Machine Learning in Education: A Bibliometric Review of Research Trends and Future Directions

La Ili[1], Dafid Slamet Setiana[2], Anggit Prabowo[3], Sarfa Wasahua[4], Nanang Khuzaini[5], Muhammad Irfan Rumasoreng[6], Anasufi Banawi[7]

[1]*University of Halu Oleo, Kendari, Indonesia*
[2]*Yogyakarta State University, Yogyakarta, Indonesia*
[3]*Ahmad Dahlan University, Yogyakarta, Indonesia*
[4,7]*Ambon State Islamic Institute, Ambon, Indonesia*
[5,6]*Mercu Buana University Yogyakarta, Yogyakarta, Indonesia*

Abstract:- Machine Learning (ML) in Education is the application of Machine Learning technology in an educational context; the main objective of this study is to update the current knowledge frontiers around investigations related to research trends on Machine Learning in Education and, identify key research topics and analyze their evolution over time. Bibliometric Analysis has been applied in this article, analyzing 472 academic articles related to Machine Learning in Education from Scopus after several data cleaning and preparation steps. The R package "Bibliometrix" was mainly used to analyze this content. Our study has two parts, and the performance analysis contains five categories (Annual Scientific Production, Most Relevant Sources, Most Productive Authors, Most Cited Publications, and Most Relevant Keywords). Science mapping includes country collaboration analysis and thematic Analysis. We analyzed the thematic map by dividing the entire bibliographic dataset into four quadrants to present the thematic evolution over time. This study is one of the most comprehensive bibliometric reviews analyzing Machine Learning in Education related studies. We explain how the results will benefit the understanding of academic research interests to improve the quality of future research on Islamic Education.

Keywords*: Machine Learning, Education, Bibliometric Analysis, Research Trends*.

1. Introduction

Education continues to transform with the development of technology, and the development of Machine Learning-based learning technology has become one of the main pillars in enriching and improving the learning experience [1]–[5]. In this era, machine learning serves not only as a tool but also as a catalyst for innovation in education [6]–[8]. To understand the impact and future direction of Machine Learning applications in the educational context, a bibliometric analysis is required to provide a comprehensive overview of research trends and developmental directions.

Machine Learning has a significant impact on education, especially in higher education, where machine learning can be used to predict student dropouts and improve pedagogical practices [9]–[12]. Machine Learning can also be used to analyze factors affecting students' educational outcomes and create personalized learning plans [13]. In the field of educational science, Machine Learning can assist in the Analysis of high-dimensional datasets and the development of advanced educational processes [14]. However, the proper use of Machine Learning methods requires a basic understanding of concepts and data literacy [14]–[16].

Machine Learning is a branch of computational algorithms that allows computers to learn from data and develop behaviors based on empirical evidence [2]–[5], [17], [18]. [19]–[22], and differs from traditional programming by automatically building a set of rules using algorithms [22]. This field, which has its origins in statistics, probability theory, and neuroscience, aims to make computers learn and has a wide array of applications in various fields [23]–[25].

This article aims to present a comprehensive bibliometric review of the relationship between Machine Learning and Education. A bibliometric approach can be used in mapping emerging research trends [8], [26], [27], identifying key concepts that dominate the literature [28], and exploring collaborations between researchers and research institutions [29], [30]. This bibliometric Analysis will provide an in-depth insight into how Machine Learning has been applied in the context of education, as well as provide insights into anticipated future research directions. With a dataset involving thousands of scientific publications, we will discuss the evolution of Machine Learning research in education in terms of quantity and quality. In addition, we will look for patterns of collaboration between researchers, institutions, and countries, which can provide further understanding of the globality and diversity in the use of Machine Learning in education. This research will provide an in-depth view of the progress made, challenges faced, and potential future research in the field of machine learning and education. With a better understanding of the trends and future directions, this article is expected to provide guidance for researchers, education practitioners, and policymakers to engage more effectively in integrating Machine Learning to improve the quality of learning and teaching.

2. Machine Learning in Education and Its Research Lines

In bibliometric analyses, the number of citations in a study can provide powerful insights into developmental trends in a field [31]–[33]. The number of citations is often used as an indicator of the level of impact and relevance of a scientific work. Research on Machine Learning and education shows that the development trend of education is strongly influenced by Google Collaboratory or Colab. Google Collaboratory, or Colab, is a cloud computing platform that provides free access to graphics processing machines (GPUs) and tensor processing units (TPUs) to support Python code execution [34], [35], on the other hand, quantitative approaches in the context of education and machine learning to evaluate the extent to which a policy, procedure, or system can be regarded as fair or unfair. This involves using quantifiable metrics and indicators to assess the level of inequality or bias in a system or policy. This quantitative approach allows researchers and practitioners to have a more precise and measurable understanding of the level of fairness or injustice in a system or policy, including in the fields of education and machine learning [36].

In the development of education in the medical field, the presence of Artificial intelligence (AI) driven by Machine Learning (ML) algorithms as a branch of computer science that is rapidly gaining popularity in the healthcare sector being able to educate the next generation of medical professionals with the right ML techniques will allow them to be part of the data science revolution that is developing today [37] and Virtual reality simulators track all movements and forces of simulated instruments, generating huge data sets that can be further analyzed with machine learning algorithms. These advances can improve the understanding, assessment, and training of psychomotor performance. Machine Learning to Assess Surgical Expertise (MLASE) was developed to help computer science, medical, and education researchers ensure quality when producing and reviewing virtual reality manuscripts involving machine learning to assess surgical expertise [38].

Dropping out of school is a serious problem for students, society, and policymakers. Predictive modeling using machine learning has great potential in developing an early warning system to identify students who are at risk of dropping out early and help them [38]. The development of AI technologies for use in education and training so that they can be used to help assist students and support teachers and how best to inform data analysis through the application of learning science research and AI algorithms that can rapidly analyze rich educational data. Such AI algorithms and technologies can then help to improve faster, more nuanced, and individualized scaffolding for learners [39]. Further, preparing high school students to become informed citizens and critical users of AI technologies and develop their foundational knowledge and skills to support future endeavors as AI-empowered workers, reflecting on successes and lessons that support student engagement and conceptual learning about AI, changing attitudes towards AI, and fostering future self-conceptions as AI-empowered workers [40].

ML technology is expected to contribute significantly to early and rapid diagnosis of Autism spectrum disorder (ASD) in the coming years and be available to clinicians in the near future. ASD diagnosis based on (a) Structure magnetic resonance image (MRI), (b) functional MRI, and (c) hybrid imaging techniques in the past decade [41]. Machine learning is seen as an important means to realise the clear progressive trend towards precision education in the field of education [42]. Further to the role of ML in decision-making, the development of Algorithmic decision-making (ADM) is becoming increasingly important in all areas of social life. In higher education, ML systems have many uses as they can efficiently process large amounts of student data and use this data to generate effective decisions. Despite the potential advantages of ADM systems, fairness issues are gaining momentum in academic and public discourse. Students' judgment of fairness differs with respect to Algorithmic decision-making (ADM) vs. human decision-making (HDM) in the context of higher education. Our survey results show that the participants rated ADM higher than HDM in terms of procedural and distributive fairness. Regarding the subsequent effects of justice perceptions, we found that (1) both distributive justice and procedural justice perceptions had a negative impact on the intention to protest the ADM system, whereas (2) only procedural justice perceptions had a negative impact on the likelihood to leave. Finally, (3) distributive justice, but not procedural justice perceptions, have a positive effect on organizational reputation [43].

3. Method

Data Collection and Preparation

The database used in this research comes from Scopus (Core Collection) using keywords (topics), namely machine learning "W/3" education with Advanced query Search within Article title, Abstract, and Keywords starting from 1997 - 2023. The documents searched (articles, conference proceedings, books, book chapters) are stored with full notes and cited references. Citations in the Scopus database contain citation information, including Author(s) consisting of Document title, Year, EID, Source title, Volume, issue, pages, Number of citations, Source & document type, Publication stage, DOI, and Open access. Bibliographic information consists of Affiliation, Serial identity (e.g., ISSN), PubMed ID, Publisher, Editor, Original document language, Correspondence address, and Abbreviated source title. Abstract & keywords consist of Abstract, Author keywords, and Indexed keywords. Funding details consist of the number, Acronym, Sponsor, and Text of funding. Other information consists of Trade names & manufacturers, Accession numbers & chemicals, Conference information, and Include references.

Bibliometric Analysis Strategy

Bibliometric Analysis in this study used the R package "Bibliometrix". [44], In the initial stage, the results of research analyses related to machine learning in education were reviewed and reported in five categories: Annual Scientific Production, Most Relevant Sources, Most Productive Authors, Most Cited References, and Most Relevant Keywords. In the knowledge mapping stage, country collaboration networks were plotted based on the normalization of association strength [45]–[48]. Furthermore, Vosviewer-assisted bibliometric Analysis helped create an interlinked research network [49]–[51] by using its clustering algorithm. To study research topics and their temporal evolution. Bibliometrix allows plotting thematic maps for each period based on shared word networks and clustering [44], [52].

4. Results and Discussion

The Scientific Evolution of Machine Learning in Education

An important initial stage to know is to measure the impact and influence of publications based on the number of citations received by the researcher's work before analyzing the number of publications; citation analysis using k-indicators can measure the impact and influence of publications based on the number of citations received by the researcher's work [53]. Information about the Machine Learning in Education publication is presented in the following figure,.

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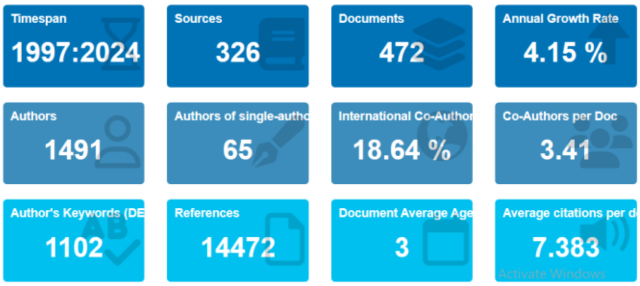

Figure 1. Main Information on Machine Learning in Education

Figure 1 shows that 472 academic publications were collected according to the search strategy. There were 326 sources, consisting of journals, books, etc., that published all the bibliographic data obtained, including 1,491 authors. The average number of citations per article was 3.41, and the number of authors per article was 3. A total of 14,472 references. Annual growth rate is a measure that describes the average percentage change in a value or amount from one year to the next [54]. Thus, it can be seen that the growth of Machine Learning in Education Publications was 7.4%.

Wang and Chai have introduced the concept of K-indicators to quantitatively describe the stage of development of a discipline [55], which is measured using the ratio between the number of keywords. The K-Indicator of scientific literature related to machine learning in education is 0.42, which means it is currently at the normal scientific stage. This stage means the development of the subject over a long period of time, with the formation of more mature concepts; this stage is expected to move to the post-normal stage with less innovation and scientific vitality as described in Kuhn's paradigm mapping of scientific revolutions [56]–[60].

Annual Scientific Production

Annual Scientific Production in bibliometric Analysis serves as a quantitative indicator to measure the number of scientific works produced by an entity during a given year [61]–[63]. Bibliometric Analysis uses bibliographic data, such as scientific publications, to evaluate the impact, productivity, and trends in a particular research field. Here is the Annual Scientific Production of 27 years of scientific publications related to machine learning in education

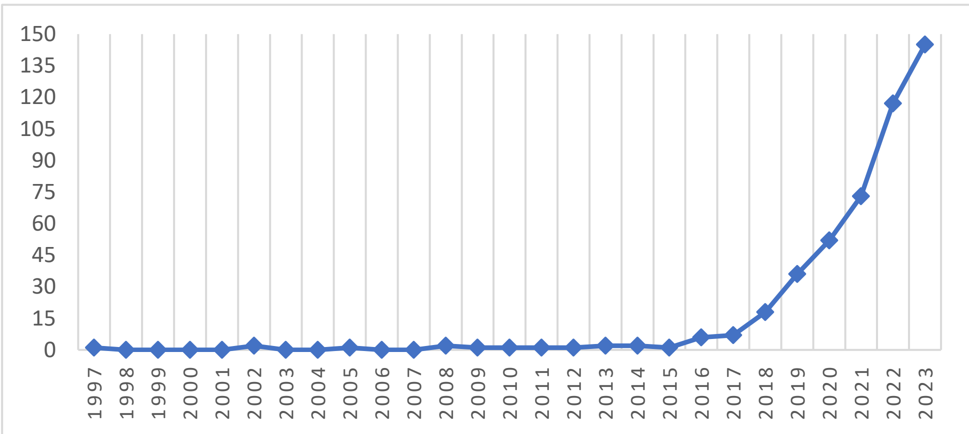

Figure 2. Annual Scientific Production

Figure 2 shows that the Annual Scientific Production graph is linear, indicating that scientific production in a given period increases at a relatively consistent rate over time. The Annual Scientific Production graph of Machine Learning in Education shows a linear increase in scientific production; this can be interpreted as the number of publications or scientific activities increasing at a fixed rate every year. There are several indications that cause publications related to this topic to continue to increase, namely The development of machine learning technology that supports its application in education, increased capability and availability of more sophisticated machine learning algorithms that stimulate the interest of researchers to explore its application in the context of education [64], [65], Another thing is Technology Adoption in Education System so that educational institutions and government adopt machine learning technology in education system [66], [67], this creates an ecosystem of research and development in this area.

Most Relevant Sources

In bibliometric Analysis, "Most Relevant Sources" refers to publications or sources that are considered most relevant and significant in a given research field or topic to identify the most relevant Research Trends and Focuses to help researchers and decision-makers understand the evolution of research and the priority of dominating topics [68]. Here are the top 10 most relevant sources on Machine Learning in Education.

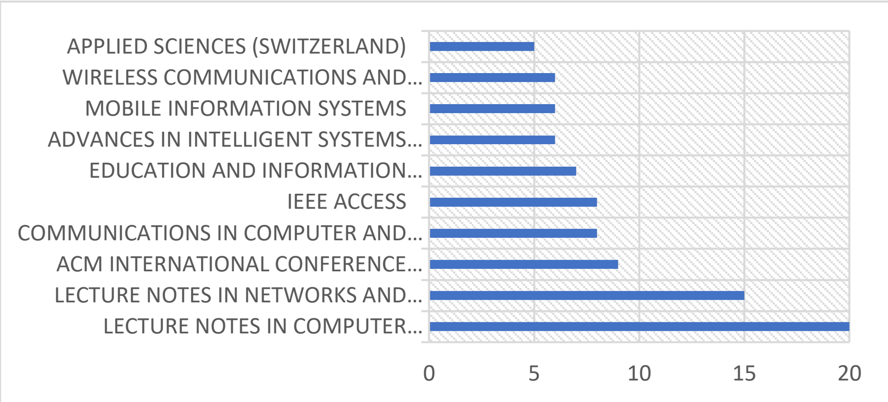

Figure 3. 10 Most Relevant Sources

Figure 3 shows that the most relevant source in this field is Lecture Notes in Computer Science, Publisher: Springer Nature, Subject area: Computer Science: General Computer Science Mathematics: Theoretical Computer Science, Source type: Book Series, Scopus coverage years: from 1973 to Present, and Lecture Notes in Networks and Systems, Publisher: Springer Nature, Subject area: Computer Science: Signal Processing Engineering: Control and Systems Engineering Computer Science: Computer Networks and Communications, Source type: Book Series, Scopus coverage years: from 2016 to Present are the two sources that most consistently discuss Machine Learning in Education in the form of international seminars that discuss the development of AI in all fields of education. Figure 2 also shows that Machine Learning in Education is still very dominantly sourced from computer science.

Most Productive Author

Knowing the most influential authors helps researchers in the selection of the most relevant sources of information to gain a better understanding of recent developments and key issues in the field [69]. This and identifying Authors who are frequently cited or have a major impact in a particular field of research by knowing these authors help identify research trends and directions taken by the scientific community, and Researchers and decision-makers can use this information to assess the quality and significance of the research. Here are the ten most prolific authors,

Table 1. 10 Most Relevant Author

Rank	Authors	Articles	Articles Fractionalized
1	LI Y	6	3,23
2	Sharma A	6	1,62
3	Vartiainen H	6	1,04
4	Jormanainen I	4	0,98
5	Sanusi IT	4	1,57

6	Toivonen T	4	0,98
7	Chen X	3	1,67
8	Giannakos M	3	0,62
9	Huang J	3	0,64
10	Kahila J	3	0,48

Table 7 shows that Li, Yu D. from the Ministry of Education of the People's Republic of China, Beijing, China. 423 Citations by 403 documents, 27 Scopus Documents, with 12 h-index with Sharma, Anand from Mody University of Science and Technology, Lakshmangarh, India, 232 Citations by 222 documents, there are 62 Scopus Documents and nine h-index and Vartiainen, Henriikka from Itä-Suomen yliopisto, Kuopio, Finland 663 Citations by 523 documents, 48 Scopus Documents, 15 h-index are the most popular authors in this field, each researcher focuses on different areas but includes machine learning.

Most relevant keyword

Most relevant keywords help in identifying the main focus of research in a field [70], [71], provide insight into the topics that the scientific community pays the most attention to [72], reflect shifts in research focus or new developments in the field, serving as a guide for researchers conducting literature searches [73]. The most relevant keywords are presented below:

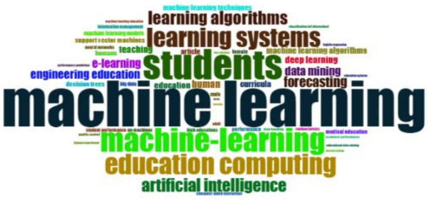

Figure 4(a) WordCloud

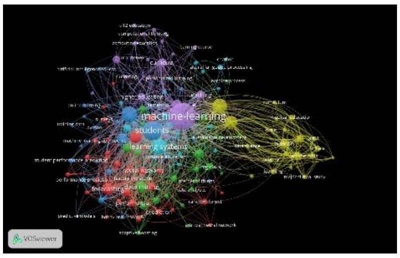

Figure 4(b) Co-ocurance

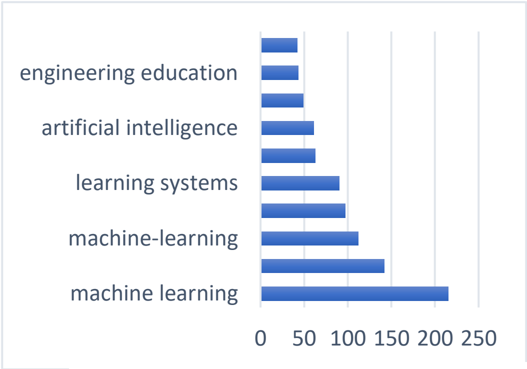

Figure 4(c) Most Frequent Words

Figure 4. Most relevant keyword

From Figure 4(a), (b), and (c), it can be seen that the keywords in the field of machine learning and education are related to students, learning systems, AI, and data mining. The integration between machine learning, education, students, learning systems, artificial intelligence (AI), and data mining has the potential to bring about major changes in the way education is delivered and understood. The integration of machine learning, education, students, learning systems, AI, and data mining can improve the efficiency, effectiveness, and personalization of education, creating a learning environment that is more adaptive and responsive to students' individual needs.

Country Collaboration Network

VOSviewer helps create visualizations that can provide a deeper understanding of collaborative relationships between countries in different research fields. Such analyses can support strategic decision-making, help researchers identify collaboration opportunities, and provide policy insights into international scientific cooperation. Vosviewer presents country collaboration networks based on the frequency of co-occurrence by default [45], [45], [46], [50], [51], [74].

The network between countries is presented below:

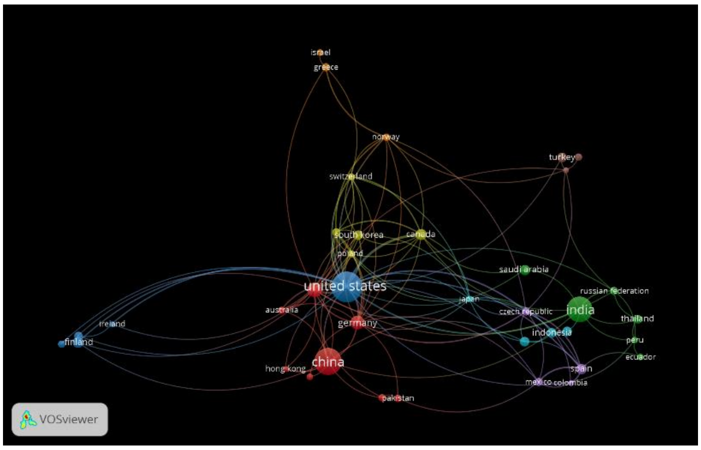

Figure 5. Country collaboration network

Figure 5 shows that there are 38 countries divided into 8 clusters, with the United States, China, and India being the most influential countries in machine learning in education. In the era of digital transformation, innovation in education technology is becoming increasingly important to meet challenges and optimize the learning process. Among various countries in the world, the United States, China, and India dominate the stage as the most influential countries in implementing Machine Learning in Education. They have played a central role in leading and shaping the development of machine learning technologies, bringing about fundamental changes in the global education paradigm. The United States, particularly through technology innovation centers such as Silicon Valley, plays a leading role in the research and development of machine learning-based education technologies. Schools and universities in the US are adopting these technologies to improve teaching methods and bring innovation to the learning experience. Heavy investments from the private sector and government support have made the US a leader in creating innovative solutions that utilize artificial intelligence to improve the education process. China, as a fast-growing economy, has made a huge surge in the application of machine learning in education. The country is showing its seriousness in advancing the education sector through technology by allocating massive resources and incentivizing innovation. Many Chinese tech companies are playing a major role in creating artificial intelligence-based educational solutions, and their universities are becoming important research centers in exploring the potential of technology to improve the quality of education. India, with its large population and rapid technological development, has started utilizing machine learning to improve the education system. Indian universities and higher education institutions are engaged in innovative projects, creating widely accessible learning solutions. Government support and a passion for integrating technology in education create a conducive environment for the development of machine learning in education in the country. Through the development of machine learning in education, the United States, China, and India are not only changing the way education is delivered in their respective countries but also playing a key role in shaping the future direction of global education. Their active involvement in creating an innovation ecosystem that supports the transformation of education has a significant impact on the way we understand and face the challenges of education in the 21st century.

To make it easier for researchers to trace the most influential countries in this field, the following ten countries are presented as follows:

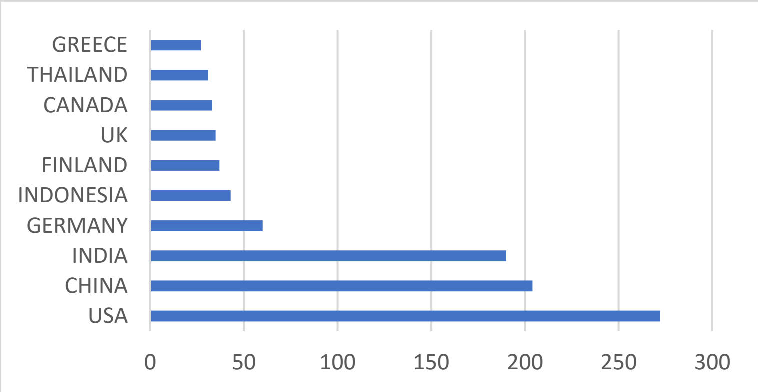

Figure 6. Top 10 most productive countries

Thematic Analysis

Thematic Analysis is a qualitative research method used to identify, analyze, and report thematic patterns or main themes in qualitative data [75]–[77]. Methods are crucial to bibliometric Analysis in measuring and analyzing the amount, distribution, and impact of published scientific literature.

The Thematic Analysis of machine learning in education for the period 1997-2023 is presented in Figure 7. Each circle represents a cluster, and the size of the circle indicates the size of the cluster. The first quadrant (central and developed) is the motor theme space, the second quadrant (Central and undeveloped) is the primary and transversal theme space, the third quadrant (Peripheral and developed) is the highly developed and isolated theme space, and the fourth quadrant (Peripheral and undeveloped) as the developing or declining theme space [78], [79].

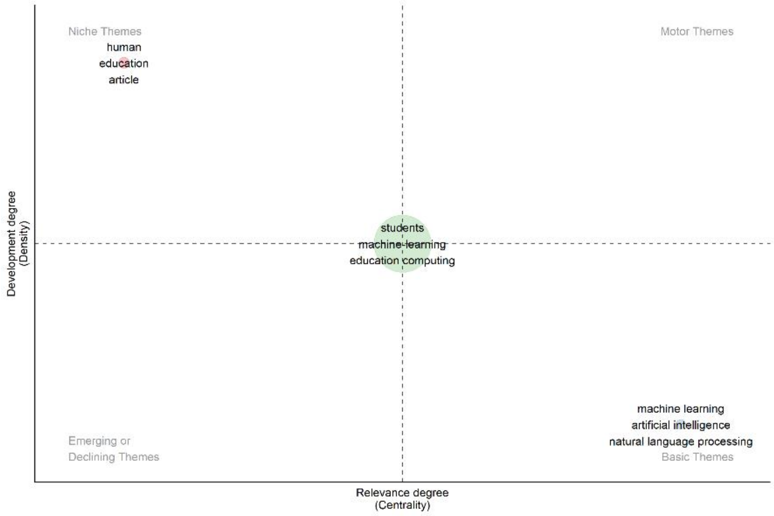

Figure 7. Thematic Map

There is something very interesting in Figure 7. Namely, the topic of machine learning and educational computing is at the center point, which indicates that the development of these topics has been widely discussed but still not very relevant to education; on the other hand, the discussion of these topics is temporal but still very relevant in the future. The topic of machine learning related to artificial intelligence and natural language processing is a major topic that needs to continue to be examined in the future to improve the quality of education. Machine learning, as a branch of artificial intelligence, has opened up new opportunities in changing the education paradigm. The ability to process data intelligently and provide adaptive solutions makes machine learning the key to improving students' learning experience. Similarly, natural language processing, which enables more effective communication between humans and computers through natural language understanding, contributes greatly to the improvement of interaction in learning contexts.

5. Conclusion

A general approach to analyzing and describing the research trends related to machine learning in education has been presented in this article. This study has largely expanded the amount of bibliographic data compared to previous studies. With an overview of bibliographic data from Scopus, the main point of this study is the excellence in describing the current research areas on machine learning in education. In short, this research aims to provide a comprehensive overview of how machine learning has been applied in the context of education, what the trends are, and possible research directions for the future. The conclusions and findings from the research can provide important insights for researchers, practitioners, and policymakers in the field of education and technology. "Linear positive growth" indicates that over a period of time, research in the field of machine learning in education shows a consistent and regular increase or progress. Positive linear progression indicates that this increase occurs at a relatively steady pace and consistency, and machine learning in education research continues to develop as an important and rapidly growing research domain. This statement illustrates that the interest, investment, and contributions in this field are experiencing parallel and positive growth over time.

Mapping science by analysing country collaboration networks, where a series of country collaboration patterns have been identified. The countries of the United States, China, and India have relatively high levels of international collaboration. Countries that are also influential in this study are Germany, Indonesia, Finland, UK, Canada, Thailand, and Greece. Thirty-eight countries divided into eight clusters are presented as nodes in the network. Detailed information on the ten most productive countries has been presented further in the study. Among these countries, through the development of machine learning technology in education, the United States, China, and India are not only changing the way of education in their respective countries but also playing a key role in shaping the future direction of global education. Their active involvement in creating innovation ecosystems that support education transformation has a significant impact on how we understand and face the challenges of education in the 21st century.

Thematic Analysis of the topic of machine learning and educational computing is at the center, which indicates that the development of the topic has been widely discussed but is still not very relevant to education; on the other hand, the discussion of this topic is temporal but still very relevant in the future. The topic of machine learning related to artificial intelligence and natural language processing is a major topic that needs to continue to be examined in the future to improve the quality of education. Machine learning, as a branch of artificial intelligence, has opened up new opportunities in changing the education paradigm.

Machine Learning in Education discussion with Publisher: Springer Nature, namely Lecture Notes in Computer Science and Lecture Notes in Networks and Systems in the form of Book Series are the two most consistent sources that discuss Machine Learning in Education in the form of international seminars that discuss the development of AI in all fields of education. Figure 2 also shows that Machine Learning in Education is still very dominantly sourced from computer science. The evolution of this research is at the normal science stage. This stage means the development of the subject over a long period of time, with the formation of more mature concepts; this stage is expected to move to the post-normal stage with less innovation and scientific vitality.

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