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# Knowledge Mapping of Deep Learning in Mathematics Instruction: A Bibliometric Study

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**ABSTRACT**
This study provides a comprehensive bibliometric mapping of the emerging research landscape on deep learning in mathematics education—an area experiencing rapid expansion yet lacking systematic synthesis. Utilizing metadata from 386 Scopus-indexed documents published between 2020 and 2025, the analysis employs VOSviewer to examine co-authorship patterns, keyword co-occurrence, and thematic clustering. Results show a sharp rise in publications, with a peak in 2024, reflecting the accelerating urgency of AI integration in educational contexts. Leading research hubs, such as the University of Auckland and Beijing Normal University, and dominant contributors from the United States and China, underline the global and collaborative nature of this field. Journal articles (40.9%) and conference papers (38.9%) constitute the primary publication formats. Four thematic clusters emerge, covering pedagogical applications, technological development, advanced approaches such as federated and personalized learning, and broader AI-in-education frameworks. The study's novelty lies in offering the first focused bibliometric overview specifically targeting deep learning within mathematics education. Its contribution is to clarify research trends, identify influential actors, and map thematic directions, thereby providing a strategic foundation for future investigations and evidence-informed innovation in mathematics teaching and learning.
**Keywords:** artificial intelligence, bibliometric analysis, deep learning, mathematics education, VOSviewer

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## Introduction

As it develops theory Study since the constructivist era, the focus of education has shifted from just delivering material to forming a deep understanding of conceptual understanding. Constructivism sees learning as an active process, where students build knowledge by linking new experiences to existing framework knowledge (Aditomo et al., 2024). In this era, it is no longer enough for students to just know " what ", but also be aware of "why " and how to apply it in a real-world context. That is what becomes the foundation for *deep learning* as an approach to learning. Concept This was introduced by Säljö (2013) when researching how students understand academic material. They identify two approaches: the surface approach (*surface learning*), which focuses on memorizing and simply finishing tasks, and the deep approach (*deep learning*), which reflects an effort to understand meaning, connecting concepts, and integrating new information into knowledge that has been previously acquired.

In its development, studies latest by (Asikainen et al., 2014) shown that this approach is not only related to the method of studying individuals, but also influenced by the perception of the environment, as well as the individual's own close relationship with successful studies in education. Knowledge mapping in mathematics learning plays a crucial role in enhancing the understanding of complex mathematical concepts by systematically organizing information. By creating visual representations of relationships between concepts, knowledge maps help students and educators see the structure and interconnectedness of mathematical ideas more clearly. Furthermore, the application of knowledge mapping in bibliometric research allows for the exploration of patterns and trends in the mathematical literature, identifying emerging research areas, and facilitating the development of new theories. This is invaluable for charting the development of mathematical science and understanding potential research avenues. A deep learning approach then becomes an important part of the design curriculum, evaluation learning, as well as development learning based problems (PBL) and learning based projects (PjBL), which is proven capable of facilitating conceptual understanding as well as pushing reflection and metacognition (Dolmans et al., 2016).

Interestingly, in Indonesia, the Minister of Elementary and Secondary Education Regulation Number 13 of 2025, in general, officially adopts *Learning Deep* as the approach for the main start year of academic year 2025/2026, with the principle of mindful, *meaningful, and joyful* learning. The ultimate goal is to realize meaningful and inclusive education. Emphasis: This move focuses on complete content to develop competence at a high level, in harmony with characteristics of learning demanding mathematics, connectivity of ideas, and justification (Suyanto, 2025).

A number of research also show the relevance of an approach to learning in-depth in context, learning mathematics. Yuda et al (2025) find that *deep learning* strategies are capable of developing the ability to think at a high level through problem-solving activities, reflections, and connections between concepts. Findings. This strengthens the idea that learning deep can be made into a base for designing curriculum and teaching strategies in mathematics at various educational levels.

In learning mathematics, procedural ability and understanding influence each other. The master procedure can help students understand the concept, while the mastery draft will guide them in selecting and customizing the proper procedure. Therefore , emphasizing only one of them can limit the quality learn. What is more needed is


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experience learning that develops both of them in a balanced and mutually complete way (Rittle-Johnson et al., 2015).

Although the terms and application of deep *learning* learning mathematics are understood in various realms, starting from educational psychology, a research-based discipline, Mathematics education, to the Education policy field. The studies are also varied, such as: design task learning, form class discussion, using diverse representations, giving room for students to experience the process of " struggle", understand the concept, and use a strategy of creating inclusive and equitable classes. Diversity often makes things difficult for researchers and practitioners. For example, descriptions are often incomplete, such as who the most influential authors and journals are, what themes are strengthened, and what topics are still seldom researched. In the Indonesian context, the need for will mapping becomes more relevant because the curriculum is independent in a way that explicitly emphasizes the importance of supporting practices and research achievement, learning to deep learning. Research on the application of deep learning in mathematics education generally focuses on the use of artificial intelligence models or learning strategies aimed at improving understanding, problem-solving skills, or personalizing student learning. For example, studies have reviewed various applications of CNN and RNN models for analyzing student behavioral data and providing individualized feedback (Li, 2024; Orhani, 2024; Subroto et al., 2024).

Meanwhile, bibliometric studies using a knowledge mapping approach, such as Mapping Knowledge Domain Analysis in Deep Learning Research of Global Education (Pan et al., 2023), use tools like CiteSpace to map the global network of authors, institutions, keywords, and publication trends in the field of deep learning education (Pan et al., 2023). The main difference between these two types of research is that applied deep learning research examines what and how deep learning is used in the context of mathematics learning, while bibliometric research using knowledge mapping examines what has been researched, trends, and future research directions in the field. Thus, bibliometric research provides a knowledge map of the literature, while applied research provides empirical evidence and implementation of technologies or strategies.

*Systematic mapping* study against a 48-year study *of deep learning* in primary and secondary education shows that although concepts are adopted, definitions and applications are still diverse, including aspects of cognitive, pedagogical, and policy (Winje & Løndal, 2020). This reinforces the urgency of bibliometric studies to get a clearer picture of trends, themes, directions of deep learning studies in education, and mapping of how deep learning outcomes, especially in the field of Mathematics Education, are. Based on the background of the problem, the research questions are:

1. How has the volume of publications on deep learning in mathematics education evolved from 2020 to 2025?
2. What is artificial intelligence in education?
3. What are the challenges and opportunities associated with integrating deep learning into mathematics education at various levels? Which institutions and countries are leading research on deep learning in mathematics education?
4. What are the main themes and clusters identified in research on deep learning in mathematics education?
5. How do trends in deep learning research correlate with the adoption of artificial intelligence?

## Methods

The method used in this research is a literature study with bibliometric analysis using the VOSviewer application. Bibliometric analysis plays a role in mapping the cumulative direction of scientific research and providing a comprehensive overview of scientific output and its development over time in a particular field of study (Putri et al., 2021). Bibliometric visualization is used to present a structural representation of a research area. In this study, visualization was carried out with the help of Krisanti et al. (2025) VOSviewer software, which is an application used to map bibliometric networks that describe the connections between authors, sources, countries, and keywords (van Eck & Waltman, 2017). VOSviewer provides three types of displays: *network visualization*, *overlay visualization*, and *density visualization*. This approach uses bibliometric analysis to examine data related to trends in *deep learning approaches* to mathematics learning.

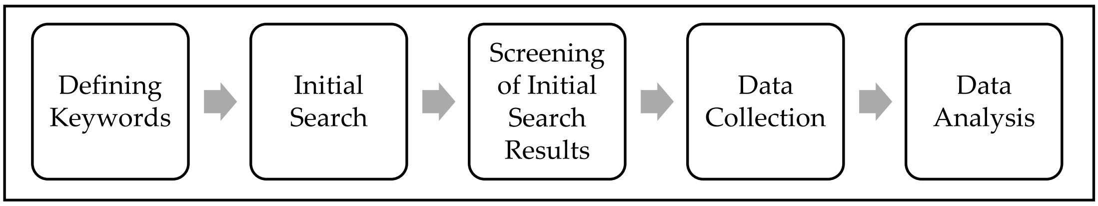


**Figure 1**. Research flow (Damarsha et al., 2023; Dawana et al., 2022; Haryandi et al., 2021; Suprapto et al., 2021)

The data analysis procedure using the bibliometric method is shown in the Figure 1. The research data was obtained from Scopus, known as one of the largest databases, which covers various disciplines, such as natural sciences, computing, and other fields. The (Liu et al., 2021; Tupulu et al., 2024) data collection process was conducted through Scopus with a publication period limit between 2020 and 2025. The search was


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conducted using the keywords *deep learning* and mathematics learning, focusing on the title, abstract, and keywords of the articles. From the search results, many documents were obtained, which were then saved in CSV format. The metadata was then analyzed using the VOSviewer application to produce visualizations of the patterns and network structures formed. Search in data scope( TITLE-ABS-KEY ( deep AND learning ) AND TITLE-ABS-KEY ( mathematics AND education ) ) AND PUBYEAR > 2020 AND PUBYEAR < 2025.

Prior to network analysis, the metadata dataset was systematically cleaned: the process included record deduplication, normalization of author names and affiliations (e.g., unifying spelling variants and acronyms), keyword standardization (unifying synonyms and terminology variations), and manual inspection of ambiguous entries. This cleaning step was essential to minimize artificial bias in the resulting link strength measures and cluster structure.

Network processing and visualization were performed using VOSviewer software (Saputra et al., 2023). In VOSviewer, metadata is utilized to construct several types of analytical networks, including: (1) co-authorship networks at the author/affiliation/country level to identify collaboration patterns; (2) keyword co-occurrence networks to map research themes and conceptual structures; (3) citation, bibliographic coupling, and co-citation analysis to evaluate citational relationships between documents and literature groups. The clustering procedure uses the VOS clustering algorithm with association strength normalization, a standard approach to balance the effects of absolute frequency and relative linkage between entities. The link counting method is implemented using full counting so that each entity occurrence contributes proportionally to the link strength; if necessary, fractional counting can be used for alternative analysis to reduce the dominance of large contributors.

In the map parameterization stage, thresholds for occurrence and cluster sizes were set to ensure the map remained interpretable for example, setting minimum occurrence limits for keywords or authors to eliminate noise caused by single entries and overlay visualization was used to display the temporal dimension (publication year) so that the dynamics of topic evolution from 2020 to 2025 could be observed. VOSviewer output includes network maps, density maps, and cluster tables, which were then analyzed qualitatively and quantitatively.

## Results and Discussions

### Development of Deep Learning Research in Learning Mathematics

A development study of *deep learning* in learning mathematics shows a pattern of acceleration supported by two main dynamics: increasing publication volume and institutionalization of research across disciplines. Temporally, research output moved from a relatively stable basis in 2020–2022 (50–53 publications ) towards acceleration in 2023 (65 publications ) and reached a peak in 2024 (109 publications ). Decrease while in 2025 (56 publications ), it is necessary to read carefully because of the possibility of artifacts in year walk and pause indexing, without weakening the research interest. In general, this form of " fluctuating " trend is consistent with a "climbing" phase of *mainstreaming* AI adoption in education after the acceleration of digital transformation over the past several years. The temporal findings confirm that the topic is This No Again peripheral, but rather move to the current main research agenda in mathematics education.

**Table 1.** Research development on deep learning in mathematics learning

| Year of Publication | Number of Publications |
|---|---|
| 2025 | 56 |
| 2024 | 109 |
| 2023 | 65 |
| 2022 | 53 |
| 2021 | 53 |
| 2020 | 50 |

Based on Table 1, the dynamics of publications on *deep learning* in mathematics learning in 2020–2025 show a "fluctuating but increasing" pattern from a relatively stable base to a sharp spike, then a decline again due to the possible effect of the current year's data. Quantitatively, the baseline phase of 2020–2022 was in the range of 50–53 articles (an increase of +3 publications or ±6% from 2020 to 2021, then stagnant in 2021 to 2022), followed by an acceleration from 2022 to 2023 to 65 publications (+12 or ±22.6%), and a peak in 2024 with 109 publications (+44 or ±67.7% compared to 2023). In 2025, 56 publications were recorded, a decrease of 53 compared to 2024 (±48.6%), but caution should be exercised in interpretation, as the 2025 data is likely incomplete (the year is still ongoing and there is a gap in indexing). These figures are derived directly from Table 1.

Summarized in terms of medium-term growth measures, the compound annual growth rate (CAGR) from 2020 to 2024 is approximately 21.5% per year, with an average absolute increase of approximately 14–15 publications per year over the same period. Interestingly, 2024 alone accounted for approximately 28% of the total publications from 2020–2025, marking the year as a highly productive "positive outlier." These indicators are consistent with the narrative that *deep learning* is gaining increasing visibility and priority in the mathematics education research ecosystem, as AI technology matures, data/computational access increases, and publication forums (conferences and journals) expand the space for contributions to the *education-AI intersection*. Thus, the 2024 surge can be read as a phase of widespread adoption (mainstreaming), while the temporary decline in 2025 is more accurately understood as an artifact of the calendar and indexation process rather than a weakening of research interest.

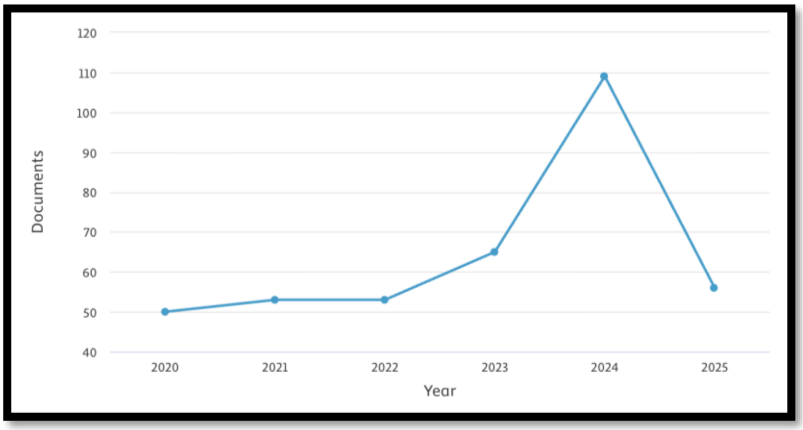


**Figure 2**. Documents by Year

This graph (Figure 2) visualizes data from Table 1. The pattern shows a drastic spike in 2024. This sharp increase can be attributed to the expanding use of AI in education, the emergence of *learning analytics-based research*, and the increasingly widespread adoption of digital education policies post-pandemic. This trend indicates that the topic of *deep learning* in mathematics learning is becoming a significant global focus.

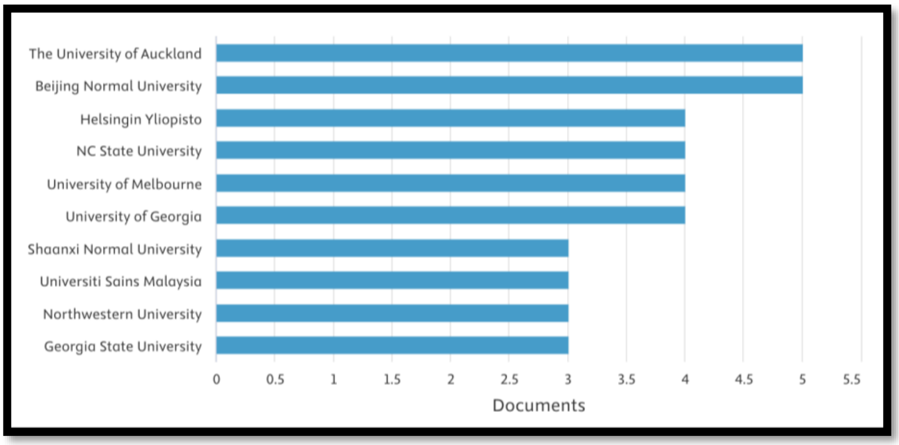


**Figure 3.** Documents by affiliation

Figure 3 illustrates the distribution of publications by institution or affiliation. This demonstrates which institutions are most active in *deep learning research* in mathematics. This analysis is crucial for identifying leading research hubs. The dominance of certain institutions may reflect the presence of consistent research groups, strong research funding, or productive interfaculty collaborations. Based on affiliation data, the most productive institutions in this research are The University of Auckland and Beijing Normal University, each with five papers. Several other universities, such as Helsinki, NC State University, the University of Melbourne, and the University of Georgia, also made significant contributions.

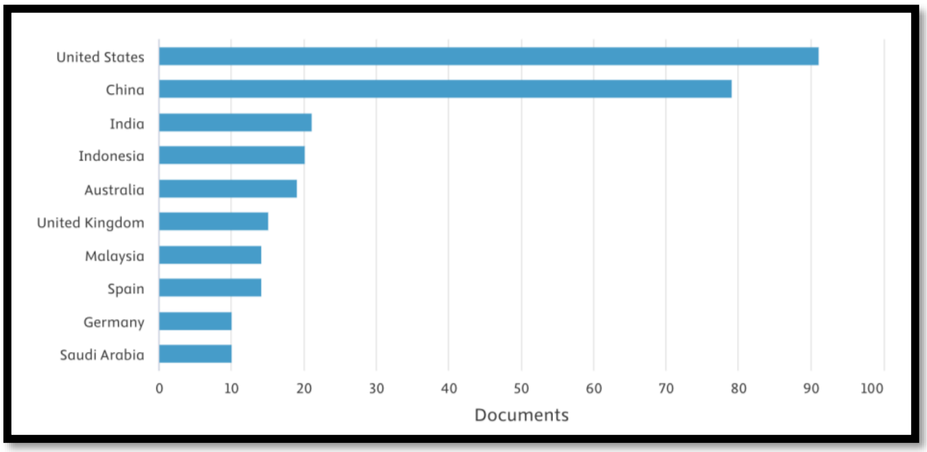


**Figure 4.** Documents by country or territory

The distribution of publications by country reflects the global distribution of research. Countries with advanced technological research ecosystems (e.g., the United States, China, the United Kingdom, India) typically Figure 4. This highlights the research gap between developed and developing countries. However, the trend of research globalization allows other countries, including Indonesia, to contribute to expanding *deep learning studies* in mathematics. The graph shows that the United States is the country with the highest number of publications, followed by China. This confirms the dominance of these two countries as major research centers in this field. Other countries such as India, Indonesia, Australia, and the United Kingdom also make significant contributions, albeit on a smaller scale.

Figure 5 shows the composition of publication types researching deep learning in mathematics, dominated by two main channels: journal articles at 40.9% and conference papers at 38.9%—nearly 80% in aggregate—indicating a combination of rapid dissemination channels (conferences) and more rigorous peer-reviewed channels (journals). The next largest share is *conference reviews* (6.5%), *book chapters*

(5.4%), books (3.6%), and *review articles* (2.3%), which together reflect efforts to consolidate and synthesize knowledge, albeit still limited, making the field appear to be in a growth phase with a steadily maturing publication ecosystem. Minor categories such as editorials (1.3%), *errata* (0.5%), *notes* (0.3%), and *retracted papers* (0.3%) demonstrate the existence of scientific curation and correction mechanisms, while also emphasizing the importance of methodological standards and data transparency. Overall, this profile suggests a dynamic research landscape: many early innovations and findings are presented at conferences, some of which are then developed into more mature journal articles, while the small proportion of comprehensive reviews leaves room for future *state-of-the-art reviews* and *meta-analyses.*

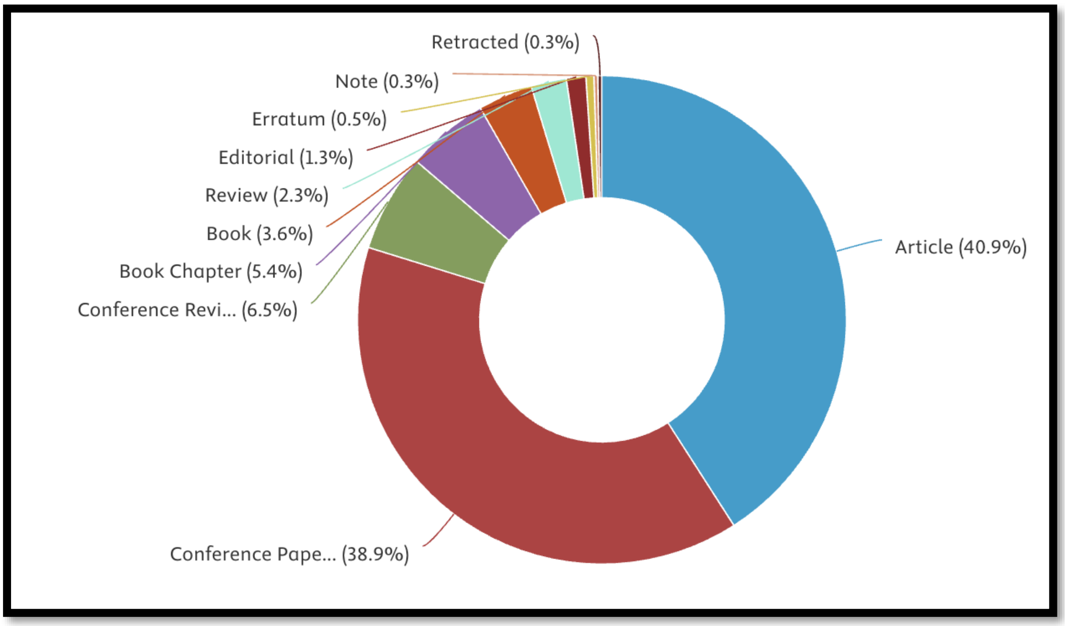


**Figure 5.** Documents by type

Figure 6 shows the distribution of disciplines that have contributed to publications on *deep learning research* in mathematics. The largest contributions come from computer science (24.6%) and social sciences (21.9%), demonstrating the interdisciplinary nature of this research, supported by advances in computing technology, while examined from the perspectives of education and social interaction. Engineering (15.8%) and mathematics (13.5%) follow, confirming that *deep learning applications* are not only theoretically relevant but also closely related to the technical implementation and scientific content of mathematics itself.

Other fields that contributed, albeit smaller, were decision sciences (4.4%), physics and astronomy (4.3%), and psychology (3.5%), indicating that *deep learning* is also utilized in decision-making, pure science modeling, and the study of behavior and cognitive learning processes. Meanwhile, contributions from multidisciplinary sciences (1.6%), medicine (1.3%), and health professions (1.1%) were relatively small, but still important because they show the penetration of this topic in the cross-disciplinary domains of health and education. The other category (8.1%) indicates a diversity of unclassified disciplines, reflecting the breadth of research coverage.

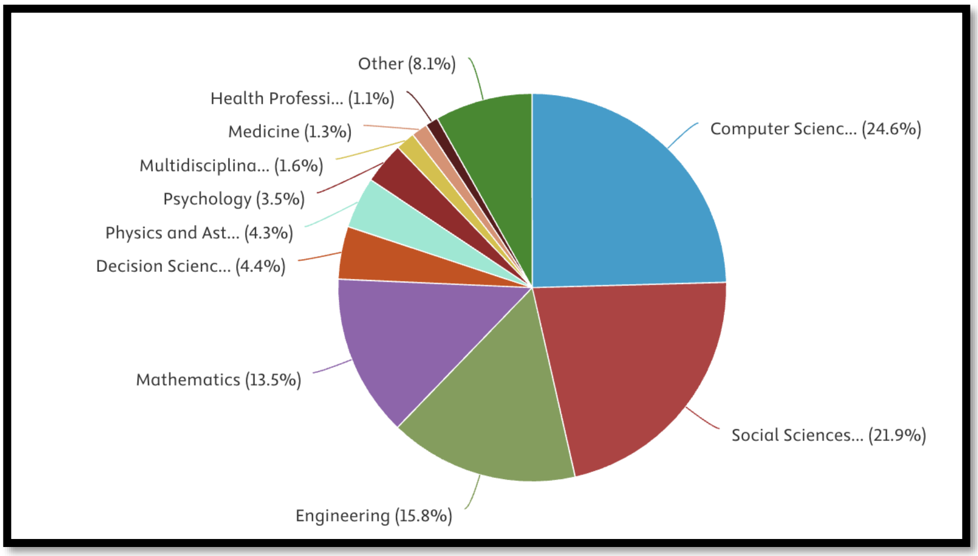


**Figure 6.** Documents by subject area

Overall, this distribution demonstrates that *deep learning research* in mathematics instruction is rapidly expanding across the computational, social, engineering, and mathematical domains, but is also beginning to expand into nontraditional fields. This indicates that this issue has become a complex and dynamic interdisciplinary research topic, while also opening up opportunities for broader interdisciplinary collaboration in the future.

**Visualization of Research on Deep Learning in Mathematics Learning**

In August 2025, bibliometric data were retrieved from the Scopus database covering the period 2020–2025. The search was conducted using a search string combining the primary keywords "deep learning" and "mathematics education" to capture relevant publications on that topic. The initial search yielded **386** metadata records. For each record, a set of essential bibliographic variables was extracted, including: author name, article title, year of publication, journal name, publisher, number of citations, and URL/document identifier (DOI/link). This metadata was exported from Scopus in a format compatible with bibliometric tools (e.g., CSV/RIS/BibTeX) for further processing.

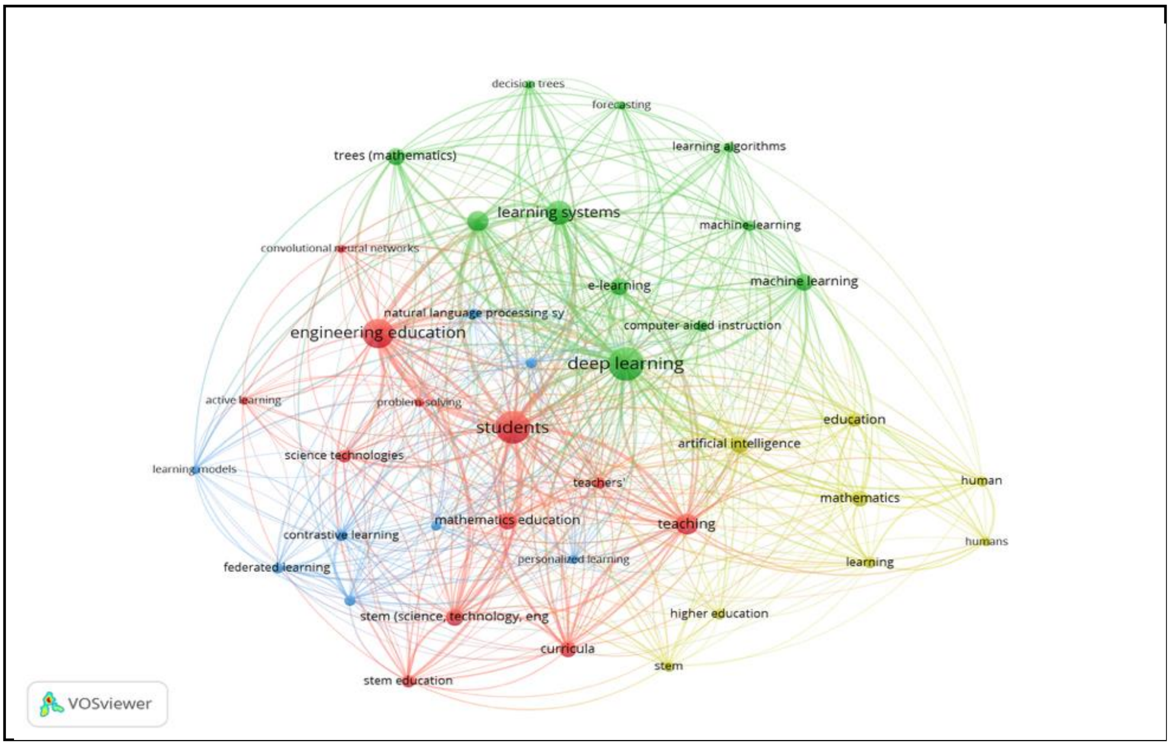


**Figure 7.** Visual development map based on shared words

Based on the co-occurrence visualization shown in Figure 7, there are 4 clusters with the most frequently appearing keywords, namely pedagogical aspects, advanced and innovative topics, artificial intelligence, and education integration.

**Table 2.** Distribution of research on deep learning in mathematics learning

| No | Cluster Name | Item | Number of Items |
|---|---|---|---|
| 1 | cluster 1 | active learning, convolutional, curricula, engineering education, mathematics education, problem-solving, science technologies, STEM, students, teachers, teaching | 12 items |
| 2 | cluster 2 | computer-aided instruction, decision trees, deep learning, e-learning, educational computing, forecasting, learning algorithms, learning systems, machine learning, machine-learning, trees (mathematics) | 11 items |

| | | | |
|---|---|---|---|
| 3 | cluster 3 | adversarial machine learning, contrastive learning, deep neural networks, federated learning, learning models, natural language, personalized learning, student learning | 8 items |
| 4 | cluster 4 | artificial intelligence, education, higher education, human, humans, learning, mathematics, STEM | 8 items |

**Cluster 1: Pedagogical Aspects**

The first cluster focuses on pedagogical aspects, including *active learning*, *problem-solving*, STEM, curriculum, and the role of teachers in mathematics learning (Table 2). This theme emphasizes that *deep learning* is not only understood as an artificial intelligence algorithm, but also as a pedagogical approach that encourages students to actively build conceptual understanding, connect ideas across disciplines, and develop critical and creative thinking skills. The presence of keywords such as *"teachers"* and *"teaching" shows that research in this cluster often examines how teachers can integrate deep learning*- based technology to improve the quality of learning. Thus, this cluster emphasizes that the successful implementation of technology in education is highly dependent on appropriate pedagogical adaptation.

**Cluster 2: Technological Aspects**

The second cluster focuses on the technical aspects of *deep learning*, including *machine learning*, *computer-aided instruction*, *learning algorithms*, and *e-learning*. The primary focus of research in this cluster is on the development and application of technological tools and computational algorithms to support the learning process. Studies in this group often seek to optimize machine learning models for effective use in mathematics learning, for example, through *forecasting*, recommendation systems, or data-driven learning adaptation. Thus, this cluster emphasizes that the development of *deep learning* in mathematics education is closely linked to advances in information technology and artificial intelligence.

**Cluster 3: Advanced and Innovative Topics**

The third cluster contains more advanced themes such as *adversarial learning*, *contrastive learning*, *federated learning*, *deep neural networks*, and *personalized learning*. This focus marks a more advanced and innovative research direction, where *deep learning* is used not only as a learning tool but also to develop more adaptive, secure, and individualized learning models. For example, *personalized learning* enables learning experiences tailored to students' abilities and learning styles, while *federated learning* opens up opportunities for cross-institutional collaboration without having to share raw data, thus maintaining privacy. Thus, this cluster represents a growing research frontier with significant potential for transforming mathematics education in the digital age.

**Cluster 4: Artificial Intelligence and Education Integration**

The fourth cluster focuses on *artificial intelligence* in general and its applications in higher education, STEM, and mathematics. This cluster positions AI as a broad framework underpinning *deep learning* and highlights how this technology is integrated into educational contexts. Studies in this cluster primarily address policies, implementation strategies, and the impact of AI use on the quality of learning in higher education and STEM fields. Thus, this cluster serves as a bridge between artificial intelligence theory and educational practice, demonstrating how AI can be a catalyst in creating more effective, efficient, and relevant learning systems.

Bibliometric results indicate that research on *deep learning* in mathematics learning experienced significant growth between 2020 and 2025. Publication trends fluctuated but tended to increase, peaking at 109 publications in 2024. This sharp increase can be attributed to the increasingly widespread adoption of artificial intelligence (AI) technology in education, particularly following the COVID-19 pandemic, which accelerated digital transformation (Zawacki-Richter et al., 2019).

The distribution of publications by affiliation shows the dominance of large institutions such as the University of Auckland and Beijing Normal University. This indicates that research centers in developed countries remain the primary drivers of this study, which is also reflected in the distribution of publications by country, with the United States and China topping the list. This dominance of these two countries is consistent with reports (UNESCO, 2023) stating that AI research in education remains concentrated in countries with strong research ecosystems and funding, although contributions from developing countries, including Indonesia, are beginning to emerge, albeit on a smaller scale.

In terms of publication types, journal articles (40.9%) and conference papers (38.9%) dominate. This finding indicates that research on this topic is still in its infancy, with rapid dissemination through conferences and progressing toward maturity through publication in reputable journals. Furthermore, Figure 5 demonstrates the interdisciplinary nature of this research. The dominance of computer science (24.6%)

and social sciences (21.9%) demonstrates the intersection of technological advancements and pedagogical approaches.

The analysis of research themes yielded four main clusters. Cluster 1 emphasizes pedagogical aspects such as *active learning*, problem-solving, STEM, and the role of teachers, demonstrating how *deep learning* is viewed as a pedagogical approach capable of enhancing student engagement (Leon et al., 2025). Cluster 2 focuses on technical aspects, such as *machine learning* and *computer-aided instruction*, highlighting the importance of developing algorithms to support adaptive learning (Bozkurt et al., 2021; Dogan et al., 2023). Cluster 3 highlights cutting-edge research directions, such as *federated learning* and *personalized learning*, which have significant potential for creating more individualized learning experiences (Khosravi et al., 2022). Meanwhile, Cluster 4 highlights the general integration of AI into higher education and STEM, thus serving as a bridge between AI theory and educational practice (Ajayi, 2024).

Overall, these findings confirm that *deep learning research* in mathematics learning has progressed from an exploratory stage to more mature applications. This development reflects the transformation of education, which increasingly relies on intelligent technology, while also opening up opportunities for further research emphasizing ethical aspects, data privacy, and the long-term impact on learning quality.

**Recommendations and Implications**

Development research to front ideally balance three current : (i) amplification foundation pedagogical so that technology *deep learning* truly mediate understanding concepts and thinking strategies mathematical, not just automation ; (ii) improvement *rigor* methodological through longitudinal study, replication cross context, and evaluation causal to achievements learning; and (iii) data governance and ethics — including privacy, *bias*, and model explainability — especially in scenarios *personalized* and *federated learning*. With an increasingly diverse ecosystem mature (indicated by publication volume, domain expansion, and diversity), channel dissemination, the field is at the right momentum for transition from *proof-of-concept* to practice, with measurable instructional benefits for learning mathematics.

## Conclusion

Based on all the table and image data, it can be concluded that the study of *deep learning* in learning mathematics has experienced rapid development and shows significant trends over the last decade. Improvement publication from 2020 to peak in 2024 indicates that this topic is getting more attention from the community of global academics, although 2025 data shows a decline, while the possibility of a big influential factor is time-unpublished publications that are complete. In institutions, several large universities from various countries have become centers of research, with the United States and China dominating global contributions.

From the side of publications, articles, journals, and proceedings, conferences dominate, signifying that research is still at the stage of intensive development, with many new ideas being tested and disseminated through scientific forums before being published in more established channels. Distribution field knowledge shows a characteristic interdisciplinary approach from studying this, where *deep learning* is not only relevant in the realm of computer knowledge, but also in social, engineering, psychology, and health knowledge.

More continues, results clustering show the existence of four main dimensions of research: pedagogical, technological, methodological, innovative, and AI integration in education and STEM. This shows that studies about *deep learning* in learning mathematics are not limited to a single direction, but develop in various directions in accordance with the needs of academia, technology, and society. Thus, it can be concluded that *deep learning* has transformed into one of the main areas of study in mathematics, an interdisciplinary field, adaptive to technological development, and has the potential for a big transformation in practical learning in the digital era.

The limitations of this study include the exclusive reliance on the Scopus database, which may result in a biased representation of the research landscape by omitting studies not indexed in this database. Additionally, the research is limited by the timeframe of 2020–2025, which might not capture emerging trends or research published after this period. The study also lacks a more comprehensive analysis of non-English language publications, which could have provided a more global perspective, particularly from regions with developing research ecosystems. Furthermore, the clustering process used in the bibliometric analysis could benefit from a more detailed examination of temporal evolution, as the study primarily focuses on the immediate trends without fully addressing long-term shifts in research priorities. Lastly, ethical considerations related to AI in education, such as data privacy and algorithmic biases, were not thoroughly explored, which could have enriched the discussion on the societal implications of deep learning in mathematics education.

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## Author's Declaration


| | | |
|---|---|---|
| Author Contribution | : | Author 1: Conceptualization, Writing - Original Draft<br>Author 2: Writing - Review & Editing<br>Author 3: Validation<br>Author 4: Supervision |
| Funding Statement | : | Authors are required to provide a clear statement of all funding sources that supported the research reported in this manuscript. |
| Conflict of Interest | : | The authors declare no conflict of interest. |
| Additional Information | : | - |


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