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Educational Data Mining and Predictive Modeling in the Age of Artificial Intelligence: An In-Depth Analysis of Research Dynamics

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Abstract: This article provides a comprehensive analysis of the research dynamics on the use of Educational Data Mining (EDM) and predictive modeling (PM) in the era of Artificial Intelligence (AI) based on the review of 793 articles published between 2000 and 2024 in the Scopus database. The study employs bibliometric analysis and systematic literature review to identify emerging trends, methodologies, and applications in these fields. The main objective of the study is to examine the primary methodologies and innovations within AI, especially in the context of EDM and PM. It highlights how these technologies can optimize the prediction of student performance, support personalized learning, and enable timely interventions through the analysis of student data. The study also examines the role of AI in improving teaching practices, ensuring that educators maintain control over the system and minimize potential biases. Furthermore, the article addresses the ethical implications of AI implementation in education, such as privacy protection, algorithm transparency, and equity in access to learning. The findings suggest that AI has the potential to significantly improve educational outcomes and optimize student tracking, resource allocation, and the overall effectiveness of educational institutions. The responsible implementation of AI in education is emphasized to ensure inclusive and fair environments for all students.

Keywords: educational data mining; artificial intelligence; predictive modeling; learning analytics; scientific production

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Academic Editor: Paolo Bellavista

Received: 11 December 2024
Revised: 10 February 2025
Accepted: 11 February 2025
Published: 14 February 2025

Citation: López-Meneses, E.; Mellado-Moreno, P.C.; Gallardo Herrerías, C.; Pelícano-Piris, N. Educational Data Mining and Predictive Modeling in the Age of Artificial Intelligence: An In-Depth Analysis of Research Dynamics. *Computers* **2025**, *14*, 68. https://doi.org/10.3390/computers14020068

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1. Introduction

In the last decade, Artificial Intelligence (AI) has burst into various areas of society, profoundly changing sectors such as healthcare, industry, the economy, and, of course, education. In this context, the use of advanced data mining and predictive modeling (PM) tools has gained unprecedented relevance, offering innovative solutions to address current educational challenges. These advances allow for comprehensive, real-time analysis of educational data, allowing for predicting behavior, improving learning, and, in general, transforming educational management at a global level [1,2].

Educational Data Mining (EDM) refers to the application of data mining techniques in the educational field, with the aim of discovering hidden patterns that help to improve teaching-learning processes. PM, on the other hand, is a technique that uses historical

data to predict future events or behaviors. These tools, when implemented with the support of AI, allow for accurate predictions based on large volumes of data from students, teachers, and other stakeholders in the educational environment [3]. The combination of both disciplines is beginning to redefine the educational landscape, optimizing student performance, identifying the factors that influence their success or failure, and personalizing teaching processes to better fit the needs of each student [4].

The convergence of data mining, PM, and AI has the potential to transform education into a more efficient, inclusive, and accessible system. As educational institutions adopt these technologies, new possibilities open up to personalize learning, more effectively track student progress, and improve data-driven decision-making. However, this transformation is not without its challenges [5,6]. Despite the progress made, there are technical, ethical, and social obstacles that must be overcome to ensure that the use of AI in education is fair, accessible, and effective [7].

The purpose of this paper is to provide a comprehensive analysis of the current state of research in the area of EDM and PM, especially in the context of AI. This paper examines how these technologies have been used in education and what their most notable impacts are, as well as the challenges and opportunities they present for future research. Furthermore, it seeks to provide a critical overview of the research dynamics in these fields, highlighting emerging trends and innovative applications that can significantly improve performance and equity in educational systems.

Throughout this paper, several issues related to EDM and PM will be addressed, starting with a theoretical introduction of each of these concepts, followed by a discussion of how they have been implemented at different levels of the educational system. Concrete examples of how these tools are being used in practice to predict student academic performance, improve classroom management, detect behavioral patterns that can influence learning, and generally transform traditional pedagogy will be analyzed. Furthermore, it will be examined how AI is enabling deeper analysis of educational data, making these processes more effective and efficient.

The analysis of research dynamics in this field reveals several trends. Firstly, it is possible to observe an increase in the number of studies examining the relationship between the use of EDM and the improvement of academic performance. This includes the implementation of PM to identify students at risk of failure, the personalization of learning according to the style and pace of each student, and the optimization of assessment methods. Secondly, the use of PM has been a key approach to decision-making in education as it allows predicting academic outcomes and providing early interventions to students in need. This improves the efficiency of the educational system and promotes more inclusive education, helping to reduce dropout rates and improve equity in access to educational opportunities [8,9].

The article will also discuss the challenges associated with the use of these technological tools in education. One of the main issues is data quality and privacy as EDM and PM systems rely on large volumes of information, often containing sensitive data about students. Furthermore, the use of AI raises ethical questions related to algorithmic bias, transparency, and accountability in data-driven decision-making. These issues are critical to ensure that the use of these technologies is beneficial to all educational actors and does not perpetuate inequalities or exclude certain groups of students.

The main objective of this article is to provide a comprehensive overview of current research in these fields, highlighting not only their applications but also the challenges that need to be overcome for the use of EDM and PM to be truly transformative for the education system. It also aims to offer recommendations for future lines of research, considering the

impact of AI in education and how this technology can be used ethically and effectively to improve student learning and academic performance.

This study represents a significant contribution to the field of educational research, offering a detailed review of the current dynamics in data mining and PM and how these disciplines are being revolutionized by AI. Through a critical analysis, it aims to offer a solid foundation for understanding how these technologies can be used to improve the education system and ultimately benefit students and educational institutions globally.

In this way, this research focuses on how advanced modeling techniques can be applied to analyze and improve learning personalization and academic performance in various educational settings.

A key contribution of this work is the identification of patterns and trends in the use of predictive technologies in the educational field through a bibliometric analysis using SciMAT and a systematic review of the literature. This methodological approach enables the mapping of research evolution, identifying the main emerging technologies, the most relevant approaches, and key advances in data mining and PM applied to education. The contribution of this study is based on the structured analysis of 793 publications from 2000 to 2024, allowing us to understand how these technologies can transform teaching methods and support informed decision-making to improve student performance. Furthermore, the impact of these tools on enhancing educational equity has been assessed by analyzing the distribution of research trends and the extent to which personalized solutions are tailored to students' individual needs. The results of this study are grounded in the co-word analysis and thematic evolution of the field, ensuring a robust and data-driven contribution to literature [10].

As a major innovation, this research offers a renewed perspective on the potential impact of AI on learning personalization, suggesting that the integration of PM can not only optimize academic performance but also promote greater equity in access to educational resources. Furthermore, we have highlighted how AI can facilitate the design of more dynamic learning environments where students receive the necessary support according to their individual characteristics. Finally, this study contributes new lines of research that focus on examining the future applications of AI and PM in education, suggesting paths for future research that seek to maximize the benefits of personalized education and expand its reach globally.

The article is structured as follows: Section 2 provides a comprehensive literature review, examining the key concepts of EDM and PM, with a particular focus on the role of AI in these areas. Section 3 details the methodology, combining a bibliometric analysis of 793 articles from the Scopus database with a systematic review of the literature. Section 4 presents both quantitative and qualitative results, highlighting trends in the use of AI and PM in educational research. Section 5 discusses the findings in the context of previous studies, analyzing the implications for educational practices and technologies. Lastly, Section 6 outlines the main conclusions and suggests directions for future research in the field.

2. Theoretical Framework

This section provides an in-depth exploration of the theoretical foundations underpinning the application of EDM and PM in the context of AI within educational systems. The theoretical framework offers a comprehensive analysis of these evolving fields and presents an overview of their current state, emphasizing the major theoretical concepts and research dynamics that have shaped these domains. The purpose of this section is to contextualize the integration of AI-driven data analytics in education, identify the key

challenges involved, and examine the transformative potential of these technologies in educational practices.

2.1. Educational Data Mining

EDM is an interdisciplinary field at the intersection of education and data science, focused on the application of data mining techniques to educational data to uncover patterns and trends that can improve teaching, learning, and educational management. EDM involves the use of computational tools, algorithms, and statistical methods to analyze vast amounts of student data, such as academic performance, behavior patterns, interactions with digital content, and engagement with learning platforms [11,12].

One of the primary goals of EDM is to enhance the personalization of learning. Traditional educational models often treat students as a homogeneous group, applying the same teaching methods and content to all students. In contrast, EDM allows for a more individualized approach, tailoring content and learning strategies to the needs, abilities, and progress of each student. For example, by analyzing a student's past performance data, EDM systems can recommend appropriate learning resources and predict potential areas of difficulty, enabling early interventions.

In recent years, EDM has shown significant potential in various applications, such as predicting student performance, identifying at-risk students, and improving learning outcomes. For instance, PM developed through EDM can be used to forecast whether a student is likely to pass or fail a particular course, which can prompt timely interventions by educators or academic advisors [13,14]. These PM leverage historical data to identify patterns and make accurate predictions, thus improving decision-making processes in educational settings.

Furthermore, EDM is also useful in providing insights into broader educational trends. By analyzing aggregated data from multiple students, educators and researchers can identify trends related to curriculum effectiveness, teaching methods, and student engagement [15–17]. This macro-level analysis helps educational institutions to assess the overall impact of their educational practices and adjust their strategies accordingly to meet the needs of their students.

2.2. Predictive Modeling in Education

PM is a statistical and computational technique used to forecast future outcomes based on historical data. In the context of education, PM has become a powerful tool for assessing student performance, engagement, and progression, as well as predicting potential challenges such as student dropout or failure [18]. PM rely on sophisticated algorithms and machine learning techniques to generate insights from data, which can then be used to inform educational practices.

The application of PM in education can take many forms. One common use is in predicting student academic achievement. By analyzing a range of factors (such as past grades, attendance, socioeconomic background, and learning behaviors), PM can generate accurate forecasts of students' future performance. These models provide valuable insights into which students may be at risk of falling behind, enabling early interventions such as personalized tutoring, counseling, or additional academic support. PM also helps educators to identify students who may benefit from more challenging coursework or advanced learning materials, ensuring that each student receives an educational experience that is tailored to their needs [19,20].

Another important application of PM is its role in course planning and curriculum design. By analyzing large datasets, PM can identify patterns in student learning preferences, content consumption, and engagement with educational materials. This information

can be used to redesign curricula, develop more effective teaching strategies, and enhance overall learning outcomes. PM also enables instructors to adjust the pacing of lessons and allocate resources more efficiently, optimizing both teaching and learning experiences [20].

Additionally, PM has a key role to play in identifying at-risk students and preventing school dropout. Data collected from various student interactions, such as online quizzes, assignments, forum participation, and attendance, can be analyzed to detect signs of disengagement or academic struggles [21]. Early warning systems powered by PM can alert educators to students who may be at risk of failing or leaving school, allowing them to provide timely support and prevent negative outcomes.

While PM offers significant advantages, it is important to note that the accuracy and reliability of these models depend on the quality and comprehensiveness of the data used. Inaccurate or incomplete data may lead to incorrect predictions, which could affect the educational interventions implemented [22]. Therefore, it is key for educational institutions to ensure that the data used in PM is both accurate and representative of the student population.

2.3. AI and Its Application in Education

AI has become an integral part of the digital transformation in education, bringing new opportunities to enhance learning experiences, personalize education, and improve teaching practices. AI in education encompasses a wide range of technologies, including machine learning, natural language processing, and deep learning algorithms, all of which work together to analyze data, automate processes, and adapt learning experiences to meet the unique needs of individual students [23,24].

One of the most significant ways AI is transforming education is through adaptive learning systems. These systems use AI algorithms to analyze student data and dynamically adjust the content, difficulty, and delivery of educational materials in real time. For example, an AI-driven learning platform can assess a student's progress on a particular subject and modify the learning path accordingly [25]. If a student is struggling with a specific topic, the system may offer additional resources or practice exercises to help them to master the material before moving on to more advanced topics.

AI also offers personalized learning experiences that are tailored to the unique needs and learning styles of individual students. By analyzing data such as previous academic performance, learning speed, and preferred learning methods, AI systems can deliver customized content that caters to each student's strengths and weaknesses. This personalization helps students to learn more effectively, reducing the frustration and disengagement that can arise from a one-size-fits-all approach to education [26,27].

Furthermore, AI technologies have the potential to automate various administrative tasks that currently consume valuable time and resources. Grading assignments, assessing student progress, and generating reports are some of the tasks that can be automated using AI, allowing educators to focus more on teaching and engaging with students [28]. In addition, AI systems can provide real-time feedback to students, helping them to understand their mistakes and improve their performance more quickly.

AI can also assist in teacher training and professional development. By using AI to analyze classroom interactions and instructional practices, educators can receive personalized recommendations for improving their teaching techniques. AI-powered platforms can provide teachers with insights into their students' learning progress, suggest new pedagogical approaches, and offer resources for professional development [29,30].

Despite the many advantages AI brings to education, its implementation is not without challenges. One of the major concerns is the potential for bias in AI algorithms. AI systems are trained on data, and if the data used to train the models contains biases or reflects

existing inequalities, the AI algorithms may perpetuate or amplify these biases [31,32]. For example, if an AI model is trained on data from a particular demographic group, it may not perform as effectively for students from different backgrounds. Ensuring that AI systems are fair and unbiased is critical to their success in education.

2.4. Ethical and Technical Challenges in Implementing AI in Education

While AI holds great promises for transforming education, its implementation raises significant ethical and technical challenges that need to be addressed to ensure its effective and responsible use. The ethical challenges of AI in education are multifaceted and include concerns related to data privacy, algorithmic transparency, and fairness.

- Data Privacy and Security: One of the primary ethical concerns related to AI in education is the collection and use of student data. AI systems rely on vast amounts of data to function effectively, including sensitive personal information about students. These data may include academic performance, behavioral data, learning habits, and demographic information [33,34]. Protecting these data and ensuring that they are used responsibly is essential. Educational institutions must adhere to strict data privacy regulations, such as the General Data Protection Regulation (GDPR) in Europe, to ensure that students' personal information is not exploited or misused [35].
- Algorithmic Transparency and Accountability: Another ethical issue is the opacity of AI algorithms. Many AI systems, particularly machine learning models, operate as "black boxes", meaning that it is difficult to understand how they make decisions. In educational settings, where AI-driven decisions can significantly impact students' futures, this lack of transparency is problematic [36]. For instance, if an AI system recommends a student for remedial support or suggests a particular learning path, it is key for educators and students to understand how the decision was made. Ensuring the transparency and explainability of AI algorithms is necessary to build trust in these systems and ensure that they operate fairly [37].
- Bias and Fairness: AI systems can perpetuate existing biases if they are trained on biased data. For example, if an AI model is trained on data that reflect societal inequalities, it may reinforce those biases and result in discriminatory outcomes. In education, this could mean that certain groups of students may receive inaccurate predictions or less favorable treatment based on their gender, race, or socioeconomic status [38]. To address this challenge, it is essential to ensure that the data used to train AI models are diverse and representative of all students and that the algorithms are regularly evaluated for fairness [39].
- Technical Challenges: In addition to the ethical concerns, there are several technical challenges associated with implementing AI in education. One of the primary challenges is the quality and availability of data. AI systems rely on accurate, complete, and well-organized data to function effectively [40]. However, many educational institutions face challenges related to data quality, such as missing or incomplete information, inaccurate data, and inconsistent formats. Educational institutions must invest in data infrastructure and ensure that their data are of high quality and properly structured for AI applications [41].

Another technical challenge is interoperability. Many educational institutions use a variety of digital platforms, learning management systems (LMSs), and other educational technologies that may not be designed to work together seamlessly. This lack of interoperability can make it difficult to integrate AI systems across different platforms and share data between them, limiting the potential impact of AI on educational practices. Ensuring that AI systems can work across diverse educational technologies will be essential for their widespread adoption [42,43].

2.5. The Transformative Potential of AI in Education

Despite the challenges, AI holds transformative potential for the future of education. The ability to personalize learning, predict student outcomes, and enhance teaching practices could revolutionize educational systems around the world. By leveraging AI technologies, educational institutions can provide more individualized learning experiences, improve student outcomes, and create more efficient and effective learning environments [44,45].

AI can help to level the playing field by providing personalized support to students, particularly those from disadvantaged backgrounds or those with learning disabilities. Through adaptive learning technologies and PM, AI can identify students who may need additional support and provide them with the resources they need to succeed. Additionally, AI can help to reduce educational inequalities by providing equitable access to high-quality learning resources, regardless of a student's geographic location or socioeconomic status [46].

As AI continues to evolve, its potential to transform education will only increase. The integration of AI into educational systems offers a unique opportunity to reimagine the way we teach and learn, creating more flexible, efficient, and inclusive learning environments [47,48].

3. Materials and Methods

The study focuses on analyzing the dynamics of research related to EDM and PM in the context of AI. The aim is to provide a comprehensive overview of the trends shaping the development of this field from the earliest available studies in 2000 to the most recent publications in 2024. This analysis combines a systematic qualitative review with advanced bibliometric methods, enabling the identification of key research areas and potential future directions. The research is particularly relevant due to the increasing integration of AI in educational contexts, where data mining and predictive techniques are employed to optimize teaching, learning, and educational outcomes.

To conduct this study, a set of 793 academic articles was collected by performing a keyword-based search in the Scopus database. The selected terms ("education", "teaching", "learning", "artificial intelligence", "data mining", and "predictive modeling") were chosen to ensure a broad yet focused representation of the field. The initial search aimed to gather all relevant publications within the defined timeframe. Subsequently, a data cleaning process was undertaken to remove duplicates and inconsistencies, such as variations in author names or abbreviations. This was fundamental to enhance the reliability of bibliometric analysis.

To analyze the dataset, the Science Mapping Analysis Tool (SciMAT) was employed, providing a detailed review of thematic areas and term co-occurrence networks. Additionally, VOSviewer (version 1.6.20, Leiden University, Leiden, The Netherlands) was used to create visual network maps, representing the frequency of key terms and their connections across the body of literature [49]. The co-occurrence analysis enabled the identification of dominant and emerging research trends, illustrating how the use of AI has evolved in relation to EDM and PM.

Through the bibliometric review, the most frequently occurring keywords were identified, offering insights into the thematic focus of the field. These terms were ranked using relevance scores based on their frequency in titles, abstracts, and keywords. The results revealed a strong focus on topics such as adaptive learning systems, personalized education, ML algorithms, and educational analytics. The analysis also highlighted the growing significance of ethical and practical challenges, including data privacy, algorithmic bias, and the equitable implementation of AI technologies in education [50,51].

The network maps generated by VOSviewer illustrated the evolution of research themes over time. Clusters of related terms were identified, reflecting interconnected areas of study. For example, one cluster might focus on predictive analytics and its applications in identifying at-risk students, while another might center on the integration of AI-driven adaptive learning platforms. These clusters provided a nuanced understanding of how various subfields interact and how they contribute to the overarching goals of improving educational practices through technology [52,53].

This study further examines the methodological approaches used in the selected articles. A considerable proportion of the research employs ML models such as decision trees, neural networks, and support vector machines to predict educational outcomes. These models are often trained on large datasets derived from LMS, online platforms, or standardized assessments. The findings suggest a steady improvement in predictive accuracy and the scalability of these models, enabling their application in diverse educational contexts.

The bibliometric review also sheds light on the temporal dynamics of research activity in this area. The early 2000s saw a modest number of studies focused on basic data mining techniques applied to educational datasets. However, the mid-2010s marked a significant shift, with the advent of more sophisticated AI algorithms and increased computational capacity. This period coincides with a surge in publications examining deep learning and its potential to revolutionize personalized education. More recently, the COVID-19 pandemic acted as a catalyst for research on AI-driven tools to address challenges in remote and hybrid learning environments.

Despite these advancements, the study identifies several limitations and challenges that remain unresolved. For instance, while bibliometric analysis provides a quantitative overview of research trends, it does not fully capture the qualitative dimensions of how AI and PM impact teaching and learning in real-world settings. Factors such as teacher adaptation, student engagement, and the contextual nuances of educational environments are often underexplored. Future research could address these gaps by incorporating qualitative methods, such as case studies or interviews with educators and students.

Another limitation of the current analysis is its reliance on articles indexed in Scopus, which excludes other potentially relevant sources, such as conference proceedings, technical reports, and book chapters. Expanding the scope to include these types of publications could offer a more holistic view of emerging trends and applications. Additionally, ethical concerns related to AI, such as issues of equity, transparency, and accountability, are often treated as peripheral topics rather than integral components of educational research. Addressing these concerns will require interdisciplinary collaboration between technologists, educators, and policymakers.

The study also recognizes that the evolution of research in this field is influenced by external factors. Changes in educational policies, technological advances, and global events, such as the pandemic, have shaped research priorities and applications. For example, the urgent need for scalable, AI-driven solutions during the pandemic accelerated innovations in remote learning and student performance tracking. However, the long-term implications of these developments remain unclear, highlighting the need for ongoing investigation.

This study provides a comprehensive analysis of research dynamics in EDM and PM within the context of AI. By combining systematic review and bibliometric techniques, it identifies key trends, challenges, and opportunities in the field. The findings underscore the transformative potential of AI in education while also highlighting the need for ethical and context-sensitive approaches. As the field continues to evolve, future research should aim to bridge the gap between technological innovation and its practical, equitable implementation in diverse educational settings.

The literature segmentation process and the application of the analysis model used in the study are described. For this purpose, the Science Mapping Analysis Tool (SciMAT) was used, which allowed a detailed bibliometric analysis of the selected articles to be carried out [54]. SciMAT was used to process the literature and perform a visual mapping of the main trends and relationships between the different studies on EDM, PM, and AI in the educational field.

To ensure the relevance and quality of the included articles, inclusion and exclusion criteria were established. The selected articles had to be directly related to the use of EDM techniques and PM and their implementation in education with the support of AI. Studies that did not explicitly address the application of these technologies or that lacked results applicable to improving academic performance or personalizing learning were excluded. In addition, a visualization of the methodological process has been included, showing how the articles were segmented and grouped according to the key themes identified, allowing a more structured analysis of the emerging trends in this field. This segmentation and visualization were essential to understanding the main areas of research and the most-used methodologies in the reviewed studies.

4. Results

This section presents the temporal distribution of publications in the field of EDM and PM from 2000 to 2024. It includes an analysis of the evolution of keywords and research lines during this period, shedding light on the thematic focus and technological advancements that have shaped the domain. Additionally, future research directions are identified using score relevance, offering insights into emerging trends and priorities for advancing personalized learning and optimizing teaching methodologies through AI-driven approaches.

4.1. Assessment of the Evolution of Scientific Output

The evolution of scientific production in the field of EDM and PM between 2000 and 2024 (Figure 1) reflects a panorama of transformation, consolidation, and boom, with differentiated patterns that can be classified into three main phases: the beginning and initial growth (2000–2013), consolidation and expansion (2014–2019), and boom and maturity (2020–2024). This analysis, based on the data provided, reveals both the magnitude and the dynamics of the development of this interdisciplinary field, in which AI, data analytics, and educational sciences converge.

During the first phase, between 2000 and 2013, scientific production was limited and characterized by slow initial growth. In this period, only 33 cumulative articles were published, representing barely 9% of the total produced until 2024. This initial performance can be attributed to the fact that the technologies necessary to apply data mining and PM techniques in the educational field were still in development, as were the technological infrastructures and databases that make data mining possible. Annual production in this period ranged between 1 and 12 articles per year, reflecting an incipient interest in the area. However, it is important to note that, although the volume of publications was low, the annual percentage growth rates in some years were notable. For example, in 2000 and 2001, the growth was 200% and 133%, respectively, although these figures reflect increases on very small numerical bases. Beginning in 2013, the field experienced a significant leap, marked by a 371% variation in the number of articles published. This growth can be explained by the rise of LMS and the increasing access to large volumes of educational data, which laid the foundations for the future expansion of this discipline [55].

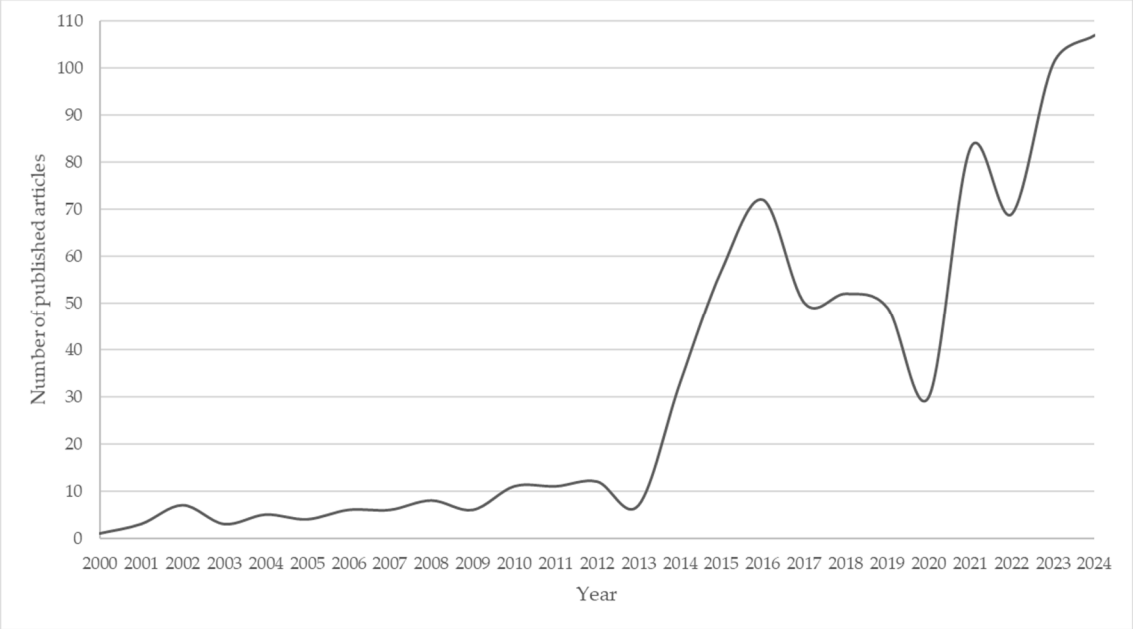


Figure 1. Dynamics of research publications over time (2000–2024).

The second phase, between 2014 and 2019, marks the period of consolidation and the expansion of research in EDM and PM. During this period, there was a notable increase in the number of annual publications, reaching an average of 52 articles per year. By 2019, the cumulative number of articles stood at 299, representing approximately 76% of the total accumulated to that date. This sustained growth suggests a consolidation of the area as an established field of research, driven by the convergence of technological advances in AI, the availability of big data in education, and the interest in improving the personalization and effectiveness of learning through analytical tools. Data mining techniques began to be integrated with pedagogical methodologies, and research examined practical applications in predicting academic performance, identifying dropout patterns, and personalizing learning trajectories [56,57]. However, despite this boom, growth during this phase was not uniform. In 2016, for example, a 31% drop in the annual variation of publications was observed, possibly due to changes in funding priorities or the saturation of certain lines of research. Similarly, in 2019, a 39% drop was recorded, which may indicate that some lines of research were reaching a maturity that required reorientation towards new challenges and research questions.

The third phase, corresponding to the period from 2020 to 2024, is characterized by the rise and maturity of scientific production in EDM and PM, largely due to the impact of AI as a driver of innovation in the educational field. In 2020, there was a significant jump in annual growth, with a variation of 177%, leading to an accumulation of 390 articles. This boom is intricately linked to the increase in the adoption of AI technologies during the COVID-19 pandemic, which accelerated the transition to digital learning environments and encouraged the implementation of PM to adapt learning experiences to the individual needs of students. From this point on, scientific production continued to expand at a remarkable pace, reaching a maximum of 107 publications in 2024, representing 30.23% of the total accumulated to that date. This sustained growth underlines the relevance of the field in the current context of digital education, where data mining and PM tools are playing a key role in informed decision-making, both at the institutional level and in personalizing learning [58,59].

A highlight of this period is the increasing diversification of research lines, which now address topics such as ethics in the use of educational data, equity in automated learning

systems, and the integration of PM with inclusive pedagogical approaches. Furthermore, advances in ML techniques, such as deep learning models and adaptive learning systems, have made it possible to examine new applications in formative assessment, the early detection of learning problems, and the improvement of educational outcomes. In this sense, research is not only focused on the development of more accurate models but also on their practical implementation in diverse educational contexts, fostering a closer connection between theory and practice [60,61].

In terms of growth dynamics, the evolution of the annual percentage change over this period shows fluctuations, reflecting both the challenges and opportunities inherent to the field. For example, the 17% decrease in 2021 suggests a slowdown after the initial pandemic-driven boom, while the 46% increase in 2022 indicates a revival of interest in new applications and approaches. These variations highlight the dynamic and evolving nature of EDM and PM research, which continues to adapt to the emerging needs of an increasingly digitalized and data-centric global education system.

Overall, the evolution of scientific production in this field reflects a journey of maturation, from its experimental beginnings to its consolidation as a key discipline to address contemporary challenges in education. As it progresses, the field continues to expand in innovative directions, guided by the intersection of AI, data analytics, and educational sciences. This historical analysis not only provides insight into past developments but also identifies emerging areas that promise to further transform the way education is understood and practiced in the digital age [62,63].

4.2. Keyword Dynamics in Scholarly Output

In recent years, the intersection of EDM and AI has become a central focus in the evolution of teaching and learning processes. The advancements in AI technologies, particularly ML and deep learning, have revolutionized how educational systems analyze and predict student performance. In this context, PM emerges as a powerful tool to optimize educational practices by forecasting learning outcomes and personalizing the learning experience.

This study delves into the research dynamics of EDM and PM, drawing insights from a comprehensive analysis of key research areas. Using co-occurrence analysis, we identified the most influential keywords and their corresponding clusters, which reflect the thematic evolution of this field. The data, extracted using VOSviewer 1.6.20 software, categorize the keywords into five distinct clusters, namely, (1) Deep Learning and Natural Language Processing in Education and Technology; (2) ML and AI Applications in Security and Engineering; (3) Feature Extraction and Pattern Recognition in ML and AI Systems; (4) Intelligent Systems and Data Analysis in Education; and (5) Knowledge Management Systems and Big Data Analytics. Each cluster highlights a key area of focus within the intersection of AI and education, providing a clearer overview of the evolving trends and research priorities in this field.

The keywords presented in Table 1 reveal the rapid integration of AI in education. Concepts such as “machine learning”, “deep learning”, and “neural networks” underscore the pivotal role of AI algorithms in enhancing learning personalization and prediction of academic success. Furthermore, keywords like “educational data mining”, “data science”, and “predictive analysis” are instrumental in the analysis of large datasets, enabling educators to identify performance trends and make informed decisions. Keywords related to “big data”, “e-learning”, and “online learning” emphasize the ongoing digital transformation of education, fostering more flexible, accessible, and tailored learning experiences.

Table 1. 30 key terms (2000–2024).

R	Keyword	N	Cluster	Links	TLS	R	Keyword	N	Cluster	Links	TLS
1	machine learning	286	2	231	1085	16	semantics	33	5	87	184
2	deep learning	105	1	156	447	17	extraction	31	1	92	157
3	forecasting	73	2	131	322	18	data science	30	1	77	163
4	neural networks	61	2	143	286	19	natural languages	30	1	79	203
5	feature extraction	61	3	123	292	20	pattern recognition	30	3	67	106
6	big data	48	5	102	188	21	information retrieval	29	5	88	164
7	natural language processing	47	1	106	307	22	feature selection	28	3	81	163
8	decision making	46	4	98	187	23	text processing	27	1	70	162
9	sentiment analysis	43	1	90	220	24	machine learning techniques	25	2	71	118
10	social networking (online)	39	1	95	197	25	internet of things	23	1	54	99
11	text mining	35	1	77	165	26	supervised learning	21	3	57	88
12	data handling	35	2	103	180	27	visualization	21	4	50	81
13	e-learning	34	4	80	147	28	data visualization	20	4	55	84
14	nearest neighbor search	33	2	91	161	29	education computing	20	4	40	75
15	educational data mining	33	4	54	103	30	computer vision	19	3	56	88

R: rank, N: occurrences, and TLS: total link strength.

By examining these trends, this analysis provides a comprehensive understanding of how AI technologies are reshaping the educational landscape, offering new opportunities for innovation, and improving learning outcomes.

Each of these clusters has a significant interrelationship in the educational field, collaborating to improve the personalization of learning, optimize educational management, and guarantee a more accessible, equitable, and quality education. A co-occurrence analysis of the keywords was carried out in the sample articles related to the research topic. Figure 2 presents the network representation of these keywords. From this analysis, it was identified that the keywords were grouped into five clusters, each with homogeneous characteristics, reflecting specific thematic areas within the field of EDM and PM.

- Cluster 1: Deep Learning and Natural Language Processing in Education and Technology

This cluster (pink) encompasses keywords related to deep learning and natural language processing and their application in various fields, particularly in education and technology. It includes topics such as sentiment analysis, social networking (online), data science, and text mining, which highlight the integration of advanced AI techniques for personalizing learning and predicting academic behaviors. The use of complex algorithms, deep neural networks, and data mining in this cluster reflects the focus on analyzing large volumes of unstructured data, such as text and interactions on digital platforms, to improve decision-making and optimize educational management [14].

This field of research is oriented toward developing intelligent systems that can adapt to the individual needs of students, using ML models that analyze complex data to detect performance patterns, personalize content, and predict outcomes. In addition, applications of emerging technologies, such as cloud computing, chatbots, emotion recognition, and face recognition, highlight the potential of AI in creating more interactive and dynamic educational environments [64].

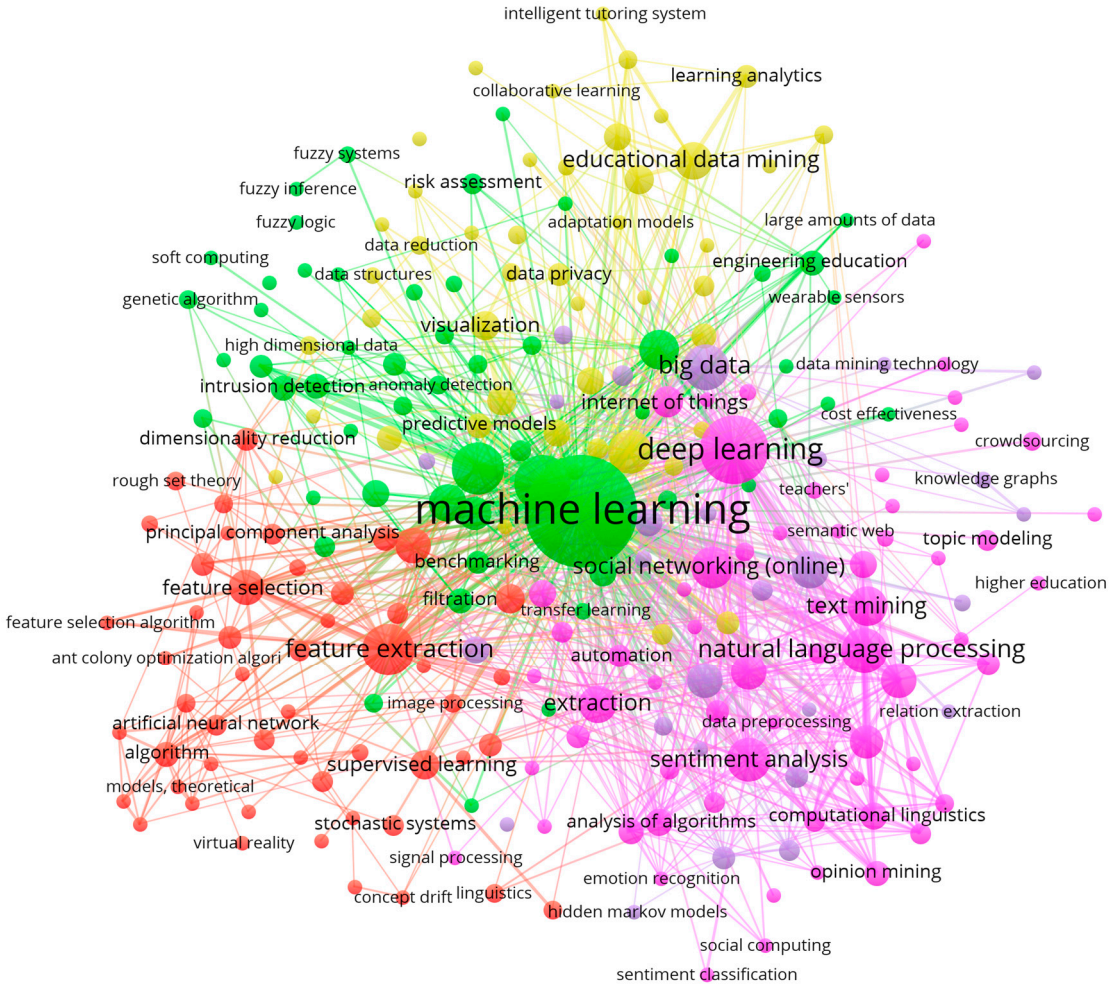


Figure 2. Keyword Co-occurrence Network (2000–2024).

- Cluster 2: ML and AI Applications in Security and Engineering

This cluster (green) is composed of key terms related to ML techniques, neural networks, and AI applied to various fields, with a particular focus on data security and engineering. Topics include forecasting, anomaly detection, ML algorithms, support vector machine, and risk assessment, which highlight the application of predictive and diagnostic models in areas such as intrusion detection and risk analysis. Also highlighted are terms such as decision tree, neural network, and swarm intelligence, which reflect the use of advanced AI algorithms to optimize processes and improve decision-making in complex environments [65].

This field of research focuses on the use of ML models to address problems such as fault detection, big data classification, and improving computer security through anomaly detection algorithms. In addition, the integration of techniques such as fuzzy logic, genetic algorithms, and radial basis function networks shows the interest in adaptive and accurate solutions in situations of high uncertainty, such as data protection and the optimization of industrial systems. The research also examines applications in areas such as engineering education and computer-aided diagnosis, highlighting the transformative potential of ML in education and medicine [66].

- Cluster 3: Feature Extraction and Pattern Recognition in ML and AI Systems

This cluster (red) focuses on advanced ML and data processing techniques, especially feature extraction and selection, pattern recognition, and the use of AI algorithms to improve the accuracy and efficiency of PM. Key terms such as feature extraction, pattern

recognition, supervised learning, and unsupervised learning indicate an intensive focus on identifying and classifying patterns within large volumes of data, which is essential for tasks such as computer vision and computer simulation [67].

One of the main contributions of this cluster lies in the use of optimization algorithms and statistical techniques to improve the performance of models. Terms such as evolutionary algorithms, reinforcement learning, and stochastic systems reflect the use of adaptive and self-adjusting approaches in solving complex problems. In addition, the use of Principal Component Analysis (PCA) and dimensionality reduction underscores the importance of reducing data complexity to improve the interpretability and performance of learning models.

This cluster also addresses the field of bioinformatics and the use of algorithms such as Ant Colony Optimization for the optimization of biological processes, which could have implications in drug discovery or genetic sequencing. The incorporation of ensemble learning and adaptive boosting indicates an emphasis on improving the accuracy of models by combining multiple algorithms. Furthermore, the exploration of decision support systems and feedback shows the potential of these models for practical applications, such as decision-making in complex environments [68].

This line of research stands out for its ability to integrate supervised and unsupervised learning techniques, together with advanced optimization and dimensionality reduction methods, in applications ranging from computer vision to stochastic systems analysis in various fields, including the health and engineering sectors.

- Cluster 4: Intelligent Systems and Data Analysis in Education

This cluster (yellow) focuses on the integration of advanced technologies, such as AI, ML, intelligent systems, and data analysis, with the aim of optimizing educational processes. It examines how digital tools, PM, and recommendation systems can improve educational efficiency, personalized learning, and the assessment of student performance.

One of the main contributions of this line is personalized education since the use of PM and ML allows content and pedagogical strategies to be adapted to the individual needs of students, favoring a more efficient learning experience. In addition, through the analysis of educational data and the use of techniques such as data mining, data visualization, and ML, the prediction of students' academic performance and the early identification of problems are facilitated, allowing for more effective interventions [69].

Another relevant aspect is the optimization of decision-making within the classroom. The incorporation of intelligent systems, such as intelligent tutoring systems or intelligent agents, helps teachers to make informed decisions about content and pedagogical approach, adapting them to the changing needs of students. Furthermore, with the increase in the use of educational data, privacy protection and information security have become key areas, driving research into technologies such as blockchain and cryptography to preserve user privacy.

The use of data visualization and visual analytics also plays an essential role in facilitating the interpretation of large volumes of educational data, helping teachers to make more informed decisions based on student behaviors and outcomes [70]. Finally, this line of research contributes to innovation in curricular design, using PM and multilayer neural networks to adapt educational curricula to the emerging needs of the technological and educational environment. Together, these investigations seek to improve teaching and learning methods, focusing on educational technology, automatic adaptation to the student, and the predictive analysis of performance.

- Cluster 5: Knowledge Management Systems and Big Data Analytics

This cluster (cyan) focuses on the integration of advanced technologies for the management, analysis, and extraction of information from large volumes of data, known as big data. Approaches such as ML, data mining, information retrieval, and knowledge discovery are examined to improve the understanding and use of data in various areas.

One of the main contributions of this line is the development of knowledge-based systems, such as information retrieval systems and knowledge-based systems, which allow large amounts of unstructured data to be processed and transformed into useful information. Techniques such as information extraction, named entity recognition, and association rule mining stand out, which allow patterns and relationships to be identified within data, facilitating decision-making in different contexts, including the criminal field, where it can be applied to predict crimes [71,72].

In addition, knowledge graphs and data warehouses are fundamental tools for organizing and representing information efficiently, which improves knowledge management within organizations. Big data analytics also plays a key role in making informed decisions and identifying trends from large data sets. Research in hidden Markov models and image segmentation also contributes to advancement in areas such as character recognition and image analysis, which have significant applications in automation and AI.

This line of research stands out for its ability to improve information management in complex contexts where semantic analysis and relation extraction are essential to understanding data and obtaining actionable insights, improving efficiency in problem solving in sectors such as information search, knowledge management, and large-scale data analysis [73].

4.3. Emerging Themes in Future Research

Table 2 presents a detailed overview of the emerging research directions identified through the cluster analysis based on the relevance scores assigned to key terms. This table highlights the most significant topics currently shaping the field of EDM and PM in the context of big data and knowledge management. The terms listed in the table represent the latest advancements and areas of focus within this rapidly evolving discipline, offering a clear indication of the trends and challenges that researchers are addressing.

Table 2. Research horizons identified through relevance scoring methods.

Rank	Future Line of Research	Relevance Score
1	Hierarchical Active Learning	10.668
2	Comprehensive Understanding	10.638
3	Vulnerability Detection Method	10.149
4	Collaborative Consortium	10.149
5	Ant Colony Optimization	10.133

Each term in Table 2 is linked to a specific cluster, providing insights into how these concepts are interrelated and contributing to the development of new methodologies in educational research. The table categorizes the terms according to their relevance and frequency of occurrence, making it possible to trace the shifts in focus and to pinpoint the most innovative areas for future exploration.

The detailed description that follows in the next sections expands on the clusters and research directions identified in Table 2, offering a comprehensive analysis of how these emerging topics are shaping the future of AI applications in education, data-driven decision-making, and knowledge discovery.

- Hierarchical Active Learning

Hierarchical Active Learning (HAL) is a line of research aimed at improving efficiency and accuracy in EDM and PM. This approach integrates the principles of active learning with hierarchical structures to optimize data selection and labeling, strategically addressing the heterogeneity and multidimensionality characteristic of educational data, such as academic records, interactions on digital platforms, and student behavior patterns [74,75].

The advancement of knowledge in this area focuses on the development of systems that reduce the dependence on massive manual labeling, prioritizing data that provide greater value to model learning. The incorporation of HAL in combination with AI can facilitate the early detection of at-risk students, improve learning personalization, and increase the accuracy of academic predictions.

The hierarchical approach allows data to be analyzed at different levels, from individual patterns to institutional trends, offering a comprehensive view that promotes more informed data-driven decisions. This opens up possibilities for significant innovations in pedagogical design and academic management, responding to the challenges of modern education [76,77].

HAL research can contribute to the advancement of knowledge in areas such as the optimization of learning algorithms, adaptability to diverse educational contexts, and the creation of scalable solutions that support the transformation of educational processes through AI.

- Comprehensive Understanding

The Comprehensive Understanding research line seeks to address the need for comprehensive analysis that connects data, models, and educational contexts. This approach focuses on going beyond isolated predictions, developing methodological frameworks that allow interpreting and contextualizing results in terms of pedagogical impact, equity in learning, and the personalization of educational experiences.

The advancement of knowledge in this area lies in the ability to integrate multiple dimensions of educational data, such as sociodemographic factors, digital interaction patterns, and academic results, with AI techniques that are not only predictive but also explanatory. This would allow identifying not only what will happen but also why it happens, offering educators and academic managers more robust tools to make informed decisions [78,79].

In addition, this approach can help to bridge the gap between technical analysis and practical applications, ensuring that PM is accessible and understandable to a wider audience, including teachers and educational policymakers. The pipeline also has the potential to address ethical and transparency issues in the use of AI in education, promoting responsible and equitable practices.

This research can advance knowledge by providing a deeper and more holistic view of how educational data can be used not only for prediction but also to improve the quality of teaching, design more effective interventions, and personalize learning processes for the benefit of students [80,81].

- Vulnerability Detection Method

The Vulnerability Detection Method research line focuses on developing advanced methods to identify critical points or vulnerabilities in educational systems through data analysis. This approach seeks to detect early risk factors that may affect student performance, equity in access to learning, or the effectiveness of pedagogical strategies [82].

The advancement of knowledge in this area lies in the creation of models that combine AI techniques and statistical analysis with a deep understanding of educational contexts. This would allow the identification of hidden patterns that may indicate structural vulnera-

bilities, such as the exclusion of specific groups of students, the ineffectiveness of certain teaching methods, or the lack of resources in critical areas.

In addition, vulnerability detection methods can help to predict and prevent problems before they manifest, providing educators and academic managers with key information to design specific and targeted interventions. This approach has the potential to transform the way educational institutions manage risks by allowing them to act proactively rather than reactively [83]. This line of research can also contribute to ensuring the sustainability of AI applications in education by identifying limitations in existing models and proposing solutions that promote their adaptability and robustness. Ultimately, research in this field will advance knowledge by improving the resilience of educational systems, fostering equity, and personalizing learning for the benefit of all students.

- Collaborative Consortium

The Collaborative Consortium research line proposes the development of interdisciplinary collaboration networks that integrate researchers, educators, technological developers, and educational policymakers. This approach seeks to enhance the exchange of knowledge, resources, and data to jointly address the complex challenges in the application of AI in education [84].

The advancement of knowledge in this area lies in the ability to bring together diverse and complementary perspectives to design PM that is more inclusive, robust, and adapted to different educational contexts. Collaborative consortia can facilitate the collection and analysis of educational data from different regions and educational levels, promoting a global approach that identifies patterns and solutions applicable on a large scale.

In addition, this approach encourages the creation of common standards for the use of educational data, guaranteeing interoperability between systems, data privacy, and transparency in the development of PM. Consortia can also promote the training of educators and academic managers, facilitating access to AI tools and strengthening their capacity to interpret and apply results in practice [85].

Research has the potential to advance knowledge by creating a shared framework that maximizes the impact of scientific findings, accelerates technological innovation, and fosters more equitable and sustainable educational solutions. This approach can be key to addressing global challenges, such as inequality in access to education and adapting to the changing needs of students in the digital age.

- Ant Colony Optimization

The line of research on Ant Colony Optimization (ACO) applied to EDM and PM focuses on the use of algorithms inspired by the behavior of ant colonies to solve complex problems related to optimization and decision-making in educational environments. This approach takes advantage of ACO's ability to find optimal solutions by simulating adaptive and collaborative processes, which is especially useful in educational systems that generate large volumes of heterogeneous data [86].

The advancement of knowledge in this area is oriented towards improving the precision and efficiency of tasks such as grouping students according to their performance, identifying patterns in learning data, and optimizing educational resources. ACO can be adapted to address specific problems in the educational field, such as personalizing learning, predicting academic trajectories, and efficiently allocating resources in online learning platforms [87].

Furthermore, this methodology has the potential to improve educational recommendation systems by identifying optimal routes for students based on their individual needs and goals. It can also contribute to improving equity in educational systems by ensuring that data-driven decisions are optimized for all students, regardless of their background.

The research can advance knowledge by providing new tools to address optimization problems in the educational context, foster innovation in the design of PM, and promote adaptive solutions that respond to the dynamic challenges of education in the AI era [86]. Some adaptive solutions that could respond to the dynamic challenges of education in the age of AI include personalized learning systems, which adjust content and pedagogical strategies according to each student's needs, interests, and abilities. In addition, predictive analytics make it possible to anticipate student performance and detect potential learning problems before they become serious. AI-based continuous assessment facilitates constant feedback, helping teachers to adapt their approaches in real time [1,88]. Adaptive learning platforms adjust the pace and difficulty level of content, optimizing the educational experience for each individual, while intelligent tutoring systems act as personalized tutors, offering support to students outside the classroom and guiding them in their learning process. These solutions not only improve personalization but also address the diversity of needs in an increasingly digitalized educational environment.

5. Discussion

The discussion of the results obtained in this study on EDM and PM in the AI era should be framed in the context of previous advances in these areas, particularly in the context of how these technologies are reshaping educational processes. The findings presented in this study reinforce and extend the ideas and conclusions of previous research while proposing new lines of research that address some of the current challenges faced by educational systems when integrating AI.

This study highlights that the combination of data mining and PM, supported by AI, has enormous potential to improve education by personalizing learning processes and optimizing the prediction of students' academic performance. This finding is consistent with previous studies, which highlighted that EDM can be a powerful tool to better understand learning and improve pedagogical intervention [89–91]. By applying advanced PM techniques, this study confirms that AI is capable of analyzing large volumes of educational data and can generate accurate predictions about student performance, identify those at risk of dropping out of school, and, even more relevantly, offer personalized interventions [6].

The study also highlights how these technologies can predict future student behaviors more efficiently than traditional interventions, allowing teachers and administrators of educational institutions to make decisions based on more accurate data. This advance is particularly significant because it aligns with the theory of personalized learning, which advocates adapting the educational process to the individual needs and characteristics of each student [92,93]. Data mining and PM open the door to more effective personalization, allowing students to receive specific educational support based on their behavior and performance patterns. This early intervention capability has been highlighted in research, which suggests that data mining could improve student retention by detecting academic difficulties early [12].

The use of AI has also been shown to be a key factor in personalizing learning, allowing systems to tailor recommendations and resources according to each student's needs. This approach contributes to improved academic performance and increases student motivation and engagement. The results obtained in this study reflect this trend and underline how AI and PM can improve the educational experience by offering materials and activities that fit each student's pace and learning style. In fact, several studies had already demonstrated the effectiveness of AI-based platforms in improving learning, reinforcing these findings by highlighting the direct relationship between personalized learning and improved academic outcomes [94,95].

In addition to educational outcomes, this study also addresses the importance of equity in access to education. As data mining and AI are integrated into educational systems, it is essential to ensure that these technologies benefit students who are already in a favorable position and help to reduce disparities in access to educational resources. This study suggests that data mining can identify not only students at academic risk but also patterns of inequality in access to resources and support [16,96]. This approach is supported by various studies, which indicate that data mining can help detect gaps in education and promote greater equity [6,92]. For example, if a student is in a situation of vulnerability or lack of resources, predictive systems can quickly identify it, allowing for early intervention that provides the necessary support to prevent them from falling into academic failure.

One of the most interesting findings in the present study is the use of PM to intervene in a personalized way. Predictive systems allow for the identification of students at higher risk and can generate adaptive interventions. This concept of personalized intervention, driven by PM, holds immense potential to revolutionize how educational institutions respond to the diverse needs of their students. By leveraging data-driven insights, institutions can tailor educational experiences to individual learning styles, pacing, and specific challenges, ensuring that each student receives the support they need to succeed [97]. PM can anticipate student struggles, enabling early interventions and targeted strategies that address academic performance, engagement, and emotional well-being. This shift towards personalized learning also empowers educators to make more informed decisions, enhancing their ability to adjust teaching methods, materials, and support mechanisms in real time. As a result, personalized interventions not only improve student outcomes but also foster a more inclusive, equitable, and effective educational environment [98].

The predictive model predicts academic outcomes and can be used to recommend teaching resources and strategies tailored to students' needs, which aligns with trends observed in other studies, which argue that personalized interventions can significantly improve teaching effectiveness [99].

In terms of future research directions, one of the key areas emerging from this study is the need to improve the accuracy and capacity of PM to address the complexity of student behavior and performance. While the results obtained are promising, current models still face challenges in terms of the accuracy of their predictions. PM systems used in EDM are generally based on structured data, such as grades and questionnaire responses, but academic performance cannot always be reduced to these factors [100]. More sophisticated models that include unstructured data, such as the analysis of students' online behavior, their interactions on digital platforms, or even their emotional well-being, could offer a more accurate and complete prediction of performance. This integrative approach has been suggested by several researchers, who argue that incorporating more types of data could improve the effectiveness of predictive systems [101,102].

Furthermore, the study highlights the importance of addressing ethical issues in the use of AI in education. As predictive systems become more deeply integrated into educational settings, issues related to data privacy, algorithm transparency, and fairness in their application must be considered. Several studies highlight the need for EDM systems to be transparent and respect student rights, which should be a priority in future research and development [103,104]. Predictive systems should be designed in a way that minimizes bias and is used fairly, without discriminating against any group of students.

In terms of future research, this study suggests that research should focus on creating more inclusive models, which can be adapted to a greater diversity of educational contexts and student populations. This includes examining the applicability of PM at different educational levels and in varied cultural contexts, which will allow for a better under-

standing of how these systems can be effectively used in different settings. Furthermore, collaboration between educational institutions, researchers, and technology developers will be key to further advance the creation of AI-based educational tools that are accessible and useful for all students.

This study confirms that EDM and PM are powerful tools to improve educational processes, allowing for personalized learning and early interventions. However, it also highlights that there are significant challenges that need to be addressed, especially in terms of accuracy, equity, and ethics. As AI continues to be a principal component of education, it is critical that future research focuses on improving the effectiveness of PM and ensuring that these benefits are equitably distributed across all students. Only then can we fully harness the potential of these technologies to transform education in positive and lasting ways.

6. Conclusions

This work has examined the impact of EDM and PM in the educational domain, especially in the context of AI, and how these tools can transform teaching and learning processes. Throughout the study, the enormous potential of these technologies to personalize learning, improve educational intervention, and offer accurate predictions on student performance has been highlighted, contributing significantly to the optimization of educational systems.

Between 2000 and 2024, scientific production in EDM and PM has evolved in three phases: initial growth (2000–2013), consolidation (2014–2019), and boom (2020–2024). The use of AI and access to large volumes of data have driven the expansion, highlighting applications in personalizing learning and improving educational outcomes.

One of the key findings of this work is that data mining and PM, supported by AI, can provide deeper insights into student behavior and needs, allowing educators to intervene early and effectively. The ability to accurately predict academic performance and dropout risk is a significant advantage of these technologies as it allows for a more detailed customization of teaching programs. By identifying behavioral patterns, the system can suggest educational interventions tailored to each student, increasing the chances of academic success, and reducing the dropout rate. This personalization, supported by predictive analytics, improves the educational experience for both students and teachers, allowing for a more student-centered approach.

This study has also shown how AI, by analyzing large volumes of data generated during the educational process, can provide teachers with valuable information about students' progress and needs. Through PM, it is possible to anticipate difficulties and obstacles before they become serious problems, allowing educational institutions to design more effective intervention strategies. The results have confirmed that the integration of AI in education improves the ability of systems to adapt to the individual needs of students, creating a more inclusive and accessible environment for all.

A fundamental aspect emphasized in this study is the importance of ensuring equitable access to AI-based educational tools, such as PM systems and data mining platforms, which are increasingly used to personalize learning and predict student performance. Ensuring that these tools are accessible to all students, regardless of socioeconomic background, is critical for fostering an inclusive educational environment. Although data mining and PM have great potential to improve academic performance, it is key that their implementation does not reproduce or amplify existing inequalities in access to education. This work highlights that educational systems must ensure that all students, regardless of their socioeconomic or cultural background, have access to these technologies. AI and data mining can help to identify gaps in access to educational resources, which could contribute

to the promotion of greater equity in education. However, for this to become a reality, a conscious and equitable approach is needed in the design and implementation of these tools.

The integration of AI in education also poses significant ethical challenges, which this work has highlighted as a key area for future research. One of the main challenges is to ensure that the use of these technologies is transparent, fair, and respectful of students' privacy. The algorithms that feed the PM must be designed in a way that minimizes bias and prevents discrimination. Transparency in decision-making processes is essential to ensure student and educator trust in these systems. Furthermore, policies need to be implemented to ensure that students' personal data are treated with the utmost respect and in compliance with privacy and data protection regulations. The results of this study suggest that future research should address these ethical challenges, ensuring that the implementation of AI in education is beneficial for all without compromising students' rights.

Despite the advances that AI has enabled in the educational field, this work also reveals that there are areas that still require further research and development. First, PM used in EDM can improve their accuracy if more types of data are integrated. Currently, systems tend to focus on structured data, such as students' grades and performance on standardized tests, but academic performance is the result of multiple factors, both academic and personal. The inclusion of unstructured data, such as the analysis of interactions on digital platforms, online behavior, or students' emotional well-being, could make PM more comprehensive and accurate, allowing for more effective interventions. The need to develop models that take these additional factors into account is a key direction for future research.

Another critical area highlighted in this work is the need to improve the adaptability of predictive systems to diverse educational contexts and student populations. As AI-based educational technology expands, it is critical that data mining models can be effectively used in different educational contexts, from primary to university education, and in diverse cultural and social settings. The study has underlined that predictive systems must be flexible enough to adjust to the particularities of each context, taking into account the different educational realities and needs of students. This will allow for even more precise personalization and greater effectiveness of interventions.

Despite these challenges, the study concludes that the integration of data mining and PM in education holds great potential to positively transform the education sector. By leveraging these advanced technologies, educational institutions can optimize teaching strategies, enhance student outcomes, and foster a more personalized, data-driven learning environment. As AI technologies continue to advance, new opportunities open up to improve teaching and learning. Predictive systems can improve retention and academic success and offer a more dynamic and flexible approach to learning, which adapts to the individual needs of students. These advances, however, must be implemented with an ethical, inclusive, and equitable vision so that the benefits of AI reach all students fairly.

Hence, this work has shown that EDM and PM are powerful tools that, if properly implemented, can significantly improve educational quality. However, it has also become clear that the development of these technologies must be accompanied by an ethical approach that ensures that all students benefit equitably and that potential biases or discrimination are minimized. The future of education, driven by AI, is promising, but it will only be successful if these challenges are addressed responsibly and consciously. The potential of AI in education is immense, and, with the right approach, it can profoundly transform the way we learn and teach.

Author Contributions: Conceptualization, methodology, software, formal analysis, resources, data curation, and writing—original draft preparation: E.L.-M. and P.C.M.-M.; investigation, validation, writing—review and editing, visualization, supervision, and project administration: E.L.-M., P.C.M.-M., C.G.H. and N.P.-P.; funding acquisition, E.L.-M. and P.C.M.-M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data were obtained from Elsevier's Scopus database (https://www.scopus.com/) accessed on 1 November 2024.

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

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