Machine Learning in Educational Data Mining: Current Trends and Emerging Gaps in Predicting Student Performance

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ABSTRACT

The growing availability of educational data and advancements in machine learning (ML) have led to its widespread application in predicting student performance. However, current research remains fragmented, lacking an integrated understanding of knowledge structures, collaboration networks, and thematic directions. This study addresses this gap through a bibliometric analysis of literature focused on ML-based student performance prediction. The study contributes a comprehensive knowledge map that identifies major research themes, key contributors, and underexplored areas within educational data mining. Using 465 Scopus-indexed articles from 2005–2025, four bibliometric techniques were applied: descriptive analysis, collaboration mapping, keyword co-occurrence, and thematic mapping. Data were processed using Bibliometrix in R and visualized via Biblioshiny. Findings reveal a sharp increase in publication trends after 2018, with China, the U.S., and India as top contributors. Despite high output, international collaboration remains limited to certain clusters, while countries like Pakistan and Indonesia show high collaborative intensity. Keyword analysis highlights “student performance” and “machine learning” as core themes, while federated learning, contrastive learning, and algorithmic fairness are emerging gaps. Non-cognitive factors such as motivation and emotional engagement are also underrepresented in predictive models. In conclusion, this study offers a systematic overview of the field, outlining its evolution, key players, and future directions. The results provide valuable insights for designing predictive models that are accurate, ethical, and contextually appropriate for higher education.

1. Introduction

In recent years, the increasing availability of educational data and advances in computing technology have encouraged the use of machine learning techniques in the context of educational data mining [1], [2], [3], [4], [5]. The application of machine learning in this field is specifically directed at predicting students' academic performance, which is an important concern for educators, educational institutions, and policy makers [5], [6], [7]. Accurate prediction of student academic achievement not only serves as a basis for early intervention and personalized learning strategies, but also supports decision-making at the institutional level, such as the student admissions process, academic advising, and student retention strategies [8], [9], [10].

Various machine learning approaches have been applied in student performance prediction research, ranging from classical methods such as decision trees, support vector machines, and logistic regression to cutting-edge approaches such as deep learning and hybrid models that utilize attention mechanisms and ensemble learning [8], [11]. These models have been used in a variety of learning environments, from traditional classrooms to online learning systems such as LMS and MOOCs [12], [13]. In addition to academic grades, behavioral data such as clickstreams, discussion participation, engagement with teaching materials, and psychosocial indicators are also widely used as predictor features [14], [15], [16]. In countries such as India, Morocco, the United Arab Emirates, and Indonesia, this approach has been tested contextually to understand the factors that influence students' academic performance [17].

Although the literature in this field is growing rapidly, there are still major challenges in the form of fragmentation of topics and approaches. Many studies are very specific in terms of data types, institutional contexts, and algorithms used, and have not yet formed a conceptually integrated knowledge framework [18], [19]. In addition, most of the existing research is experimental and focuses on evaluating the performance of the model, without examining its relationship to pedagogical, ethical, or systemic dimensions [20]. Several studies have highlighted the importance of model interpretability, prediction fairness, and cross-context generalization, but these findings are still scattered and have not been systematically consolidated [1], [21]. This condition is reinforced by the findings of Miah et al. [22], which indicate that cultural differences and national education systems can significantly affect the accuracy and generalizability of predictive models, thus requiring contextual sensitivity in the development of machine learning-based systems. Therefore, there is still a need for an approach that can provide a quantitative and systematic structural overview [23], particularly to identify relationships between studies, thematic mapping, and collaboration among actors in this field. A bibliometric approach is seen as relevant because it can fill this gap by offering a framework that is both descriptive and based on visualization and scientific connections [19]. To date, there has been no comprehensive bibliometric study that specifically maps the research structure on this topic, unlike similar studies that have been conducted on other topics such as artificial intelligence-based learning systems in general [24].

Several previous systematic reviews have attempted to outline trends and challenges in the application of machine learning for student performance prediction [24], [25], [26], [27], [28], but the approach used is generally narrative and less systematic in terms of quantitative and visualization of knowledge. In this context, the bibliometric approach becomes important because it is able to combine statistical analysis of publications with visual mapping of research structures, actors, and themes [19], [29]. Through publication frequency analysis, collaboration network mapping, keyword linkage analysis, and co-word-based thematic mapping, this approach provides a systematic framework for identifying key contributors, dominant topic clusters, and under-explored themes [18].

The main contribution of this study is to provide a quantitative bibliometric mapping of the literature related to machine learning-based student performance prediction, with a focus on identifying knowledge structures, collaboration networks, and research gaps that are still open in the application of machine learning for student performance prediction. This study also extends the bibliometric approach that has been more widely used in the STEM field, into the multidisciplinary and dynamic EDM domain [30]. The results are expected to be a reference for researchers, educators, and policy makers in designing research strategies and developing data-based education systems. This research is expected to provide a deeper understanding of the structure of knowledge in this field. In addition, the results of this study are expected to be a reference for researchers, educators, and policy makers in identifying future research directions and developing data-based implementation strategies in higher education systems.

Given the rapid growth of publications in this field, it is important to understand not only how much research has been done, but also how the direction and depth of these contributions shape the knowledge structure within it. In other words, an approach is needed that is able to connect the quantitative and thematic dimensions in the machine learning research landscape for student performance prediction. The findings of this study are expected to be able to inform various stakeholders, from academics to policy makers, about mature research areas, emerging topics, and themes that are still rarely explored, so that they can be directed towards a more strategic and impactful research agenda. Based on this background and urgency, this study is designed to answer the following questions:

RQ 1 : How have publication trends related to the use of machine learning in student performance prediction evolved over the past decade?
RQ 2 : Who are the main contributors in this field, both from the perspective of countries, institutions, and individual authors?
RQ 3 : What are the dominant themes that emerge in this study, and what are the thematic relationships between one topic and another?
RQ 4 : What research gaps can be identified from thematic mapping and current literature trends?

This article is organized into several main sections. The method section explains how we collected and analyzed bibliometric data. The results section presents the key findings based on the analysis of publication trends, important contributors, collaboration, and main themes. The discussion section offers a detailed interpretation of the findings. Finally, the conclusion section summarizes the contributions and gives suggestions for future research.

2. Method

2.1. Database Selection

The data in this study were collected from the Scopus database which has been recognized as one of the most credible and systematically curated bibliometric sources [31]. Scopus has a wide multidisciplinary coverage and provides stable and high-quality publication metadata, allowing bibliometric analysis to be carried out accurately and reproducibly. This technical advantage makes Scopus widely used in knowledge mapping studies in various disciplines, including education and computer science [18], [24]. Compared to other databases such as Web of Science or Dimensions, Scopus was chosen due to its broader coverage in the domains of education and technology, as well as the completeness and consistency of its metadata, which are crucial for reliable bibliometric analysis [29]. The search was conducted using boolean strings in the “title”, “abstract”, and “keywords” columns to capture publications relevant to the application of machine learning in predicting student performance. The search string was developed iteratively through exploration of keywords commonly used in similar literature. Although Scopus has advantages in coverage and metadata consistency, its limitations still need to be noted, including the possibility of non-indexing of publications from certain regional journals or alternative scientific sources that do not meet Scopus curation standards [31]. Therefore, the results of this study are presented taking into account the potential bias of regional representation and data accessibility. Additionally, subject area categorization in Scopus is sometimes broad and not always tailored to specific interdisciplinary domains, which may lead to potential thematic overlap or exclusion. Furthermore, the dominance of certain publishers indexed in Scopus can also influence the geographic and contextual representation of the included studies, potentially underrepresenting research from certain regions or educational systems.

2.2. Inclusion Criteria

The inclusion criteria in this study were set to ensure that only relevant and high-quality documents were analyzed. Documents included must meet the following requirements: (1) explicitly discuss the application of machine learning in the context of predicting student academic performance; (2) published in the form of scientific journal articles or conference proceedings; (3) written in English; and (4) published between 2005 and 2025. In addition, only documents with complete metadata including title, abstract, keywords, year of publication, author names, and institutional affiliations were included in the analysis stage. To obtain relevant bibliometric data that is in accordance with the objectives of the study, a search was conducted using the Advanced Search feature in the Scopus database. The search string used was TITLE-ABS-KEY ("Machine learning" AND "student performance"). This string was carefully arranged to identify articles that specifically discuss the topic of machine learning in predicting student performance. In addition to these criteria, the Social Sciences subject area was selected as an additional filter considering that Scopus does not provide a specific classification for the field of education. This selection was based on the consideration that most articles on education, including the application of machine learning in education, are classified in the social sciences domain. In this way, the search scope remains broad but remains thematically relevant.

2.3. Eligibility Assessment

The initial search phase yielded 2051 documents. The screening process was carried out in stages to ensure topic relevance, starting with eliminating studies that were not peer-reviewed journal articles and conference proceedings. This was done to maintain the integrity of the data in this study. The final results of the selection process yielded 465 documents ready for further analysis. This selection procedure is visualized in Fig. 1 following the PRISMA guidelines [32], which strengthens the systematic aspects and methodological rigor of this study. By following strict selection standards and referring to best practices in previous bibliometric studies [18], a total of 465 documents were successfully filtered for further analysis, to ensure the validity and depth of the resulting analysis. Nevertheless, it should be noted that the selection is still subject to potential bias resulting from Scopus' indexing practices, such as its emphasis on certain publishers and regional coverage, which may affect the representativeness of educational contexts analyzed in this study.

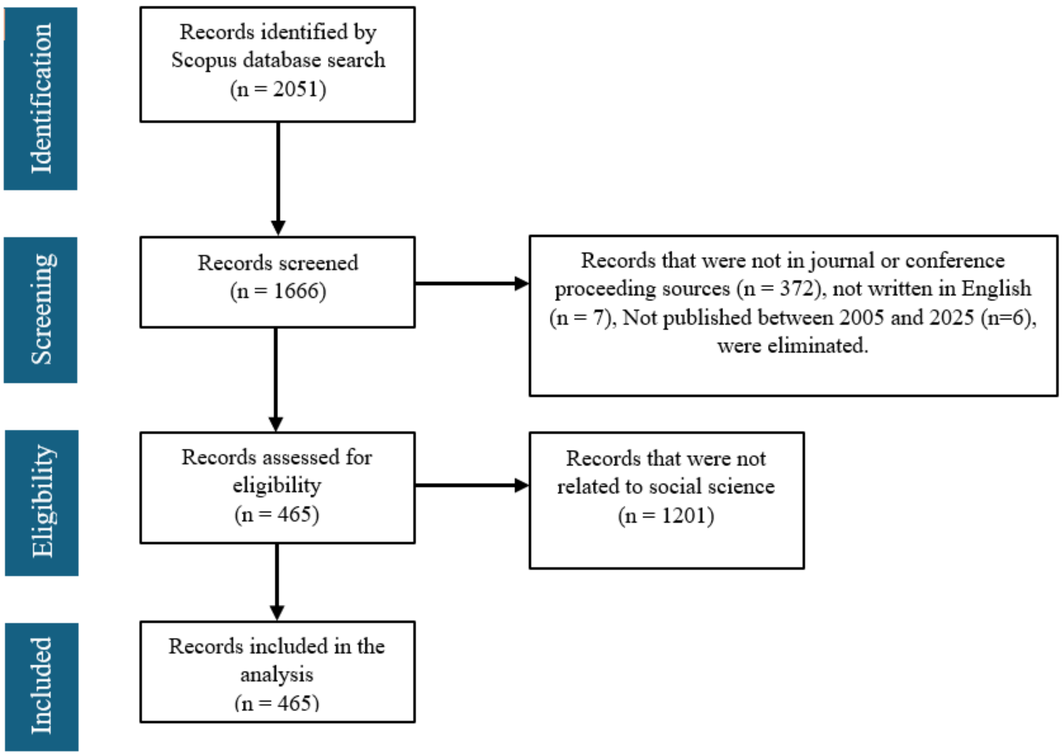

Fig. 1. PRISMA flow for record selection

2.4. Data Analysis Procedure

The data were analyzed using a bibliometric approach that includes four main stages: descriptive analysis, collaborative network analysis, keyword (co-word) linkage analysis, and thematic mapping.

The selection of this method is based on an approach that has been widely used in bibliometric research in the field of education and learning technology [18], [24]. The first stage is a descriptive analysis, which aims to identify patterns of publication growth over time, as well as to measure scientific productivity based on institutional affiliation, author country of origin, and individual contributions. These data provide an overview of research dynamics and the geographical distribution of the field studied. Next, a collaborative network analysis is carried out, mapping the collaborative relations between authors and between countries through a co-authorship matrix. The results of this analysis are visualized in the form of a network graph that illustrates the strength and intensity of collaborative relationships, and allows the identification of key actors in the scientific community concerned. This technique is useful for highlighting how knowledge is collectively constructed within a research community [18], [33]. The third stage is co-word analysis, which is conducted on the authors' keywords. This approach is used to identify the most frequently occurring terms in the articles, as well as to explore the conceptual structure and thematic direction in the literature. The results of the co-word analysis are visualized in the form of a keyword linkage network, which is then used as a basis for the next stage. The fourth stage is thematic mapping, which classifies keyword clusters into four categories based on two main indicators: density (the strength of theme development) and centrality (connectedness to other themes). The four categories produced are motor themes, niche themes, emerging or declining themes, and basic themes [29]. This mapping is not only useful for evaluating the relationships between themes, but also for identifying research areas that are still underexplored or show limited growth potential. The findings from this stage are key in uncovering emerging gaps and formulating future research directions more strategically.

2.5. Analytical Tools

The analysis process was carried out with the help of bibliometrix software [29] in the R environment, which allows for systematic and flexible bibliometric analysis. The interactive interface biblioshiny is used to simplify data visualization and exploration. The combination of these two tools has been widely used in contemporary bibliometric studies and has proven to support comprehensive literature exploration [18], [24].

3. Results

3.1. Growth Patterns of ML Research in Education

The publication trend shows a sharp increase in the number of articles discussing the use of machine learning for student performance prediction in the last two decades. After an initial period of relatively stable and low until 2017, research productivity began to experience significant acceleration since 2018. This growth has continued consistently in the last five years, with the peak number of publications recorded in 2024. This phenomenon indicates the increasing attention of the scientific community to the use of machine learning in educational data mining, especially in the context of evaluating and predicting academic performance. This development is visualized in Fig. 2, which clearly shows the annual publication growth curve. Although the data for 2025 does not cover a full year, the visible trend still shows strong interest in this topic. This data provides a strong indication that the topic of machine learning-based student performance prediction has experienced rapid growth in recent years, both in terms of quantity and in the distribution of scientific contributions.

3.2. Contributor Distribution and Collaboration Patterns

3.2.1. Distribution of Research Countries

Fig. 3 shows a spatial representation of country contributions to the literature on the use of machine learning for student performance prediction. This distribution not only highlights the numerical dominance of some countries, but also illustrates the variation in collaborative approaches reflected in the proportion of national (SCP) and cross-country (MCP) publications. SCP indicates the dominance of local contributions within a country, while MCP is an indicator of international connectedness in the knowledge production network. In general, it can be observed that countries with large research capacities such as China, the United States, and India tend to dominate in terms of publication volume, but do not necessarily have a high proportion of international collaboration. In contrast, some countries with a more limited number of publications such as Pakistan, Indonesia, and Saudi Arabia actually show a relatively high intensity of global collaboration. This indicates that contributions to the global discourse are not always correlated with the volume of output, but are also determined by openness to international cooperation.

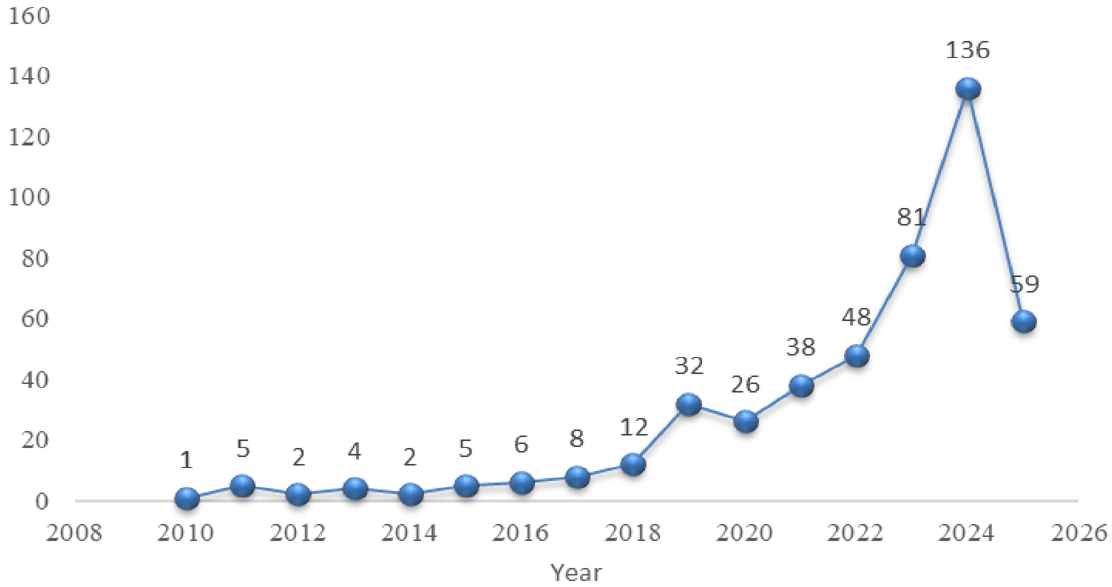

Fig. 2. Annual Scientific Production

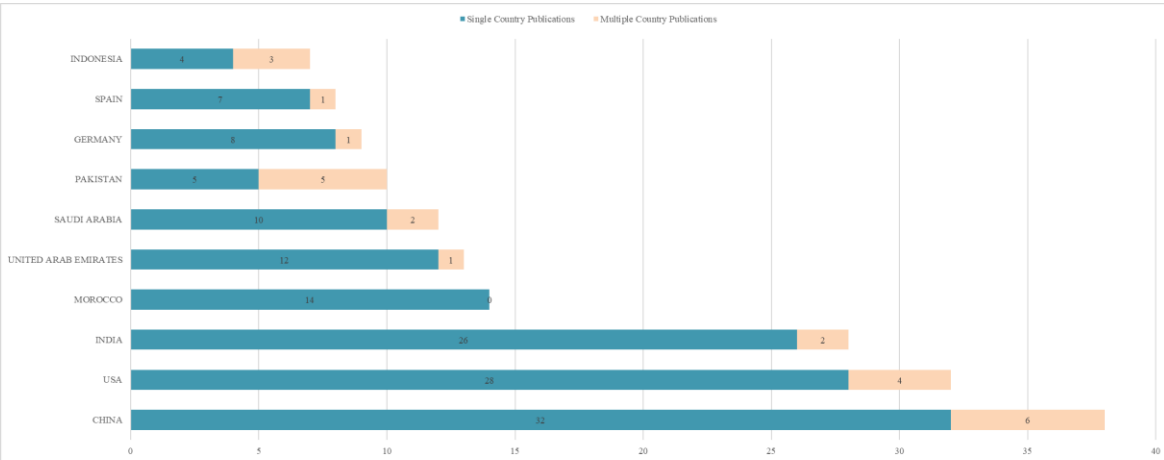

Fig. 3. Distribution of Country of Origin of Corresponding Authors by Type of Collaboration

This distribution also reflects the active involvement of certain regions such as South Asia, East Asia, and the Middle East, indicating that the issue of machine learning-based student performance prediction has attracted the attention of the academic community across regions. Indonesia's involvement, for example, shows that developing countries are also starting to be active in research collaboration networks, although they still face challenges in terms of publication capacity. The geographic contribution map presented in Fig. 3 provides important insights into how the dynamics of knowledge in the field of educational data mining are developing globally, while also underscoring the importance of encouraging cross-country collaboration to strengthen a more inclusive and geographically diverse research ecosystem.

3.2.2. Major Country Contributions in Publication and Citation

Table 1 presents the top ten countries based on two key indicators of scientific publications related to the use of machine learning for student performance prediction: the number of articles and the number of citations. The results of this analysis provide a comprehensive picture of not only a country's productivity but also the level of influence of its publications. The United States (US) ranks first in terms of the number of articles with a total of 1,027 publications, followed by China (615 articles) and India (523 articles). These three countries demonstrate dominance in quantitative contributions to the field of machine learning-based educational data mining. Meanwhile, in terms of scientific impact measured by the number of citations, China ranks first with 684 citations, followed by the US (621) and the United Arab Emirates (448). Several countries show interesting profiles. For example, the United Arab Emirates and Morocco are included in the top ten in terms of both the number of articles and citations, reflecting both the productivity and the high relevance of their publications. This shows that although the volume of publications is not as large as other large countries, their contributions are quite significant in shaping the direction of global research. Indonesia is ranked seventh in terms of number of articles (139 articles), showing promising growth in contribution to international literature, although it has not yet entered the top ten in terms of citations. This difference between productivity and citation impact can be an important indicator for developing countries to prioritize quality and international collaboration in an effort to increase global visibility.

Table 1. Country Contribution in Publication and Citation

Country Rank	Country	Number of Citations	Country	Number of Articles
1	China	684	USA	1027
2	USA	621	United Arab Emirates	233
3	United Arab Emirates	448	Spain	286
4	India	353	Saudi Arabia	132
5	Morocco	350	Morocco	222
6	Greece	292	Malaysia	187
7	Romanian	281	Indonesia	139
8	Pakistan	250	India	523
9	United Kingdom	223	China	615
10	Spain	160	Brazil	232

3.2.3. Distribution of Contributors and Literature Sources

In addition to the country distribution, this bibliometric analysis also identifies the most relevant key actors in the literature production in this area, including authors, institutions, and primary publication sources. As shown in Table 2, research contributions come from a variety of institutions and individuals, indicating that interest in the application of machine learning in student performance prediction is widespread across global research centers. Several leading institutions, such as Central China Normal University, National Central University, and San Diego State University, emerge as centers of high productivity. This suggests that this topic is supported by universities with strong research capabilities in education and technology. The diversity of institutions from Asia, North America, and Latin America also indicates that this research is cross-regional and not concentrated in a single geographic area.

In terms of authors, there is one anonymous entry that ranks first with the highest number of publications compared to the next top identified author, Balqis Albreiki. The absence of name information likely reflects deficiencies in document metadata or inconsistencies in author name spelling. This is also evident from the large number of publications without consistent primary author identification. In terms of publication outlets, the literature on this topic is spread across a variety of journals and proceedings that combine the fields of education, artificial intelligence, and information technology. The existence of proceedings such as the Frontiers in Education Conference and journals such as Computers and Education: Artificial Intelligence reflect the multidisciplinary approach that colors the dynamics of publication in this area.

Table 2. Top 10 Most Relevant Contributors in Publication

Category	Contributors
Most Relevant Authors	Not Available; Balqis Albreiki; Bouzidi Abdelhamid; Abdul Rahim Ahmad; Shafiq Ahmad; Noura Aknin; Saud Altaf; Rimsha Asad; Nafaa Jabeur; Ijaz Khan
Most Relevant Affiliations	Central China Normal University; National Central University; Thiagarajar College of Engineering; San Diego State University; Beijing University of Chemical Technology; Sao Paulo State University; Imam Abdulrahman bin Faisal University; United Arab Emirates University; Universidad De Antioquia; Worcester Polytechnic Institute;
Most Relevant Sources	Education and Information Technologies; Proceedings-Frontiers in Education Conference, FIE; Sustainability (Switzerland); Computers and Education: Artificial Intelligence; International Journal of Engineering Education; International Journal of Emerging Technologies in Learning; IEEE Global Engineering Education Conference, EDUCON; International Journal of Information and Educational Technology; Education Sciences; Journal of Engineering Education Transformations

3.2.4. International Networks Collaboration

Fig. 4 presents a mapping of the international collaboration network between countries active in research on the application of machine learning to predict student performance. This visualization shows the connectivity between countries based on the number of joint publications, where the size of the nodes reflects the volume of contributions from each country, while the thickness of the lines indicates the strength of the collaborative relationship [29]. Several key collaboration clusters stand out. China emerges as a strong and extensive hub of collaboration, actively connecting with countries such as Pakistan, the United Arab Emirates, and Saudi Arabia. India also occupies a prominent position with relatively dense connectivity to several regional research partners. The United States, despite having a high number of publications individually, shows more limited collaborative linkages in this visualization, indicating a skew toward domestic publications or internal correspondence.

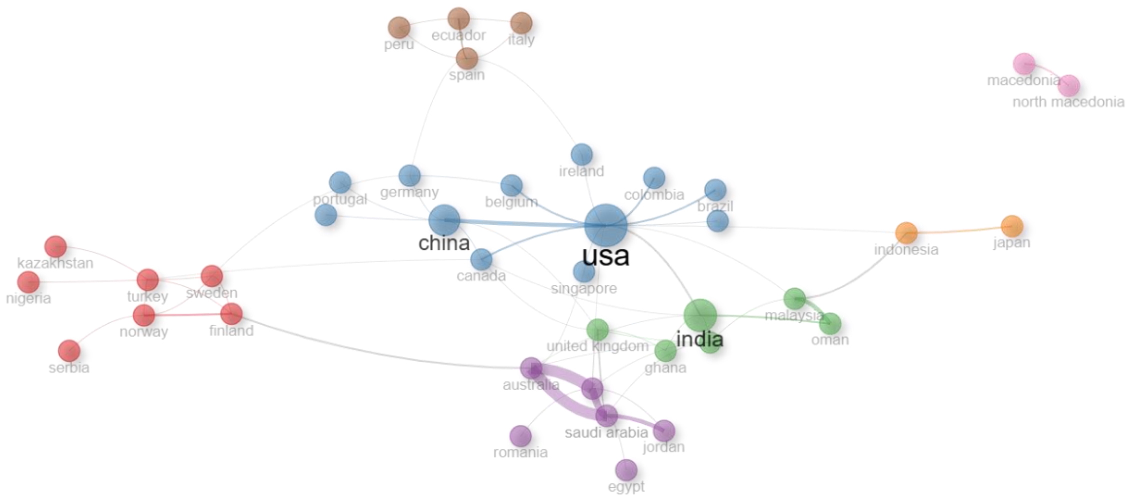

Fig. 4. International Collaboration Network

Other relatively self-contained clusters, such as those encompassing countries in Southern Europe and North Africa, show strong patterns of collaboration within their regions, but with little cross-regional connectivity. In addition, there are small collaborative nodes emerging from countries such as Japan, Malaysia, and Thailand that are beginning to engage in global networks, but remain peripheral to the network map. This network structure indicates that while international collaboration is growing, collaboration remains concentrated in a handful of countries with large research capacities and well-established research infrastructures.

3.2.5. Relational Patterns among Countries, Authors, and Keywords

Fig. 5 presents a Sankey diagram visualization depicting the relationship between the author's country of origin (AU_CO), the most frequently occurring author (AU), and the main keywords

(KW_Merged) used in the publications. This visualization shows that authors from countries such as Morocco, the United Arab Emirates, Malaysia, and Saudi Arabia play a significant role in the development of research on machine learning for student performance prediction. Authors such as Nafaa Jabeur, Abdul Rahim Ahmad, and Bouzidi Abdelhamid appear to have a strong connection to topics such as adversarial machine learning, educational data mining, and students, reflecting their research focus on the technical and applied aspects of data-driven learning. Furthermore, this visualization indicates a direct relationship between authors from certain regions and specific topics, such as strong contributions from Malaysia to data mining or from the United Arab Emirates to learning systems. This pattern shows geographic trends in topic interests and research specializations, and highlights how geographic and individual identities converge in the global research landscape.

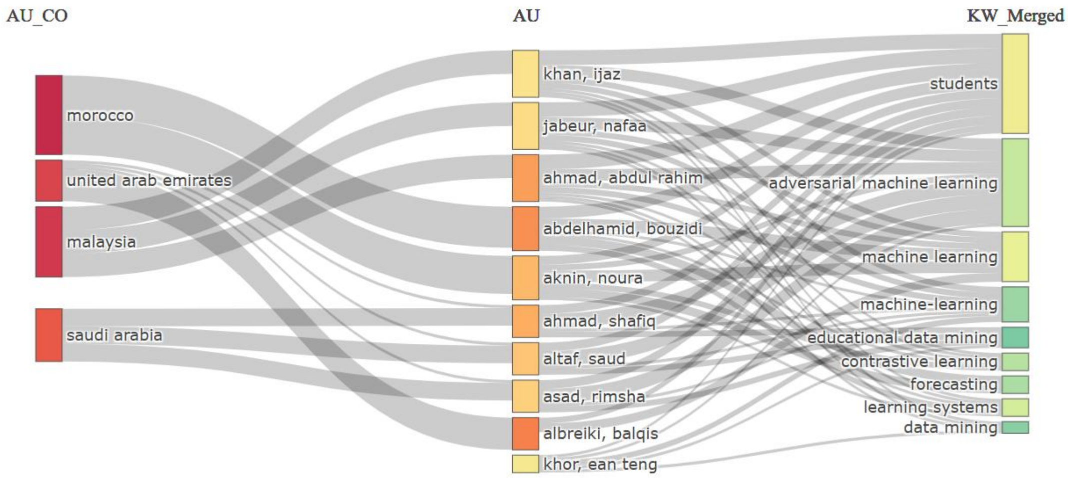

Fig. 5. Visualizing the Relationship between Countries, Authors, and Keywords

3.3. Thematic Structure and Trending Topics

Visual mapping through the keyword co-occurrence network in Fig. 6 shows the main thematic structure in the literature related to machine learning for student performance prediction. It can be seen that terms such as students, student performance, and machine learning occupy a central position, indicating their main role in the literature structure. Large nodes that are closely interconnected with other terms such as forecasting, learning systems, and educational data mining indicate topics that have been widely researched and have strong thematic connectivity [29], [34]. The colored clusters in the network represent naturally occurring thematic communities in the literature, such as adaptive learning clusters, prediction systems, and classification methods.

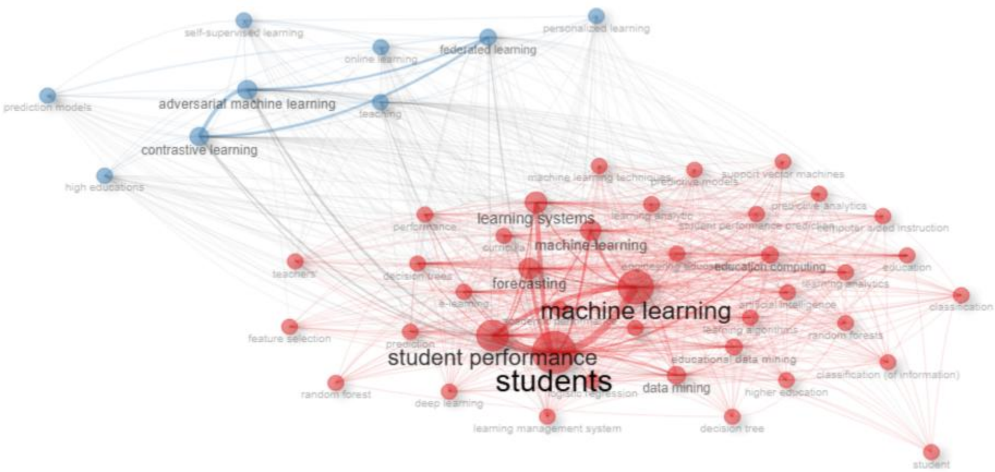

Fig. 6. Keyword Co-occurrence Network

To deepen understanding of the thematic structure and direction of research development, a thematic map analysis was conducted as shown in Fig. 7. This map maps themes into four quadrants based on two dimensions: centrality (relevance to the field) and density (level of theme development) [29]. Themes such as students, student performance, and machine learning occupy the basic themes quadrant, indicating that although these themes are very central to the literature, their depth of development is still limited.

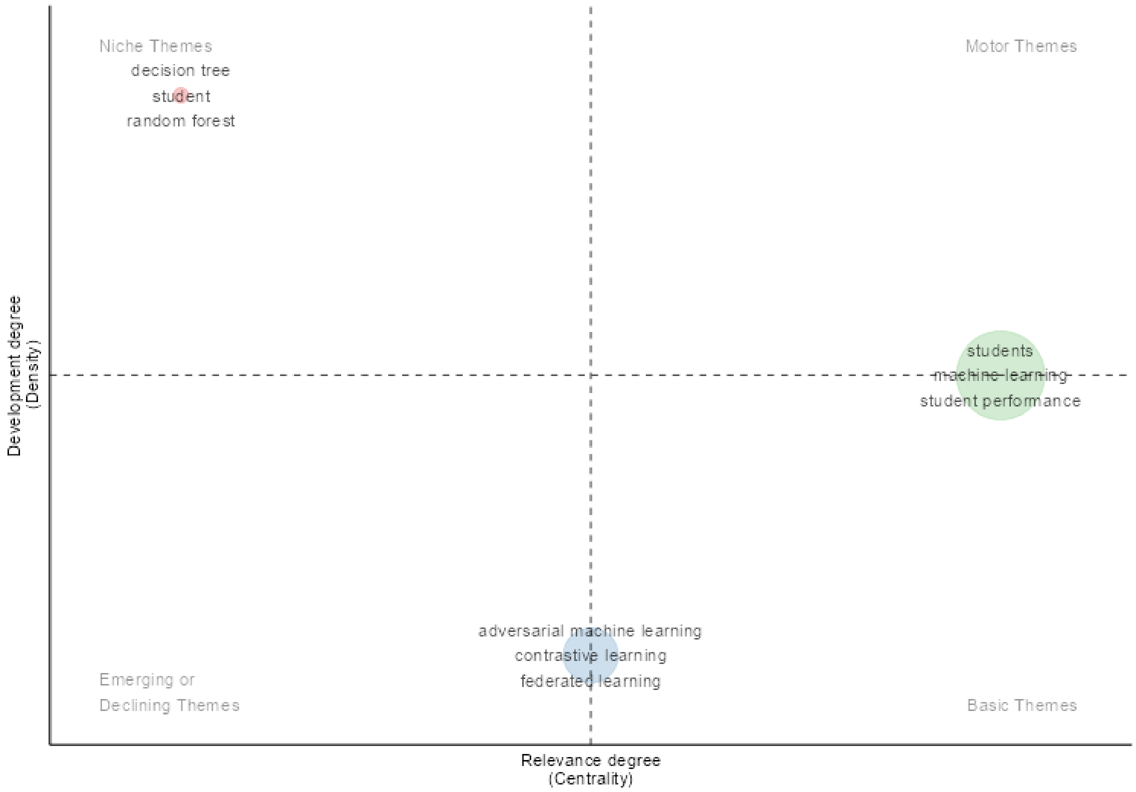

Fig. 7. Thematic Map

On the other hand, themes such as decision trees and random forests emerge as niche themes, namely themes that are quite strongly developed in certain communities but contribute less to the general knowledge structure. Meanwhile, themes such as adversarial machine learning, contrastive learning, and federated learning are located in the emerging or declining themes quadrant, which can be interpreted as topics that are still in the early exploration stage or are starting to decline in relevance. However, based on the relatively new trend of their emergence, these topics are more likely to be categorized as potential emerging gaps that require further exploration. Through the combination of visualizations in Fig. 6 and Fig. 7, it can be concluded that the current research structure is still concentrated on established general themes. However, the emergence of new topics that have not been widely explored opens up opportunities for future research to expand the scope of the study with a more sophisticated and contextual approach.

3.4. Key Contributors and Global Citation Impact

Fig. 7 displays a thematic map that provides important insights into the position and development of key themes in the literature. The themes of students, student performance, and machine learning are in the basic themes quadrant, indicating that although these topics are very central to scientific discourse, there is still great opportunity for conceptual and methodological deepening. This indicates that scientific contributions in this area can still be strengthened through more innovative and contextual approaches, for example by paying attention to aspects of personalization, the ethics of algorithm use, and model interpretability. Themes such as decision trees and random forests, which are in the niche themes quadrant, reflect the use of certain techniques that are developing in a limited community but have not contributed much to the general body of knowledge. On the other hand, the themes of adversarial machine learning, contrastive learning, and federated learning are in the emerging or declining themes quadrant. This position can be interpreted as an area that is still rarely explored in the context of student performance prediction, although all three are modern techniques that have great potential in personalizing learning and processing multi-source data.

The emergence of federated learning and contrastive learning themes as topics that are still limited in terms of density and centrality (see Fig. 7), is a strong signal that new approaches in machine learning have not been widely explored for educational purposes. In fact, in the context of data privacy and diversity of information sources, both approaches offer promising alternatives. The findings from Fig. 7, when combined with the keyword connectivity patterns in Fig. 6, also indicate a lack of integration between the themes of ethics, soft skills, or explainable AI with the domain of student performance prediction. In fact, much recent literature highlights the importance of the dimensions of interpretability and fairness in the development of predictive models for the context of higher education [1], [8], [11]. Therefore, the emerging gaps identified from this mapping include: (1) low exploration of the latest learning approaches such as federated learning and contrastive learning in the context of education; (2) the absence of topics on social and ethical dimensions in predictive models; and (3) limited exploration of non-cognitive variables such as soft skills, motivation, and emotional involvement. These gaps are important opportunities for further research aimed at developing predictive models that are not only accurate, but also contextual, fair, and widely applicable in data-based education systems.

4. Discussion

4.1. Evolution of Publications and Direction of ML Research Growth in EDM

The temporal analysis results show a significant growth in the number of publications examining the application of machine learning (ML) in educational data mining (EDM) for student performance prediction over the past two decades. The most striking spike occurred between 2018 and 2023, with a peak in 2022. This trend is in line with the massive digital transformation in the education system and the increasing need for data-driven solutions in detecting academic risks earlier [24], [35]. Before 2018, publications were relatively limited and dominated by traditional approaches such as simple regression and decision trees [8], [11]. However, post the COVID-19 pandemic, the literature shows a major shift towards the use of advanced models such as ensemble methods, deep learning, and adaptive prediction techniques [11]. This shows that the disruption of education due to the pandemic has accelerated the adoption of ML technology as an academic mitigation strategy, especially in the context of online learning. Several studies have found that the increase in ML adoption in EDM occurs not only quantitatively, but also qualitatively [36]. For example, research by Waheed [37] emphasized that during this period, the focus of research shifted from simply building classification models to designing systems that are more adaptive, interpretive, and support data-based decision-making. In addition to external factors such as the pandemic, the surge in research was also driven by the increasing availability of educational datasets, such as activity logs in LMS (Learning Management Systems), MOOC platforms, and the integration of academic information systems with predictive analytics [17].

This approach not only enables the detection of academic performance but also leads to the design of personalized and sustainable learning systems. The development of publications over time not only shows a consistent increase in quantity but also reflects the evolution of the quality of approaches and strategic directions of research in integrating machine learning into data-driven education systems. shows that ML in EDM has evolved from a limited experimental approach to a strategic and implementation-oriented field of study. The surge in publications post-2020 (See Fig. 2) reflects the systemic need for predictive learning technologies amidst the complexity of modern education systems. The significant increase observed post-2018 was likely instigated by the rapid advancement of educational digitalization due to global disruptions, including the COVID-19 pandemic, alongside the rising investment in adaptive learning technologies and machine learning-based intelligent recommendation systems [11], [17].

4.2. Key Research Contributors

The geographical and institutional distribution of publications shows an interesting configuration of research strengths in the field of machine learning for student performance prediction. Based on the analysis of the collected articles, China is ranked first with the highest number of publications, followed by the United States, India, Morocco, and the United Arab Emirates. This shows that the dominance in this field does not only come from Western countries, but is also driven by the growth of technology research in the Global South countries that are increasingly aggressive in adopting ML for education [11]. China, for example, not only excels in quantity, but also demonstrates involvement in a variety of cross-institutional and cross-disciplinary projects, supported by major investments in artificial intelligence and higher education [8]. Meanwhile, the United States' contribution remains significant despite its lower proportion of international collaborative publications compared to other countries. India and Pakistan show a rapidly increasing trend, especially in research based on engineering universities and polytechnics, reflecting a focus on applying ML to solve local educational problems.

In the institutional context, King Saud University from Saudi Arabia, Universiti Teknologi MARA from Malaysia, and several institutions from China such as Zhejiang University and South China University of Technology are ranked at the top based on publication frequency. The success of these institutions cannot be separated from the national strategy that places AI and digitalization of education as a priority for academic development [17], [35]. Interestingly, some countries such as Pakistan and Indonesia show a high level of international collaboration when compared to the total number of their publications. This phenomenon indicates that active involvement in global research networks is not always determined by the volume of academic production alone, but also by the tendency to build cross-country partnerships to strengthen research capacity [37].

These findings highlight the importance of paying attention not only to the number of publications but also to the patterns of collaboration that underlie global scientific production. The dominance of China and the United States in terms of publication volume indicates established research capacity, while the high proportion of international collaborations from countries such as Pakistan and Indonesia reflect alternative strategies for increasing scientific visibility through global networks. The implications of this distribution point to the need to strengthen multinational research networks, cross-border knowledge transfer, and institutional incentives that support active engagement in international research ecosystems. Thus, the future of research in ML and EDM will depend largely on how inclusive and collaborative the global approach adopted by the scientific community across regions is, as well as collaborative globally. While the main power is still concentrated in a few large countries, the emergence of contributions from developing countries suggests the potential for democratizing knowledge production, which can enrich the perspectives and contexts for the application of educational technology more broadly.

4.3. Dynamics of Scientific Collaboration

Collaboration networks in machine learning research for student performance prediction show complex dynamics but are still limited to regional clusters. The results of the analysis of collaboration networks between countries show that most publications are still dominated by single country publications (SCP), especially from countries with high research capacity such as China, India, and the United States. These countries tend to have established research infrastructures, allowing them to produce publications independently without high dependence on international collaboration [11], [35]. However, when viewed from multiple country publications (MCP), some countries stand out in terms of collaboration. Pakistan, for example, has a very high ratio of MCP to its total publications, with around 50% of articles co-authored by authors from other countries. Indonesia also shows a similar tendency, with 3 out of 7 publications being the result of cross-country collaboration. This fact indicates that although the volume of scientific production in these countries is not as large as that of the dominant countries, their participation in the global research community is quite active and strategic [37].

The fragmentation of collaborative networks is also evident in the structure of the global networks that are formed: clusters of collaboration tend to be isolated by geographic region and language affiliation. Collaborations between Asian countries such as China and India are not always integrated with research centers in Europe or North America. These limitations imply structural barriers to cross-cultural knowledge exchange and policy, which may affect the generalization of educational prediction models to different contexts [8]. Another limitation that emerged was the lack of multidisciplinary collaboration. Most articles were still written by teams with engineering and computer science backgrounds, without much involvement of education, psychology, or ethics experts. In fact, the complexity of the educational context requires a cross-disciplinary approach so that the prediction models built are not only statistically accurate, but also pedagogically relevant and fair [17]. Therefore, the dynamics of scientific collaboration in this field still have room to grow, especially in terms of intensity, diversification, and interregional connectivity. Strengthening international and interdisciplinary cooperation is key to creating a prediction system that is not only technically superior, but also adaptive to the diversity of education systems around the world.

4.4. Thematic Analysis and Dominant Research Trends

Thematic analysis based on co-occurrence mapping and thematic mapping revealed a diverse knowledge structure in machine learning research for student performance prediction. The results of the co-word analysis showed the dominance of keywords such as "student performance," "machine learning," "prediction," "data mining," and "educational data mining," indicating a fairly consistent research focus on the development and application of predictive algorithms in academic contexts (see Fig. 6). In the thematic map, several clusters that stand out as motor themes (central and emerging themes) include topics such as predictive analytics, learning analytics, and performance prediction. These themes reflect the integration of machine learning with learning management systems and digital environments that are actively being developed in higher education [11], [17]. The presence of this theme in the upper-right quadrant indicates that the area is well established and relevant for long-term research sustainability.

Niche themes that emerged, such as ensemble learning and intelligent tutoring systems, signaled a more technical and specific exploration in the development of predictive systems. Although their level of relevance is not as high as motor themes, these topics are important because they offer technology-based solutions that can improve the accuracy and efficiency of academic interventions [8]. Meanwhile, emerging or declining themes that were detected include those related to the latest learning models such as federated learning, contrastive learning, and adaptive boosting. The emergence of these terms reflects that this field continues to evolve following the latest algorithm trends, although its adoption in education is still limited [35], [37]. Some terms also reflect responses to new challenges in digital education, such as ChatGPT integration, learner behavior analysis, and big data-based personalization [11]. On the other hand, basic themes such as classification, logistic regression, and academic achievement still play an important role in forming the conceptual foundation of EDM research. These models, despite their simplicity, remain widely used due to their ease of interpretation and application in real educational contexts.

The results of the thematic analysis show that research in this field has not only diversified in terms of technical approaches, but has also matured in conceptual structure. The shift of several themes from niche to motor themes in the last decade indicates a healthy development dynamic. This also indicates that the integration of machine learning with the education system is not only experimental, but has become a foundation in modern learning management strategies. This study shows that the topic of ML in EDM is growing faster in the adoption of new methods but still faces challenges in integrating the context of education and technology as a whole. Several emerging themes such as federated learning and contrastive learning have not been widely developed, possibly due to limited data infrastructure, privacy constraints, and high technical requirements in their implementation in educational institutions that are not yet systemically ready. Thus, the dominant research trend in ML for student performance prediction shows a balance between methodological exploration and practical implementation. However, to ensure the sustainability of innovation, future research needs to encourage a multidisciplinary approach and consider the socio-cultural context of the education system where the model is applied [17], [38].

4.5. Future Research Paths and Exploration Opportunities

Findings from thematic mapping and publication trend analysis reveal a number of important future research opportunities to be explored further. One of the main findings is the limited exploration of the integration of non-cognitive factors such as motivation, emotional engagement, or social support in student performance prediction models. Most studies still focus on academic data and digital behavior, while affective and social factors that have been shown to have significant contributions to academic achievement are often ignored [11], [38]. In addition, there is still a gap in the adoption of approaches that ensure algorithmic fairness and model transparency. Although model accuracy is the main indicator reported in most studies, issues such as bias against minority groups, predictive inequality, and limitations in model interpretability have not been widely discussed in critical studies. In the future, research needs to combine explainable AI (XAI) principles and ethical evaluation in the development of predictive systems so that their implementation can be accepted by various education stakeholders [37].

From a methodological perspective, although themes such as federated learning and self-supervised learning are emerging as new topics, their use in educational contexts is still very limited. This opens up space for research that tests the feasibility, effectiveness, and efficiency of these cutting-edge approaches in real educational ecosystems. The adoption of these techniques also requires collaboration between AI experts, educational practitioners, and policymakers to ensure the compatibility of the technology with educational needs and ethics [8], [35]. Finally, further efforts are needed to build a holistic and contextual adaptive learning recommendation system. Studies that utilize educational big data have not fully explored the potential of cross-platform data integration such as social media, internal academic systems, and other external sources. With the growing interest in learning personalization, future research can be directed at developing hybrid models that combine machine learning approaches with behavioral analytics and humanistic pedagogy [11], [39], [40]. Future research directions should consider expanding the scope of predictor variables, maturing the ethical and interpretability aspects of the model, and exploring new technologies relevant to the global higher education context. The potential for innovation is still wide open, but its success depends heavily on a cross-disciplinary approach and sensitivity to the social dynamics in the education system. To highlight the contribution and novelty of this study, Table 3 presents a comparison with several relevant bibliometric or systematic studies in the field of education and artificial intelligence. This comparison demonstrates the unique focus and scope of the present study in contrast to previous research.

Table 3. Comparison of Related Bibliometric Studies in the Field of Machine Learning and Education

Study	Method	Focus	Number of Articles	Revealed Gaps
Alalawi et al. [41]	Systematic Review	ML in Higher Education	126	Does not include analysis of collaboration networks and thematic clusters
Kalita et al. [42]	Systematic + Bibliometric	Deep Learning in Education	39	Focuses only on DL methods, does not discuss institutional or global contributions
Aguado-García et al. [43]	Bibliometric	AI in Higher Education	181	Emphasizes ChatGPT and AI engagement, does not address student performance prediction
Nagendhra Rao & Chen [44]	Bibliometric	Data Mining in Education	1,439	Broad scope, not focused on ML for student performance prediction
This study	Bibliometric	ML for student performance prediction	465	Covers trends, country contributions, scientific collaboration, thematic mapping, and explicitly addresses recent research gaps

5. Conclusion

This study aims to map the development of literature related to the application of machine learning in educational data mining for student performance prediction through a bibliometric approach. Based on the analysis of 465 articles indexed in Scopus during the period 2005–2025, several key findings were identified. First, the publication trend shows a significant increase in the last decade, exhibiting a considerable increase post-2018, presumably propelled by the digital transformation in education and the escalating demand for predictive algorithms in online learning. This increase is influenced by the digital transformation in the education sector, as well as the increasing need for predictive systems in managing online learning. Second, the geographical distribution of publications indicates the dominance of countries such as China, the United States, and India in terms of publication volume, while countries such as Pakistan and Indonesia show high intensity of international collaboration despite having lower volumes. Third, the dynamics of scientific collaboration show that most publications are still domestic (SCP), with only a small portion being the result of cross-country collaboration (MCP). This collaboration pattern reflects the limitations in the integration of global research networks, as well as the still minimal involvement of multidisciplinary in the development of educational predictive systems. Fourth, thematic analysis identifies key emerging themes, including predictive analytics, ensemble learning, and intelligent tutoring systems. Some promising new themes such as federated learning and contrastive learning are emerging, but their adoption is still limited due to technical and ethical constraints.

The main contribution of this study is to provide a comprehensive knowledge structure map on the topic of ML for student performance prediction, as well as identifying relevant gaps for future research agendas. Future studies should test whether federated learning works well in privacy-sensitive educational settings. They should also look into using explainable AI techniques to make models more transparent and explore how non-cognitive factors like motivation and engagement can be included. Collaboration between different fields is important to tackle the ethical, teaching, and technology issues involved in creating prediction models that are aware of their context. Practically, these findings can help educational institutions create data-driven early warning systems that aim to lower dropout rates and boost student retention. Policymakers can use this information to create better regulations for AI in higher education, ensuring that innovation supports fairness, equity, and access.

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