-driven methods and automated learning systems. However, bibliometric proximity does not reveal whether machine learning is being used as an instructional tool, a research-analytics method, a content topic, or a technical modeling approach. A qualitative review of the underlying documents would be required to distinguish among these applications.

Peripheral terms such as "boundary layer flow" further indicate that some records may relate more closely to disciplinary physics modeling than to educational practice. Such terms should not be interpreted as emerging pedagogical themes simply because they appear in a recent temporal position. Their presence reinforces the need to distinguish educational applications of computational methods from technically oriented physics studies retrieved through broad search terms.

Responsible AI and Underrepresented Themes

Keywords explicitly related to ethics, privacy, algorithmic transparency, and responsible AI did not appear among the terms that met the minimum occurrence threshold. This result does not demonstrate that these topics are entirely absent from the literature. Instead, it indicates that they were not sufficiently frequent or interconnected to become prominent in the thresholded network. Their limited visibility suggests that responsible-AI considerations remain comparatively underrepresented within the analyzed corpus.

This gap is important because AI-supported learning environments may involve the collection of student data, automated recommendations, algorithmic profiling, and generated feedback. These applications raise questions concerning informed consent, data protection, fairness, transparency, accountability, and the reliability of AI-generated content. Recent educational literature emphasizes that AI integration should be accompanied by explicit ethical frameworks and the development of AI literacy among teachers and learners (Mouta et al., 2024; Biagini, 2025).

Future studies should therefore integrate pedagogical effectiveness with responsible implementation. Research on AI-supported PBL should examine how intelligent systems make recommendations, how student information is stored and used, whether feedback differs across learner groups, and how teachers evaluate AI-generated explanations. Addressing these issues would extend the field beyond technological adoption toward educationally justified and ethically responsible use.

Implications for Physics Education Research

The findings suggest that future research should move from broad technological exploration toward more focused empirical evaluation. In particular, studies are needed to determine how AI-supported PBL influences conceptual understanding, scientific reasoning, problem-solving performance, cognitive load, collaboration, and learner autonomy in specific physics topics. Such investigations should distinguish the contribution of the PBL design from the contribution of the technological tool.

The network structure also supports further examination of how AI can complement established simulation-based approaches. Rather than replacing simulations or teacher guidance, intelligent systems could be designed to provide prompts, diagnose common reasoning difficulties, recommend representational supports, and offer feedback during problem-solving activities. These functions may be especially relevant in topics involving complex mathematical relationships or phenomena that are difficult to observe directly. However, their educational value must be assessed through transparent research designs and validated learning measures.

Teacher competence represents another important research direction. Effective integration requires more than technical familiarity with AI applications. Teachers must be able to evaluate generated content, design meaningful problems, interpret learning analytics, provide appropriate scaffolding, and recognize ethical risks. Professional-development research should therefore examine the pedagogical, disciplinary, and ethical competencies required to implement AI-supported PBL in physics classrooms.

Finally, the interdisciplinary composition of the dataset offers both an opportunity and a methodological caution. Insights from engineering, medical, nursing, and professional education may inform the design of authentic problems, simulation environments, and adaptive feedback systems. However, future bibliometric studies should use more discipline-specific search strategies, carefully validate retrieved records, standardize affiliation data, and distinguish physics-education studies from adjacent educational and technical domains. Combining bibliometric mapping with qualitative systematic review would provide a more detailed account of instructional designs, educational levels, physics topics, AI applications, and reported learning outcomes.

CONCLUSION

This bibliometric analysis mapped the development of 251 Scopus-indexed publications on the intersection of Problem-Based Learning (PBL), computational methods, artificial intelligence, and physics-related education from 2016 to 2025. The findings show an overall increase in research activity, accompanied by annual fluctuations in publication output and a continuous rise in the reported citation counts. The United States was the leading contributor in publication output, citation count, and international collaboration strength, while China and Indonesia also demonstrated substantial research productivity. However, differences among publication output, citation visibility, and total link strength indicate that these indicators represent distinct dimensions of research performance.

Keyword co-occurrence analysis identified PBL as the central pedagogical concept in the analyzed corpus. PBL was strongly connected with students, simulation, curriculum, and active learning, whereas its connections with artificial intelligence and machine learning were comparatively less developed. The overlay visualization further showed that simulation-related themes were established earlier, while artificial intelligence, machine learning, and learning systems had more recent average publication years. These patterns indicate a gradual expansion of AI-related research rather than a fully established transformation of physics education.

The findings should be interpreted in relation to the interdisciplinary composition of the dataset. The presence of medical education, nursing education, controlled-study terminology, and disciplinary physics-modeling terms indicates that the retrieved literature was not restricted exclusively to physics education. In addition, the study was limited to Scopus-indexed documents, depended on the selected search terms and occurrence threshold, and remained sensitive to variations in keywords, author affiliations, and database indexing. Bibliometric indicators also describe patterns of productivity, visibility, and connectivity but do not directly establish the pedagogical effectiveness of AI-supported PBL.

Overall, the study provides a structured overview of how PBL, simulations, computational methods, and emerging AI technologies are connected within the analyzed literature. The results establish a foundation for more focused qualitative and empirical investigations into the design, effectiveness, and responsible implementation of AI-supported PBL environments in physics education.

RECOMMENDATION

Future research should complement bibliometric mapping with qualitative systematic reviews that examine the pedagogical characteristics of the underlying studies. Such reviews should distinguish the roles of artificial intelligence, machine learning, simulations, and computational modeling in instructional design, assessment, feedback, scaffolding, and problem-solving activities. They should also identify the educational levels, physics topics, research designs, and learning outcomes addressed in each study.

More discipline-specific search strategies are also recommended to reduce the inclusion of studies from unrelated educational and technical domains. Future bibliometric investigations should refine combinations of physics-education terms, conduct systematic title-and-abstract screening, standardize institutional affiliations, and report the procedures used to merge synonymous keywords. Expanding database coverage to Web of Science, ERIC, Dimensions, and relevant national indexes, including SINTA-indexed journals, may provide a more inclusive representation of research from different geographical and educational contexts.

Empirical studies should evaluate how AI and computational methods can support PBL in abstract and cognitively demanding physics topics. Priority areas include adaptive feedback, real-time diagnostic support, intelligent scaffolding, simulation-assisted inquiry, and the integration of multiple representations. These studies should use clearly defined learning measures and distinguish the effects of the pedagogical design from those of the technological tool.

Future investigations should also examine the competencies required by teachers to implement AI-supported PBL effectively. Relevant competencies include designing authentic problems, evaluating AI-generated explanations, interpreting learning analytics, providing appropriate instructional guidance, and identifying inaccurate or biased outputs. Professional-development programs should therefore integrate pedagogical, technological, disciplinary, and ethical dimensions rather than focusing only on technical tool use.

International and inter-institutional collaboration should be strengthened, particularly through partnerships involving researchers from developing countries and underrepresented educational contexts. Such collaboration can support methodological exchange, improve access to technological resources, and increase the contextual relevance of AI-supported physics education research. However, collaboration strategies should prioritize equitable knowledge production rather than citation visibility alone.

Finally, future research should incorporate responsible-AI principles, including data privacy, informed consent, algorithmic transparency, fairness, accountability, and the reliability of AI-generated feedback. Because these themes were not prominent among the keywords meeting the analysis threshold, their systematic inclusion would help move the field from technology adoption toward pedagogically justified, transparent, and ethically responsible implementation.

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Conflict of Interest Statement

Authors state no conflict of interest.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Qurrota A'yun	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	
Rahmatta Thoriq Lintangesukmanjaya		✓		✓		✓		✓	✓	✓	✓	✓		
Dwikoranto					✓		✓			✓		✓		✓
Khoirun Nisa'		✓			✓			✓	✓	✓				
Indri Hapsari Khansa		✓					✓					✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

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