Which Keywords Grouping and Novelty Trends are Driving Deep Learning Research in Mathematics Education?

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ABSTRACT

This study aims to analyze the development of deep learning research in mathematics education using a bibliometric approach. Bibliometric methods are employed to evaluate and map scientific literature through statistical analysis of publications, citations, keywords, and collaboration networks. Data were collected from the Scopus database using a specific combination of keywords, followed by screening through the PRISMA method, which resulted in 72 relevant documents for analysis. Data analysis was conducted using the R programming language to identify publication trends over time, and VOSviewer software to perform keyword grouping and keyword novelty analysis in order to reveal thematic clusters and emerging research topics. The analysis concludes that research on deep learning in mathematics education has experienced rapid growth in recent years, as evidenced by the increasing publication trends, keyword groupings that reflect the core research focuses, and the emergence of new keywords such as "Contrastive Learning" and "Adversarial Machine Learning" that offer innovative research opportunities. These findings emphasize that integrating deep learning technology into mathematics education not only aims to improve student learning outcomes but also to develop adaptive, secure, and data-driven teaching methods.

1. Introduction

Education is the fundamental foundation for shaping high-quality human resources capable of competing at the global level [1]–[3]. Through education, individuals can cultivate their potential, skills, and knowledge to address diverse challenges in life. It serves as a strategic medium for instilling positive values, ethics, and professional attitudes that strengthen the character of future generations [4]–[6]. Meaningful learning is not limited to mastering subject matter but also focuses on developing critical, creative, and adaptive thinking skills in response to change. Mathematics, as a core discipline, plays a vital role in fostering logical reasoning, analytical thinking, and advanced problem-solving abilities [7]–[9]. Through effective mathematics education, students can bridge abstract concepts with practical, real-world applications [10]. Therefore, mathematics education is an integral component of the broader educational framework and a key pillar of societal progress.

Mathematics education is a crucial component of the educational system that develops logical thinking, analytical reasoning, and problem-solving skills [11], [12]. It plays an essential role in preparing students to adapt to technological advancements and complex real-world challenges. Mathematics education serves as a medium for fostering creativity, critical thinking, and the ability to connect abstract concepts with practical applications [13], [14]. Through well-structured mathematics instruction, learners are encouraged to explore, reason, and construct knowledge in a meaningful and engaging manner [15], [16]. In the era of rapid digital transformation, mathematics education must integrate innovative approaches that enhance learning effectiveness and student engagement [17]. One of the most promising innovations involves the use of artificial intelligence to personalize and optimize the learning process [18]. Therefore, an important intersection between technological advancement and the future of mathematics education is deep learning.

Deep learning is an educational approach that emphasizes a more holistic and meaningful understanding of subject matter [19]. This approach encourages students to actively participate in the learning process through exploration, analysis, and problem-solving activities [20]. Its primary focus is on developing critical and creative thinking skills, enabling learners to connect concepts across contexts and disciplines. By fostering deeper comprehension, deep learning supports long-term knowledge retention and its application in real-world situations [21]. In mathematics education, this approach can be integrated to enhance conceptual understanding and the ability to solve complex problems. The implementation of deep learning often involves innovative strategies such as project-based learning and the use of technology [22]. Therefore, current trends indicate a growing body of research on deep learning in mathematics education.

Many studies have explored the application of deep learning in various fields, such as clinical medicine for large-scale medical image processing, data screening, disease diagnosis, and treatment efficacy evaluation, as well as in agriculture for crop classification, weed detection, and pest identification, thus requiring bibliometric analysis to comprehensively map research trends. Several papers indicate that bibliometric analysis in the medical field has successfully identified annual trends, country and institutional distributions, influential journals, and collaboration networks, while in agriculture it has mapped research focuses, dominant model architectures, and key challenges encountered [23], [24]. This study addresses that gap by conducting a bibliometric analysis that focuses on keyword clustering and keyword novelty, with a particular emphasis on deep learning research in mathematics education. The contribution of this article lies in mapping the intellectual structure of the field, identifying emerging research directions, and providing recommendations for future studies. These contributions are demonstrated through systematic PRISMA-based literature selection, network visualization using VOSviewer, and keyword novelty analysis, which together offer both a global perspective on this growing research area. Thus, the Research Question (RQ) in this paper is as follows.

RQ1. How is the publication trend from year to year on the topic deep learning research in mathematics education?

RQ2. How are the results of the grouping and keyword novelty on the topic deep learning research in mathematics education?

2. Method

2.1. Research Design & Search Strategy

This paper is a study on deep learning in mathematics education using bibliometric analysis as the primary research approach. Bibliometric analysis is a quantitative method used to evaluate and map scientific literature through statistical examination of publications, citations, keywords, and collaboration networks [25]–[30]. This method allows researchers to identify research trends, influential works, thematic clusters, and emerging topics within a specific field. By applying bibliometric analysis, this study aims to provide a comprehensive overview of the development, focus areas, and novelty in deep learning research related to mathematics education.

The search strategy in this study was carried out using the Scopus database by applying a predetermined combination of keywords to obtain relevant publications. The keywords used were (TITLE ("Deep learning") AND TITLE (Math*) AND TITLE (Educat*) OR TITLE (Learn*) OR TITLE (School*)), aimed at retrieving articles that specifically discuss deep learning in the context of mathematics education, learning, or the school environment. The logical operators AND and OR were used to both narrow and broaden the scope of the search according to the research needs. The search was focused on publication titles to ensure that the documents obtained have a high level of relevance to the research topic.

2.2. Inclusion and Exclusion Criteria

Based on the PRISMA flow diagram (Fig. 1), the inclusion and exclusion criteria process in this study began with the "Identification" stage, which yielded 220 documents from the Scopus database using the predetermined combination of keywords. All documents then proceeded to the "Screening" stage to ensure relevance to the research topic, resulting in 115 documents classified under the "Mathematics" field and limited to the publication types "Article" and "Conference Paper". After this screening process, 72 documents met the requirements. The next stage, "Eligibility," assessed the content of each document for alignment with the research focus, particularly the discussion of deep learning in the context of mathematics education. At this stage, no documents were excluded, and all 72 documents proceeded to the "included" stage. This process followed the PRISMA guidelines to ensure transparency, accuracy, and reproducibility in reporting the literature selection.

2.3. Data Analyze

Data analysis in this study was conducted using the R programming language to process the main information and analyze publication trends, providing an overview of research growth over time. Meanwhile, VOSviewer software was employed to perform keyword grouping and keyword novelty analysis, allowing for the identification of thematic clusters and the emergence of new research topics. This dual-tool approach enables both a quantitative examination of the overall publication landscape and a qualitative mapping of thematic developments in the field. The focus of this analysis is on deep learning research in mathematics education, with the aim of uncovering its intellectual structure and tracking the evolution of its core concepts. The results are expected to offer comprehensive insights into the research dynamics, which can serve as a strategic reference for future studies.

3. Results and Discussion

Before moving into the interpretative sections, the Main Information is first presented. This section aims to provide a general overview of the basic characteristics of the analyzed data [27]. The Fig. 2 shows that research on deep learning in mathematics education indexed in the Scopus database spans the period from 2013 to 2025, with a total of 72 documents sourced from 46 publication outlets, including journals and conference proceedings. The annual growth rate of 14.35% reflects an increasing level of attention from researchers toward this topic. The average document age is 2.69 years, indicating that the literature is relatively recent and aligned with current developments. Each document has an average of 10.08 citations, with a total of 2,131 references analyzed, illustrating the breadth of the literature network underpinning the research. In terms of keywords, 450 Keywords Plus and 258 author keywords were identified, serving as the primary basis for keyword clustering and keyword novelty analysis.

Regarding authorship, a total of 201 authors contributed to the publications, with 14 documents being single-authored and an average of 2.86 co-authors per document. The international co-authorship rate is 12.5%, suggesting that while the research already involves global collaboration, most partnerships still occur at the national or institutional level. The document types analyzed include 50 journal articles and 22 conference papers, indicating that journal articles dominate the dissemination of research in this field. Overall, these findings show that deep learning research in mathematics education is still in a growth phase, with considerable potential for expanding international collaborations to increase the impact and innovation of future studies.

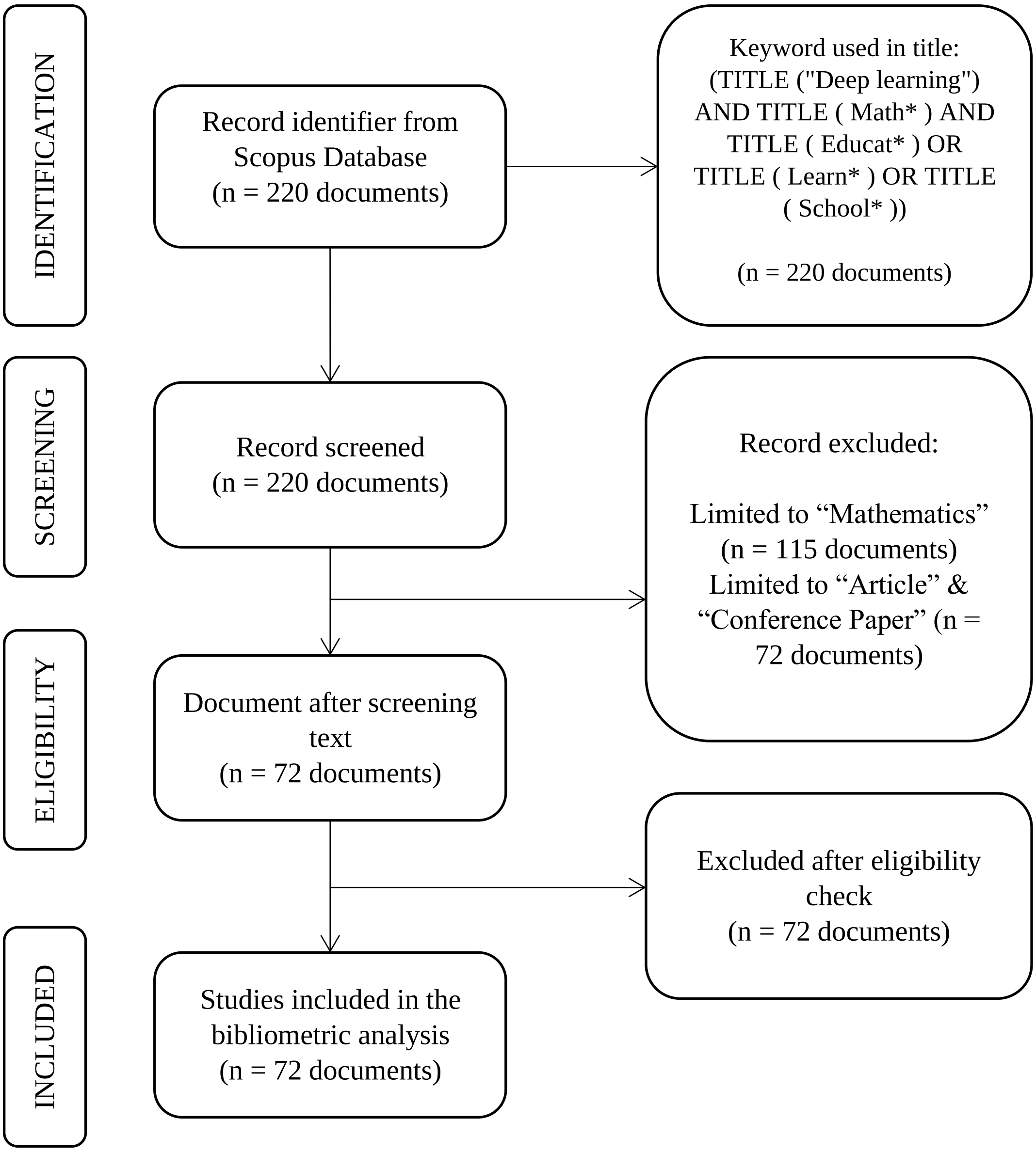

Fig. 1. PRISMA Method for Document Selection (Source: [31])

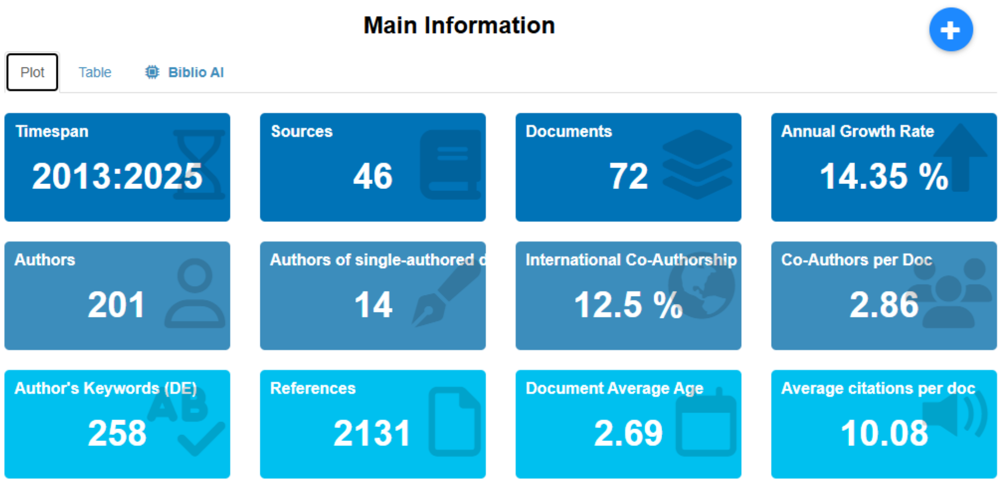

Fig. 2. Main Information about Trends of Deep Learning Research in Mathematics Education

3.1. Publications Trends

Analysis by looking at publication trends (Fig. 3) from year to year aims to understand the development and dynamics of research topics over a certain period of time [27]. This helps identify increasing interest, changes in focus, and potential future research directions.

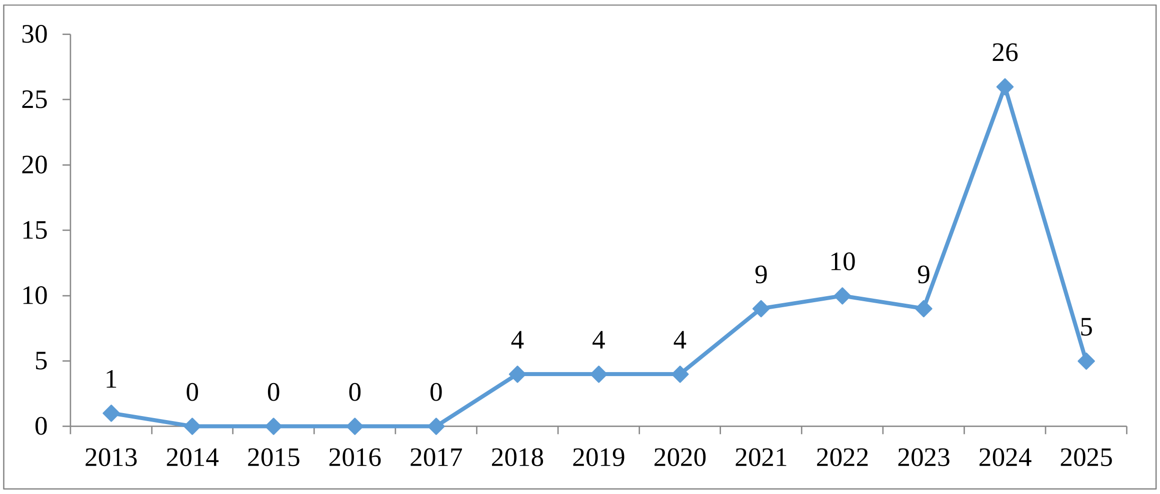

Fig. 3. Number of Publications During the Last 12 Years on the Topic of Deep Learning Research in Mathematics Education

Based on Fig. 3, research related to deep learning in mathematics education first appeared in 2013 with only one document, followed by a stagnation period from 2014 to 2017 with no new publications. A significant increase began to emerge between 2018 and 2020, during which the number of publications remained stable at four documents per year. The next surge occurred in 2021 and 2022, with nine and ten documents respectively, indicating a growing interest and research focus in this field. The peak of publications was recorded in 2024 with 26 documents, driven by the increasing interest of researchers in applying deep learning to mathematics education.

This trend indicates that deep learning research in mathematics education is a growing field that has been attracting increasing attention from the academic community, particularly over the past three years. The sharp rise in 2024 can be attributed to the rapid advancement of technology and researchers' growing awareness of its potential applications in mathematics learning. Although the number of publications decreased to five documents in 2025, this does not necessarily reflect a decline in interest, it may be due to the current publication year not yet being complete. Overall, this pattern underscores the need for bibliometric analysis to map trends, identify research opportunities, and understand the future direction of deep learning in mathematics education.

3.2. Keyword Grouping

Keyword grouping aims to identify the main themes that are developing within a particular field of research [27]. This process also helps map the relationships between topics, revealing the intellectual structure and dominant areas of study. From Fig. 4 and Fig. 5, several clusters can be identified, each of which has been assigned a specific name by the authors. These cluster names are presented in Table 1 for clearer reference.

The cluster titled "Computational Models for Problem Solving" contains a collection of keywords related to advanced computational models such as convolutional neural networks, contrastive learning, and character recognition, which play a crucial role in the application of deep learning in mathematics education. In this context, these technologies can be used to solve complex mathematical problems, model differential equations, and identify patterns in student learning data. The use of these computational models also enables the development of adaptive learning systems that can adjust the material and difficulty level to suit the student's abilities [32]. Furthermore, the application of methods such as adversarial machine learning can help test the robustness of learning models to data variations. This approach is relevant in modern mathematics learning because it integrates large-scale data processing with more effective problem-solving strategies. As a result, teachers and researchers can design more personalized and data-driven learning solutions.

The cluster titled "Predictive Modeling and Data Analysis" includes keywords related to predictive modeling, such as forecasting, statistics, and fuzzy neural networks, which can be used to analyze student performance or predict mathematics learning outcomes. In the application of deep learning in mathematics education, these predictive models are useful for identifying students who require specific interventions or additional materials. For example, predictive algorithms can process test and assignment data to identify trends in student performance improvement or decline over time. In-depth data analysis can also help educators design more effective, evidence-based teaching strategies [33]. Furthermore, predictive modeling can be used to optimize the curriculum according to student needs and the demands of 21st -century competencies [34]. Thus, this cluster emphasizes the importance of integrating statistical analysis and computational models in the development of deep learning-based mathematics learning methods.

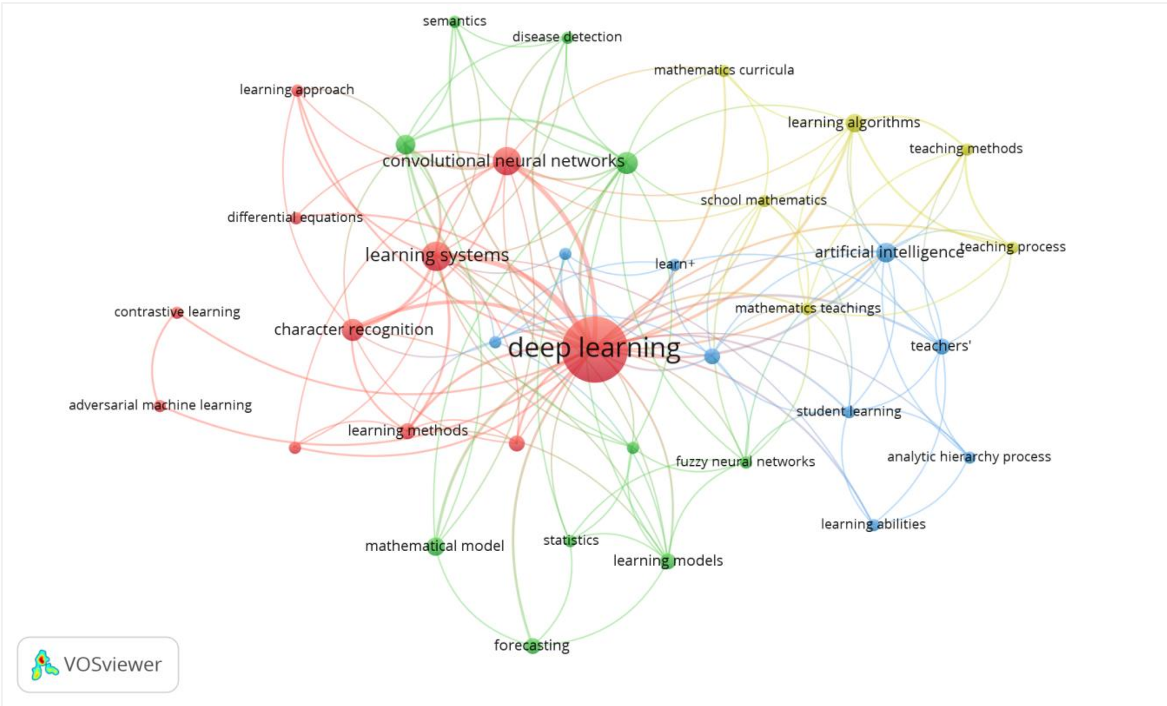

Fig. 4. Network Visualization (Analyze using VOSviewer)

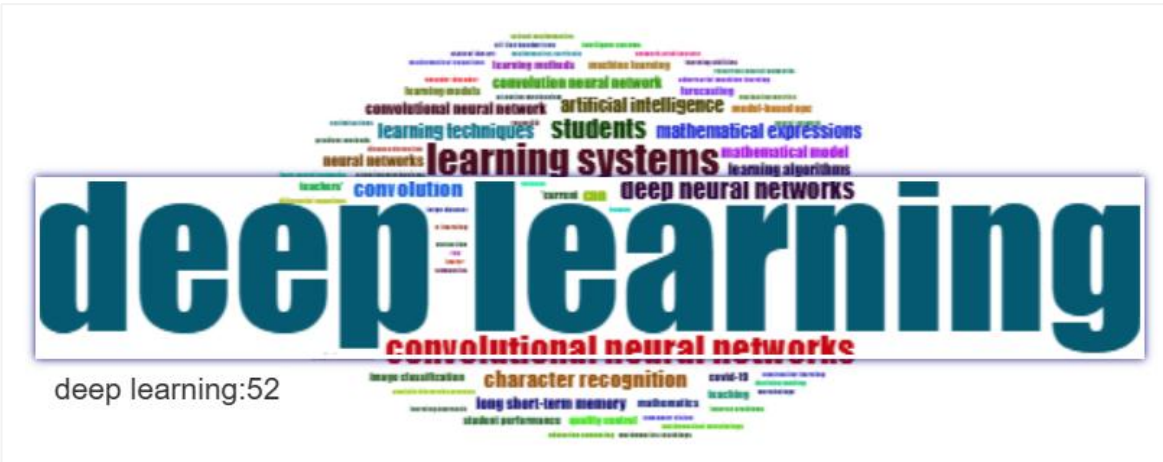

Fig. 5. Word Cloud (Analyze using R Program)

Table 1. Keyword Grouping Based on Network Visualization on Topic Deep Learning Research in Mathematics Education

No	Color	Keywords	Group Name
1	Red (11 items/30.55%)	Adversarial Machine Learning, Character Recognition, Contrastive Learning, Convolutional Neural Network, Deep Learning, Differential Equations, Learning Approach, Learning Methods, Learning Systems, Machine Learning, Mathematical Morphology.	Computational Models for Problem Solving
2	Green (10 items/27.78%)	Convolution, Disease Detection, Forecasting, Fuzzy Neural Networks, Learning Models, Learning Techniques, Mathematical Equations, Mathematical Model, Semantics, Statistics	Predictive Modeling and Data Analysis
3	Blue (9 items/25%)	Analytic Hierachy Process, Artificial Intelligence, E-Learning, Education Computing, Learn+, Learning Abilities, Student Learning, Student Performance, Teachers'.	Intelligent Systems for Academic Performance
4	Yellow (6 items/16.67%)	Learning Algorithms, Mathematics Curricula, Mathematics Teachings, School Mathematics, Teaching Methods, Teaching Process.	Curriculum Strategies and Instructional Methods

Source: VOSviewer

The cluster titled "Intelligent Systems for Academic Performance" consists of keywords that emphasize the use of intelligent systems such as artificial intelligence and analytic hierarchy processes to support students' academic achievement. In mathematics education, these systems can be used to identify students' learning styles, measure their abilities in real-time, and provide automated feedback. The use of e-learning combined with AI technology enables flexible and adaptive learning to individual needs [35]. Furthermore, this technology can manage and analyze large amounts of data from various student interactions with digital learning platforms. By utilizing deep learning, these intelligent systems can personalize the learning experience, thereby enhancing understanding of mathematical concepts. Ultimately, the integration of these intelligent systems helps maximize students' academic potential through a measurable and data-driven approach.

The cluster titled "Curriculum Strategies and Instructional Methods" includes keywords related to curriculum strategies and teaching methods, such as teaching methods, teaching process, and mathematics curriculum. In the context of deep learning in mathematics education, the focus of this cluster is how technology can be used to design and implement a curriculum that adapts to technological developments. This approach allows mathematics learning to focus not only on mastering concepts but also on developing critical thinking and problem-solving skills. Deep learning technology can help identify the effectiveness of teaching methods through the analysis of student learning data [19]. Furthermore, this data-driven teaching method can help teachers dynamically adapt teaching strategies to meet student needs. This cluster emphasizes that the successful implementation of deep learning in mathematics education also depends heavily on curriculum design and innovation in teaching methods.

3.3. Keyword Novelty

Keyword novelty analysis in VOSviewer aims to identify emerging research topics that are beginning to develop within a specific field [27][36]. By recognizing newly introduced keywords, researchers can discover open research opportunities with high potential for contribution.

In Fig. 6, the keyword novelty analysis reveals several terms that have recently emerged in research related to deep learning in mathematics education. The yellow color in the VOSviewer visualization indicates keywords that are relatively new in use by researchers. Among these, two standout keywords are "Contrastive Learning" and "Adversarial Machine Learning." These terms have not yet been widely applied in publications on deep learning in mathematics education, making them potential focal points for future studies. This finding highlights opportunities for developing new methodologies and applications in this field.

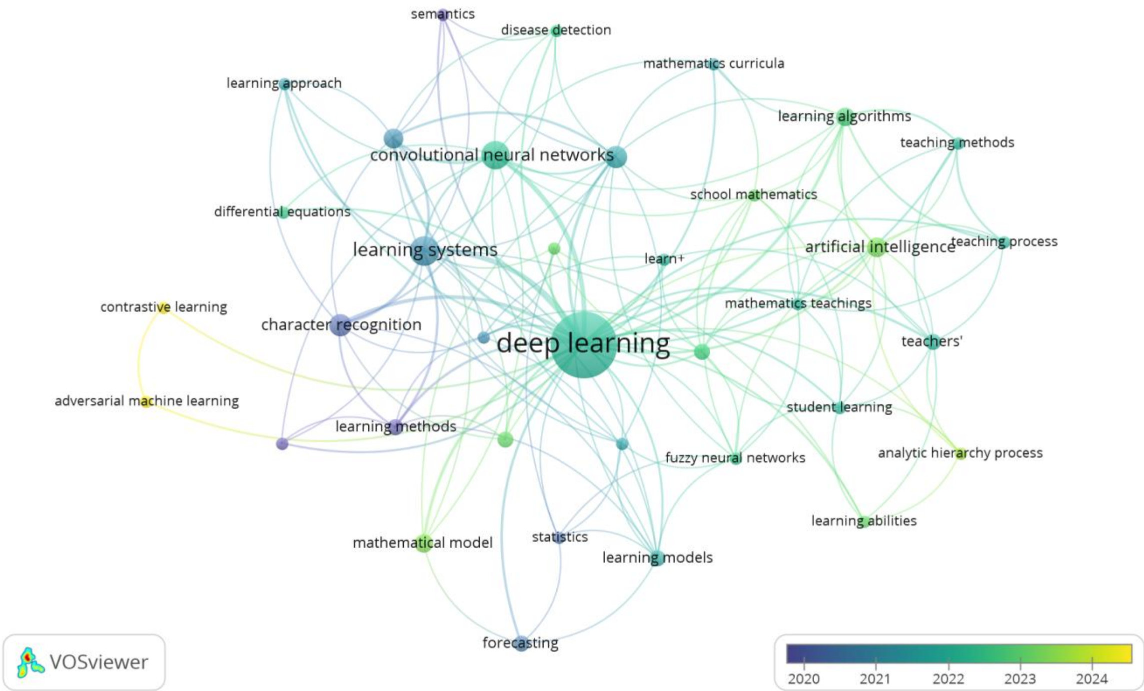

Fig. 6. Keyword Novelty (Analyze using VOSviewer)

The keyword "Contrastive Learning" refers to a machine learning approach that leverages comparisons between data to produce more meaningful representations. In the context of deep learning for mathematics education, this method could be used to differentiate students' understanding patterns based on their interactions, answers, or problem-solving strategies. Applying contrastive learning can help AI models detect subtle differences between varying levels of student comprehension. This has the potential to enhance personalized material recommendations or tailored exercises. Therefore, using this keyword could open new research opportunities that integrate learning behavior analysis with advanced AI techniques.

Meanwhile, "Adversarial Machine Learning" is a branch of machine learning that focuses on making models more resilient to intentional attacks or disruptions. In deep learning–based mathematics education, this concept could ensure the reliability of automated assessment systems, especially against inconsistent or manipulated input data. For example, an AI-driven grading system could be trained to remain accurate even when students provide unconventional or incomplete answers. Additionally, this approach can enhance the security and robustness of adaptive learning systems. Thus, adversarial machine learning stands out as a critical research area that could significantly contribute to developing stronger and more secure mathematics learning technologies.

4. Conclusion

The analysis concludes that research on deep learning in mathematics education has experienced significant growth, particularly in recent years, with a sharp increase in the number of publications in 2024 indicating growing interest and research focus in this field. Through keyword clustering, four main themes were identified: computational models for problem-solving, predictive modeling and data analysis, intelligent systems for academic achievement, and curriculum strategies and teaching methods, reflecting the diversity of approaches and applications of deep learning in mathematics education. Furthermore, keyword novelty analysis indicates promising new research opportunities, particularly in the concepts of "Contrastive Learning" and "Adversarial Machine Learning", which are not yet widely applied but have great potential to improve learning personalization and the robustness of AI-based learning systems. Thus, this trend underscores the importance of bibliometric analysis to map developments, identify research opportunities, and guide the future application of deep learning in mathematics education.

Declarations

Supplementary Materials: The supplementary materials of this study include the complete dataset retrieved from Scopus and the visualizations generated using R Program.

Author Contribution: Z: Conceptualization, Writing – Original Draft, Editing and Visualization; SR: Review & Editing, Formal analysis, and Methodology; AW & PW: Validation and Supervision; RNG: Writing – Review & Editing; TW: Validation and Supervision. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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