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Systematic Review

Applications of Artificial Intelligence Models in Educational Analytics and Decision Making: A Systematic Review

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Abstract: Education plays a critical role in society as it promotes economic development through human capital, reduces crime, and improves general well-being. In any country, especially in the developing ones, its presence on the political agenda is necessary. Despite recent educational advances, those developing countries have increased enrollments, but academic performance has fallen far short of expectations. According to international evaluations, Latin American countries have made little progress in recent years, considering the level of investment in education. Thus, Artificial Intelligence (AI) models, which deal with data differently from traditional analysis methods, can be an option to better understand educational dynamics and detect patterns. Through a literature review using the PRISMA methodology, we investigated how AI has been used to evaluate educational performance in basic education (elementary and high school) in several countries. We searched five platforms, resulting in a total of 19,114 works retrieved, and 70 articles included in the review. Among the main findings of this study, we can mention: (i) low adherence to the use of AI methodology in education for practical actions; (ii) restriction of analyzes to specific datasets; (iii) most studies focus on computational methodology and not on the meaning of the results for education; and (iv) a less trend to use AI methods, especially in Latin America. The COVID-19 pandemic has exacerbated educational challenges, highlighting the need for innovative solutions. Given the gap in the use of AI in education, we propose its methods for global academic evaluation as a means of supporting public policy-making and resource allocation. We estimate that these methods may yield better results more quickly, enabling us to better address the urgent needs of students and educators worldwide.

Keywords: assessment; educational indicators; educational system; data science; machine learning; artificial intelligence

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1. Introduction

Education has been associated with better use of economic growth that a country achieves in a period. In part, the association stems from the accumulation of human capital generated by investments in education [1,2]. To maintain the positive impacts of these dynamics, efforts must be made through constant monitoring of the educational system. One of the main challenges in evaluating the educational system refers to the type of metrics to be used.

Indicators, which are defined as "a measure used to compare quantities", are one of the ways to assess the state of the educational system [3]. Simple and composite indicators are two types of indicators that can be used: simple indicators provide direct information about the educational system (e.g., the number of graduates in a given school cycle, total enrollment per school year, and the number of students in a classroom). Composites, on the other hand, link multiple variables at once (e.g., the number of professors per 1000 students and the number of graduates in relation to enrollment) [4,5].

There is no single simplified measure capable of evaluating the educational system globally, where all schools could be classified and ordered using a single measure. There are indicators for certain aspects so far, but they are insufficient to measure the different factors of the educational system. Considering this limitation, another choice is to combine several indicators, which will naturally increase the complexity of the analyses but may provide a more informative educational perspective.

In recent years, the educational structure in Latin America (LA) has undergone significant modifications, including an increase in the number of students enrolled in elementary and secondary school [6,7]. However, despite this progress, school performance in many LA countries continues to fall below expectations when compared with countries with similar levels of Gross Domestic Product (GDP) and educational expenditure [8]. Addressing this performance gap remains a critical challenge for the region.

As not all children are assured attendance, the benefits associated with school insertion are not universal, and low-income families find it more difficult to participate in this expansion [9,10]. There are other aspects such as ethnicity, gender, and geographic location that make it impossible to access the advancements seen in LA countries in recent years; therefore, examining the traits that help students to perform better in school and focusing resources on these factors is critical.

In international assessments such as the Programme for International Student Assessment (PISA), all LA countries score lower than the Organization for Economic Co-operation and Development (OECD) average in all three areas assessed by the test (science, reading, and mathematics). Latin America has a history of deficient performance and low participation in international assessments. For countries such as Bolivia, French Guiana, Guyana, Suriname, and Venezuela, data referring to academic evaluation were not identified, which can be compared on the same basis, meaning that they are applied in a uniform way as the evaluations carried out by the OECD or Progress in International Reading Literacy Study (PIRLS) and Trends in International Mathematics and Science Study (TIMSS), for example. Thus, a robust and comparative assessment of LA countries is unfeasible. In a brief analysis of the PISA results, the scores in the assessments have barely increased during the last decade. On average for this period, the increase in performance for LA countries did not exceed seven points [11], consolidating a scenario of stagnation. In some nations, the scores of the last exam (2018) were lower than the scores of the 2009 exam. Of the LA countries participating in the PISA, only Peru maintains a continued increase in assessments.

It should be noted that concomitantly with restrictive education, LA countries in general also have low values for development indicators, such as the Human Development Index (HDI), one of the main metrics used to assess and compare the development of countries [12]. The next three sections focus on the main references of the revised bibliographic review, where the role of education as a fundamental element for economic growth via human capital, the main characteristic applications of Artificial Intelligence (AI) and AI in the educational scope, and its aspects were considered. Then, the method to develop this systematic review is detailed, and we present the main results to support the discussion, conclusions, and future trends. The main contributions of this study include an overview of the application of AI models in the evaluation of educational performance in basic education (elementary and high school), the main characteristics of the studies included, and some contributions to the application of AI methods in education.

2. Economic Growth: Human Capital

Human capital can be defined as a set of skills intrinsic to the individual (e.g., formal education, experience, creativity, and health consolidate aspects that increase the productivity of workers and companies) [1,2,13]. The accumulation of human capital brings numerous social benefits, in addition to contributing to an increase in GDP and wage levels, a reduction in crime, and greater social welfare which are conditions positively related to social capital. One of the main reasons for government officials and other workers to incorporate education into their political agendas is the strong link to human capital, seen as a relevant factor for sustained economic development [14–16].

In recent studies, new characteristics have become associated with human capital, such as energy, capacity for innovation, and lifestyle, as they would be associated with greater companies' efficiency. However, as these characteristics are difficult to be identified and measured, few studies assess them directly. Therefore, to include the human capital variable in economic growth models, those associated with education become a more reliable estimate [17].

Years of schooling, as well as school performance, are often associated with increased individual earnings, which would be an indication of greater economic activity. Recently, some studies have suggested that cognitive skills would have a greater impact on wages than school performance [18]. However, this association incorporates a series of elements linked to the students' family and cultural environment, a condition that makes it difficult to analyze the real effect of this condition on economic growth, according to salary levels, for example. Thus, currently for some countries, as these data are unavailable, alternative proxies for assessing economic growth and development are traditional educational indicators.

Among the main challenges in education, we highlight the reduction of school dropouts, an increase in academic performance, a reduction of failures, and the universalization of education, financing, and resources for the educational system. Several countries have their indicators at stable levels, with no increase or decrease in academic performance. Some issues (classified as basic in developed countries) can be crucial barriers in the developing world, which are reflected in elements of delay for school development (e.g., difficulty with means of transportation or even the limitations in the distribution of water and sewage).

Therefore, for developing countries, a variable that represents cognitive abilities in a national scenario becomes unfeasible [19]. An alternative is an analysis that is based on existing data, such as government research analyses referring to basic education, as it is a fundamental educational level in the composition of the Human Capital of a country. The next section elucidates some of the main elements concerning AI and some of the benefits obtained with the use of its techniques in different areas of knowledge.

3. Artificial Intelligence Applications

Artificial Intelligence is a field of study where agents can perceive the environment and make decisions [20,21]. In this case, computers perform cognitive functions similar to human ones considering the ways of learning, understanding, reasoning, and interacting [22]. Different methods and algorithms are used in product development and different forms of data analysis. To improve the efficiency of processes, AI methods help decision-making, simplifying the process of analyzing information, and making it more agile, even with exhaustive amounts of data. In this sense, the utilization of AI-supported actions is believed to be crucial for fostering economic growth.

The existence of such data in different origins and structures defines a complex approach, which takes us to the perspective of Big Data, which can be defined by the foundations, also called "Vs" of Big Data [23]: (i) volume—the amount of information that is handled, processed, and interpreted; (ii) variety—the number and complexity of the types of information contained in the database; and, (iii) velocity—the data flow, that is, the rate of entry and exit of new information [23–25]. It is noteworthy that other factors are important, and new "Vs" are added to show the entire structure of Big Data. For this work, another element should be mentioned: the value of data: through them, several companies have generated positive results that outweigh any cost of information management [23,25].

Some studies indicate that the use of AI techniques can increase world economic production by between 14 and 16% by 2030 [26–28]. Historically, technological innovations can increase the GDP of economies; however, the changes are not immediate. It will be necessary to adapt the structure of the production to the new scenario, either with the acquisition of new technological devices (e.g., computers, servers, etc.)—which require investment, or even in the hiring of trained professionals, who will need to acquire new skills, due to market demands and job reallocations.

In recent years, the growth in the use of AI methods has been so great that it has now become the basis of several processes. The range of algorithms used in problem-solving has increased, and old techniques have been improved thanks to recent computations. Compared with previous processes, it is noted that the introduction of AI has revolutionized several areas of knowledge with the addition of new tools that maximize economic gains, mitigate errors, and increase productivity and efficiency [27].

Among the most diverse fields, we highlight the improvement in communication and languages due to translation tools (e.g., Google Neural Machine Translation) that convert human speech into text, which consequently generated the "voice search" tool, enabling the development of virtual assistants such as Alexa, Cortana, and Siri that have revolutionized the Internet of Things (IoT) and smart home market [29], and ChatGPT, a recently available tool that has the ability to talk to the user, answering various questions, and with the ability to perform complex search tasks, among other functions involving language [30].

In economics, advances in the use of AI took place in two contexts: the recommendation of products according to the profile of users and the forecasting of asset prices in the stock market [31,32]. By directing product advertising to customers based on research carried out by them, the chances of making sales are greater. On the other hand, the stock market, designated by the high volatility of stock prices, which are priced according to numerous factors, usually when using machine learning methods, tends to make better predictions than traditional models. The banking system has used this type of resource to assess credit granting or predict defaults. Due to the associated benefits, it has become increasingly common in the practices of financial institutions to generate ratings and forecasts to offer any product to their customers. In electronic commerce, a common strategy in virtual media (email, social networks, browser ads) is based on different AI methods, which can learn the user's tastes and generate more relevant suggestions for a specific profile.

Another prominent field is fraud detection (e.g., emails have a system to filter messages received by importance and the possibility of being spam). With the evaluation of an initial set of frauds, it is possible to assess the similarity with new messages, filtering incoming messages and, consequently, establishing a greater degree of security for the user [33]. Finally, applications of AI models are image recognition methods with the potential to aid clinical diagnoses. The function of this analysis feature is not to replace healthcare professionals, but to assist with the early detection of comorbidities which facilitates diagnostics, saves resources, and increases the speed of the process [34,35].

Among the main challenges in education, we can list the reduction of school dropouts, in which the recognition of the conditions that are reflected in dropping out of school is fundamental for the improvement of the educational system as a whole [35]. So, to design proper policies, it is necessary to identify the main factors that are associated with better student outcomes, on which policymakers should specifically act, mitigating financial and time losses, and increasing the chances of success. Thus, the implementation of related policies needs to be improved through efforts so that financial, physical, and resources can be managed with greater efficiency and quality. This encourages the use of original approaches for evaluating educational performance, to form new insights into the creation of public policies. It is essential to understand what are the factors and main characteristics of students' success in the educational decision-making process.

The goal of this research is not to list all applications of AI, but rather to emphasize those that have had the biggest positive effects across a variety of domains and the ways in which they relate to various modern scientific and technological developments. Considering these facts, why not employ similar strategies to encourage educational changes, considering the unique characteristics of the areas where improved educational performance is needed?

4. AI for Education: New Methods of Analysis

Currently, different methods of AI are used in the field of education [36]. In searches for surveys and recent reviews in the area [37–39], we found that the main objectives of studies that use AI data exploration methods as the main methodology are: (i) predicting performance, and permanence in distance learning courses [40–42], (ii) identifying the probability of school dropout [43–45], (iii) predicting grades in written assignments [46], (iv) assessing student profiles [47] and, (v) school management [48].

However, few studies include data for large geographic scales, such as countries or macro-regions. In general, they tend to evaluate data for states and cities and data that do not have geographic dependence as data from Massive Open Online Courses (MOOC) where there are no defined limits. Thus, the spatial component associated with education is no longer incorporated into the models, and the geographic importance may be related to public policies committed in these places.

Despite the growing use of AI in education, few studies have been proposed that aim to foster the development of educational public policies based on insights from this methodological approach [49]. Most educational quality assessment studies are based on traditional statistical methods [50] which use limited data sets, as the structure of some methods does not allow the inclusion of an exhaustive number of variables without loss of performance of the analysis. The reduction of data complexity can consequently lead to loss of information or loss of analytical insights.

It is worth mentioning that there is currently a significant increase in the amount of data that is generated every day, as well as the temporal accumulation of information, which encourages the use of new analysis methods that are already used in other areas of knowledge [51,52]. In education, the process would not be different, whether by government research or by data generated by teaching platforms and learning environments.

The scenario becomes even more limited when the searches are restricted to LA countries. The implementation of AI methods is severely restricted in developing countries. On the other hand, the participation of those countries in this process is essential, and those that are less close to the AI may present a lower degree of economic growth, which will increase inequalities. Traditionally, developing countries already have less technological infrastructure and skilled labor, and will have to make greater efforts not to further accentuate the difference from developed economies. Maia et al. [53] mention numerous gaps in the examination of a data set of more than 90% of Brazilian public schools. A comparison of traditional and AI approaches was carried out to measure the educational and socioeconomic aspects that are related to school achievement, with the latter having the best performance–considering error metrics and determination coefficient. The distinctiveness of each school period evaluated and the distinction of the relevance of variables in the school stage became clear, making such specifications vital to incorporate in projects and public policies that decision-makers and other workers come to carry out [53].

As a result, incorporating more data into analysis has become a critical issue, not only to generate value but also to save resources, as public policies can be enhanced with new interpretations of the school setting. Highly valuable approaches can be utilized for this, as datasets in education can be simply integrated within the scope of AI [54]. Different AI approaches can generate more precise and consistent results when applied to traditional methodologies [53,55]. However, there are still a few projects in education that benefit from AI, Data Science, and Machine Learning resources. When we consider the significant increase identified in other disciplines [56], the situation for developing countries becomes much worse. Aware of this gap and the educational emergency in the region, an inquiry into the existing scenario of school performance evaluation studies in the region becomes necessary.

Nevertheless, the adaptations will have to be implemented gradually in each country, and there will be several challenges, but it is unlikely that AI will not be explored. Due to the complexity of the data, different computational structures end up being necessary. This condition hinders the rapid expansion in LA, as in some countries, the access to certain equipment is restricted.

5. Methodology

We conducted a systematic review of the literature using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards [57,58], PRISMA checklist, available in the Supplementary Material. Academic works using AI models to evaluate school performance were identified, selected, and critically evaluated. The main stages of the methodology applied in this study are summarized in Figure 1.

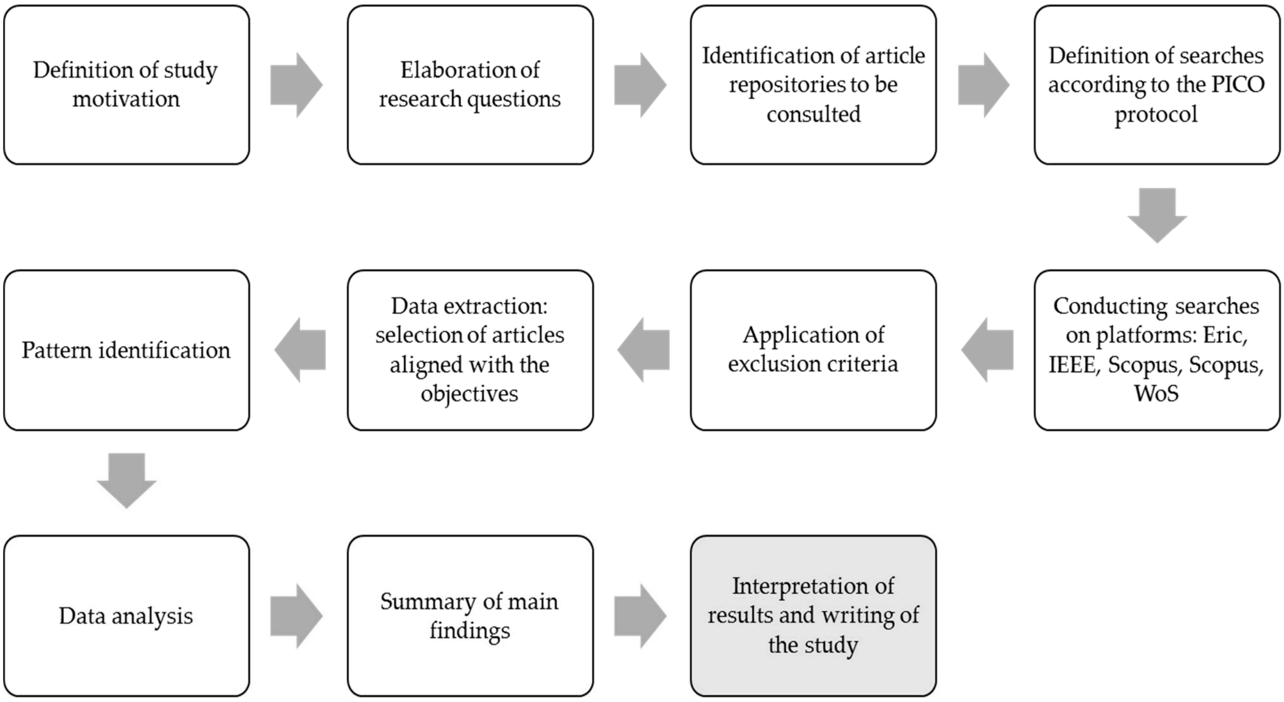

Figure 1. The main stages of the research methodology.

5.1. Research Questions and Objectives

The research question in this study was: how AI models are used to evaluate educational performance? From this perspective, the following questions were asked: (i) how have AI models been used to assess school performance?; (ii) what educational level do the studies assess?; (iii) what is the geographic origin of the data used in the articles?; and (iv) what are the main methods used to assess school academic performance?

To answer these questions, we aimed to find the main articles that addressed educational evaluation from 2000 to 2021, using AI methods to promote public policy or resource allocation and to evaluate the existence of educational performance evaluation studies using AI methods with data from LA countries.

5.2. Search Strategy

The Population, Intervention, Comparison, and Outcome (PICO) strategy [59,60] was used to conduct the review (Table 1). The population in our study was characterized as publications assessing basic education (i.e., primary, secondary, and high school levels). Initially, all studies that were within the established criteria were selected. Subsequently, those located in LA would be unified in a distinct group, but due to the small number of studies, only one group was created without distinction of the region. The intervention was considered the performance prediction assessments that incorporated at least one AI model. The comparison was based on the evaluation of the models using comparable metrics such as error metrics, accuracy, sensitivity, and so on, whereas the outcomes referred to the results of the predictor of interest: prediction of school performance.

Table 1. Main characteristics of the PICO protocol adopted by this study.

Stage	Description
Population/Problem	Studies predicting the performance of Basic Education students (elementary school, primary school, secondary school, and high school)
Intervention	Artificial Intelligence models
Comparison	Comparison between the models used
Outcome	Model performance and predictive/classifier quality
Study type	Quantitative studies

The search terms (Table 2) were applied to multiple journal platforms, including the Education Resources Information Center (ERIC), Institute of Electrical and Electronics Engineers (IEEE), Scopus, Science Direct (SD), and Web of Science (WoS). The databases were accessed via Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) journal network, with remote access provided by the Comunidade Acadêmica Federada (CAFe).

Table 2. Search terms used by journal platforms.

N	Stage	Terms
1	School Levels	TITLE-ABS-KEY ((“primary education” OR “secondary school” OR “high school”) AND (“computer science” OR “big data” OR “data science” OR “data mining” OR “deep learning” OR “artificial intelligence” OR “machine learning”))
2	Academic achievement	TITLE-ABS-KEY ((“academic assessment” OR “academic performance” OR “academic achievement” OR “academic intervention” OR “academic trajectories” OR “academic analytics”) AND (“computer science” OR “big data” OR “data science” OR “data mining” OR “deep learning” OR “artificial intelligence” OR “machine learning”))
3	Education	TITLE-ABS-KEY ((education NOT (“medicine” OR “higher education”)) AND (“computer science” OR “big data” OR “data science” OR “data mining” OR “deep learning” OR “artificial intelligence” OR “machine learning”))

5.3. Eligibility Criteria

The inclusion criteria were pre-established, and the key results of the selected studies were coded and extracted to synthesize and answer the question: how the AI used to evaluate educational performance helps in decision-making and public policy conceptions? Furthermore, because the goal of this study was to promote practical actions (e.g., manage public policies capable of optimizing school performance in a shorter period), studies that advocated these activities were sought.

The searches were conducted in September 2021 and were limited to articles published between January 2000 and September 2021. We limited the presence of keywords to titles and abstracts because of the large number of articles not being associated with the scope of work, in addition to the quantity not being subject to analysis due to the small sample size retrieved (Table 3).

5.4. Selection Process

The results of each database were combined into a single .csv file, and duplicates were removed. The Rayyan® tool was used to select articles based on titles and abstracts [61,62]. The authors JSZM and APAB participated in the selection of articles independently. In the event of a disagreement between the two reviewers, a third reviewer (JRS) was involved. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Figure 2) summarizes the selection of articles.

Table 3. List of criteria for inclusion and exclusion of articles in the review.

Inclusion Criteria	Exclusion Criteria
They must be published in english.	Articles published in a language other than English.
Articles must have been published after 2000.	Articles published before 2000.
Articles related to basic education—primary, secondary, and high school.	Articles related to higher education, children, extracurricular courses, and MOOCS.
Articles related to academic performance.	Articles related to education, but unrelated to the objectives: gamification, teacher training, salary forecasting, vocational tests, college admissions, distance education, an indication of courses for college, simulation of activities correction, digital literacy, the perspective of parents, teacher analysis, salary prediction, and vocational testing.
Consist of scholarly articles and reviews.	Papers referring to conferences, events, and book chapters.
Articles must be available in full.	Not being peer-reviewed
Studies should be limited to the areas: education, and artificial intelligence.	Studies outside the broad area of this study, for example: medicine, nursing, etc.

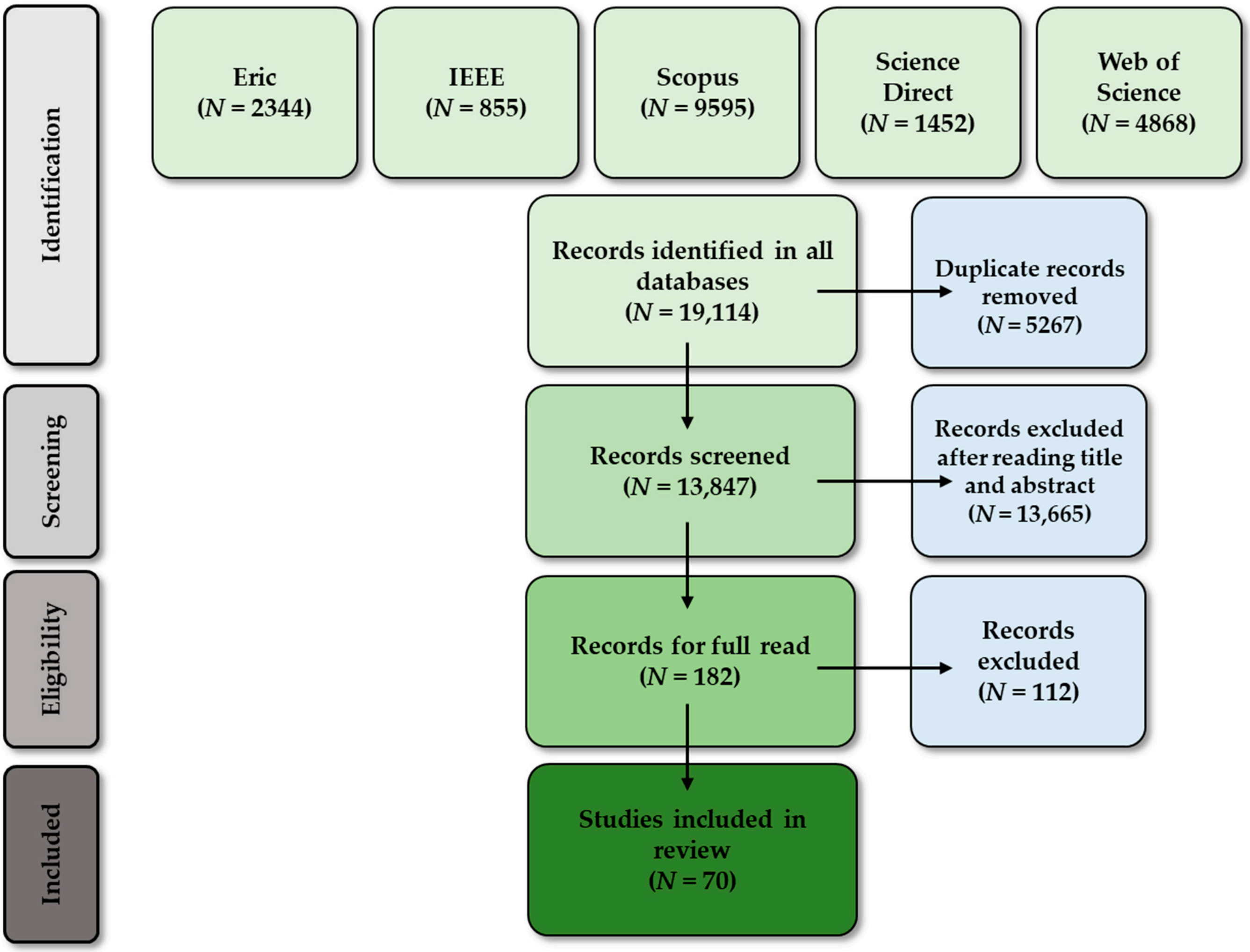

Figure 2. PRISMA flow diagram. Note: The total number of references found may vary depending on the date and time of the search.

Using the words present in the titles and abstracts of the articles selected for full reading, a graph was generated using the VOSViewer® software, a tool developed for bibliographic analysis and capable of generating networks with the selected words [63].

Figure 3 summarizes the searches carried out on the different platforms, presents the structure of the topics discussed in the articles, and the relationship between them. Each circle is called a node, which represents a keyword, and whose size indicates the frequency in titles and abstracts. The connection between the nodes is given by the lines that represent the co-occurrence between the keywords, which occur simultaneously. The thickness of the line that connects the nodes indicates the number of times that the keywords occur together in the same article. Each color represents a thematic cluster, and the cluster elements are used to identify the main subjects of the studies. We can identify 3 clusters: (i) red—the main terms referring to the school and subjects are combined; (ii) blue—consolidated by the main models of AI; and (iii) green—composed of model response elements, such as classification and feature selection.

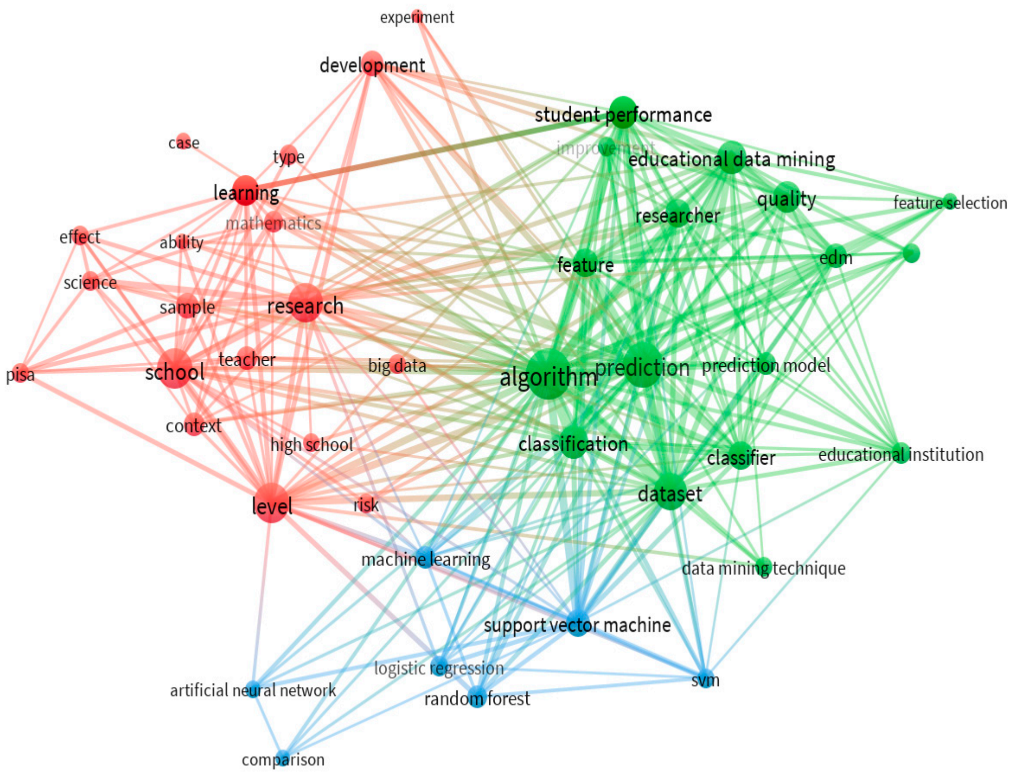

Figure 3. Visualization of bibliometric maps with the keywords of all articles obtained in the databases, after selecting the papers.

6. Results

The searches in all databases resulted in a total of 19,114 references. After removing duplicates, there were 13,847 articles to be screened by title and abstract (Table 4). Subsequently, a total of 182 studies were identified for full reading and 70 articles fulfilled the inclusion criteria (for a list of articles included, see Table A1).

The following paragraphs summarize the main findings of this study: (i) number of publications; (ii) countries with the most data analyzed; (iii) the origin of the data; (iv) education level; (v) goals of articles; (vi) most common methods; and (vii) resource used for data analysis.

The interest in the subject has increased over the years (Figure 4). In 2000, the number of publications did not exceed 100. After 10 years, the number of papers increased to 265, and from 2020 onwards, an increase in studies that evaluate the educational situation as AI models have become evident.

Table 4. Results of bibliographic search.

Rounds	Descriptions	Eric	IEEE	Scopus	SD	WoS
Round 1	School Levels	890	152	911	116	416
	Academic achievement	803	148	1288	170	824
	Education	651	555	7396	1166	3628
	Total	2344	855	9595	1452	4868
	Initial data			19,114		
Round 2	After duplicate records removed			13,847		
Round 3	Scanning the title and abstract			182		
Round 4	Select articles after reading the full text			70		

Note: Education Resources Information Center (Eric), Institute of Electrical and Electronics Engineers (IEEE), Science Direct (SD) and, Web of Science (WoS).

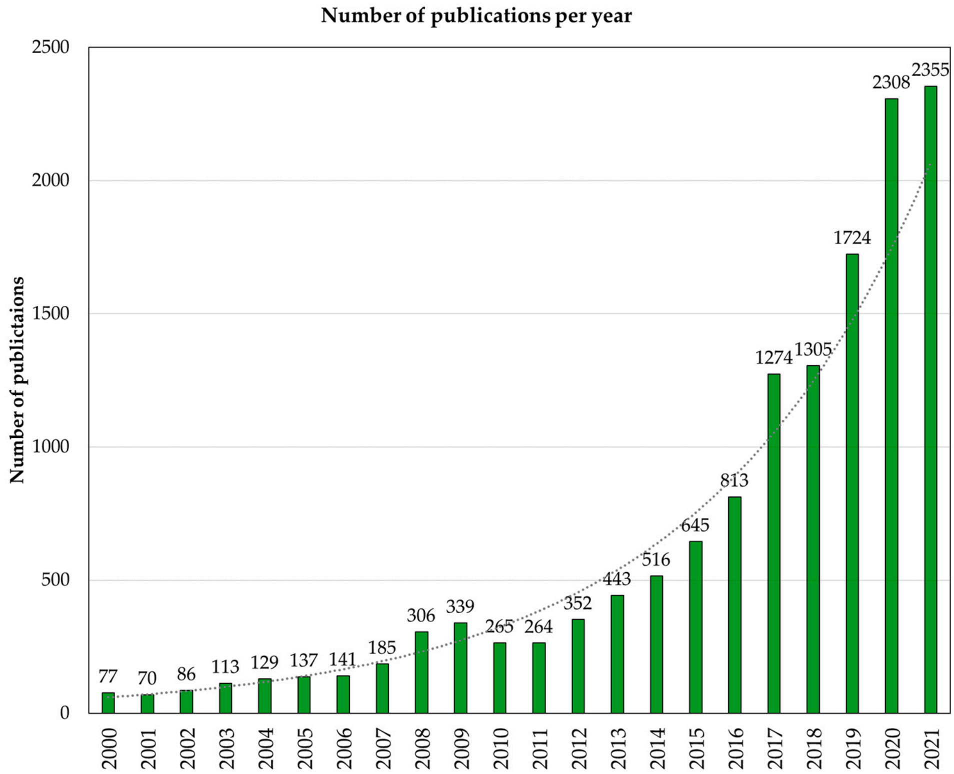

Figure 4. Number of articles published each year from 2000 until September 2021.

We observed that the year with the highest productivity in the last years of the studied period (2000–2021) was 2020, with 27 studies (Figure 5). We found that there has been an increase in interest in the evaluation of basic education in recent years, with at least one AI model considered in the analysis. Although it was not one of our objectives, there was a noticeable increase in interest in the evaluation of higher education and MOOC courses during this study. We understand that this finding may be related to several factors, including economic issues, as they are non-mandatory and usually not free educational levels. Identifying whether the student has low performance is critical as academic achievement is a proxy for dropout, which is mostly observed in these teaching modalities.

The origin of the data used was one of the conditions observed in this study. The majority of the articles used previously known data (e.g., data that was available in repositories or published in reference articles in the field of Machine Learning [64]. Those works, in general, focused on strict model comparison; thus, the use of popular data was common, as the primary goal was to validate the performance of the models. Figure 6 depicts the number of publications based on the origin of the datasets analyzed by the articles. Portugal had the highest number of articles (14), followed by Turkey (12), and Brazil (5). Another distinguishing feature was that they frequently used data from surveys such as PISA and TIMSS, with the goal of predicting educational insights.

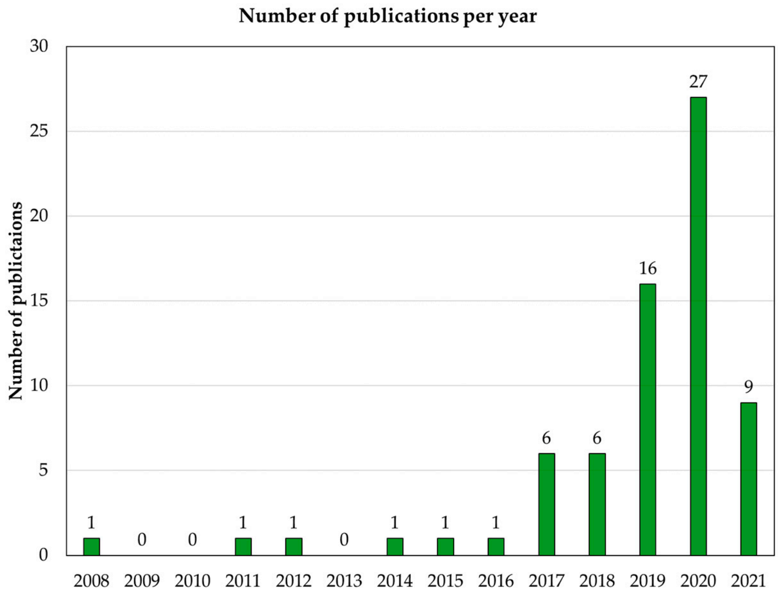

Figure 5. Number of articles published each year according to the inclusion criteria.

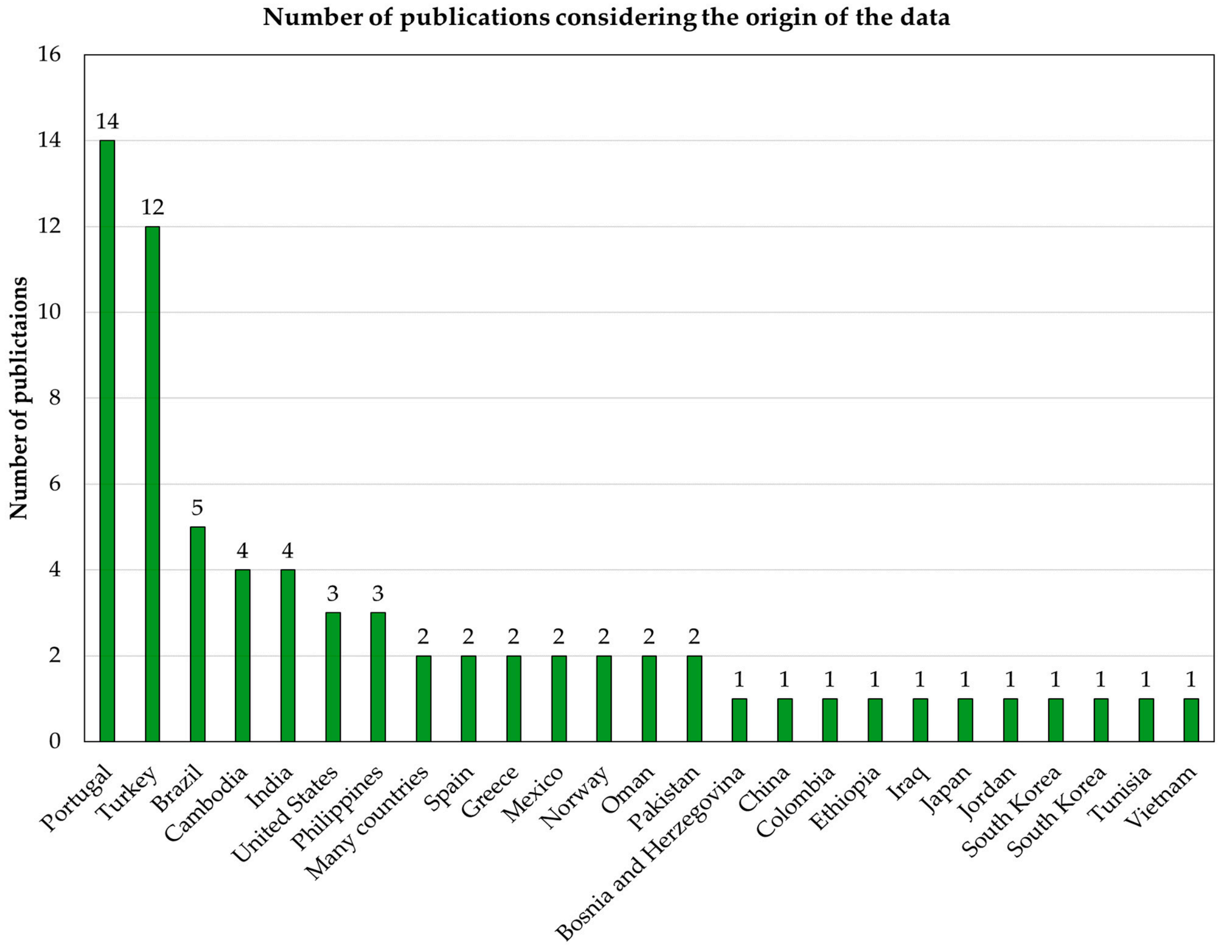

Figure 6. The number of publications by country, considering the location the dataset refers to.

Because each country follows its own classifications between the first and final grades of elementary school, and because some models include data from more than one school, it was frequently difficult to determine which school level the data were addressed at. The two levels could overlap in the same research during one year of this educational cycle, and both school levels were categorized as elementary schools with respect to the other works. The level was maintained because high school was better inside the articles themselves. Figure 7 reveals that elementary school data had the highest weight, followed by high school data, with only two researches using data from both educational cycles.

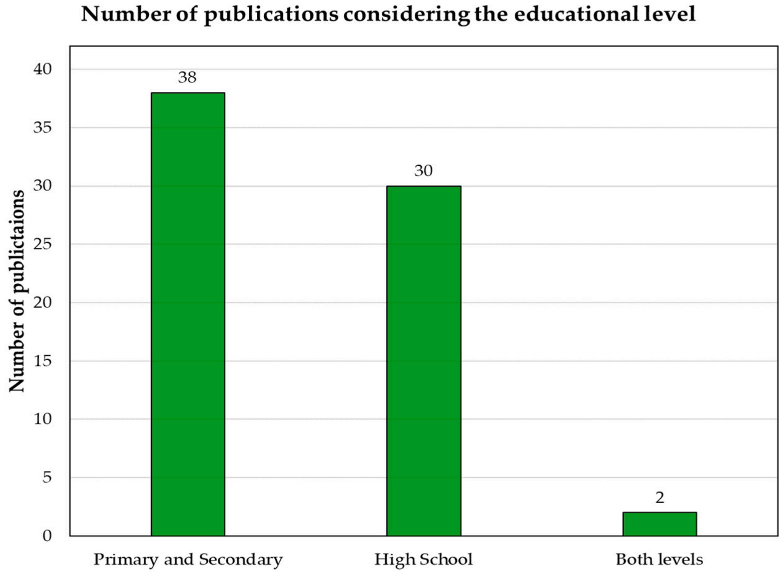

Figure 7. The number of articles by school level included in the systematic literature review.

After classifying the objectives of the included articles, we found two alternatives with the general scope of the studies: (i) Model Comparison (N = 34)—in these studies the core was based on the comparison of models, which were evaluated according with the main performance metrics: Root-mean-square deviation, Determination Coefficient, accuracy, and others. Thus, the authors prioritized the performance of the models and not the educational results; (ii) Education Performance Forecast (N = 36), with a greater chance of mentioning the use of results found during practical actions (Figure 8).

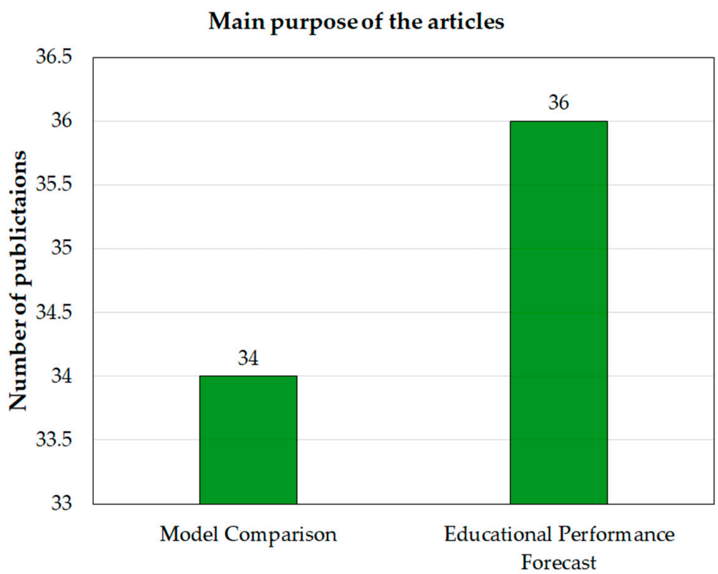

Figure 8. The articles that were included according to the main goals of the studies included.

When it comes to the methodologies used in the studies, classificatory models came on top, followed by Deep Learning methods, notably neural networks. Regression models were the third most popular type of model, while clustering was a less prevalent sort of approach with K-Nearest Neighbors being the most common. Several models were categorized as "others" since they occurred less often and were not part of the approach groupings (Figure 9).

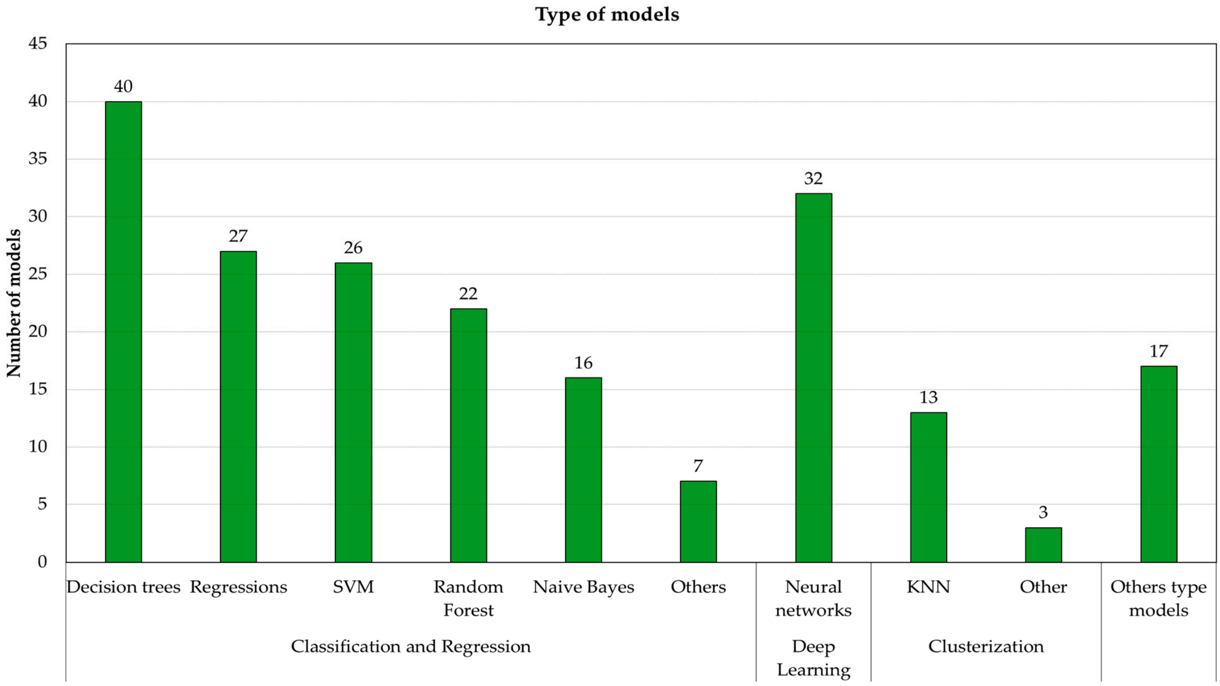

Figure 9. Types of methods used by the included articles in predicting academic performance.

Considering the location where the analyzes were performed, we found that R (N = 20) was the preferred analysis platform, followed by Weka and Python. In the other category, we found the following types of software: SPSS, Matlab, SAS, and Statistica. For 20% of the included articles (N = 14), it was not possible to identify the resource where the analyzes were performed (Figure 10).

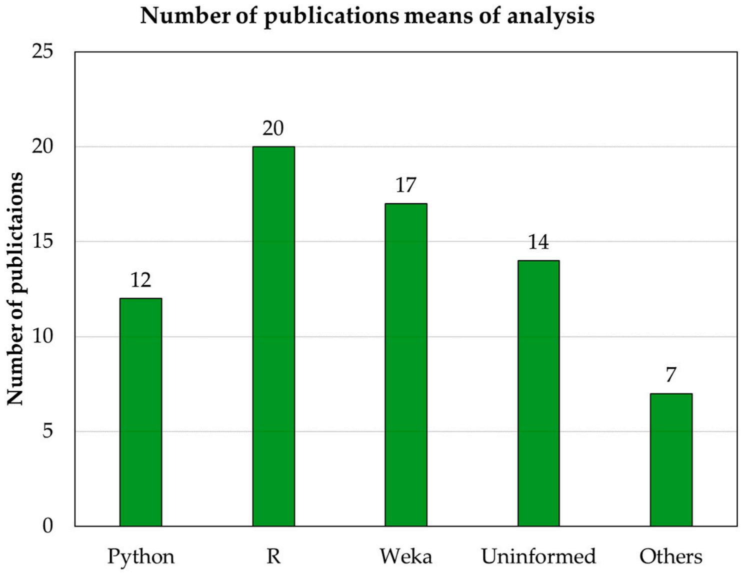

Figure 10. The number of articles considering the analysis platform, software, and programming environment.

The evaluation of the accuracy and precision of IA model performance in various studies' major goals is to pinpoint the model that performs best. As a result, education ends up serving as nothing more than a source of data for computer experiments. Although such studies may not have been aimed specifically at educators, school workers, and decision-makers, their results can still be useful in improving our understanding of education, albeit as a secondary objective of these works. However, due to the technical nature of this type of research, the implementation of practical actions may be more challenging.

7. Discussion

Despite the large number of articles identified by the initial searches and the growing popularity of the subject, no more than 70 articles were included in this work. Analyzing the connection of key terms (Figure 3), we obtained some insights for identifying characteristics of the reviewed articles, including (i) the main methodologies used, (ii) the level of schooling analyzed, and (iii) how terms related to school, subject, and assessment connect to AI models and their response elements, such as classification, prediction, and feature selection. However, only during the reading of the articles, it became evident some of the patterns and the best way to summarize and classify the analysis of the included studies.

The recent increase in the number of publications can be attributed to a growing need to adapt to new analysis methodologies and cope with the larger volume of data available. Despite the rising trajectory in the number of publications, the process is not homogeneous since no works were discovered with educational data for any country in Oceania, in addition to a high restriction for developing countries in Asia, Africa, and LA.

The works mostly use data referring to the elementary school level. The availability of data for this educational level may be higher, as many countries measure literacy levels, for example. Some authors reinforce that greater investment in initial education brings greater public income [65,66], thus, this may be another reason for the higher incidence of studies at this educational level. On the other hand, it is estimated that there is a series of data that are subject to analysis and subsidy for monitoring the high school, since there are many tests for university admission, which could serve as indicators or as a proxy of educational quality, and therefore the evaluation of these data can add value to future educational perspectives.

With regards to the application of AI methodology in education, one reason for the lower popularity of the methods is the complexity of the calculations, dynamics of the algorithms, implementation of the analyses, and interpretation of the results. These conditions make them be called "black boxes" [67,68]. Although the process for detecting patterns used in forecasts and classifications stands out due to its performance, it does not make the models transparent and easy to understand. Without a detailed and cautious analysis, which requires a certain degree of technical knowledge, it is not possible to readily understand the results without understanding the preceding structure of the model [67,68].

The difficulty in understanding all stages of the process can inhibit the use of such methods for formulating public policies and decision-making, but it is a condition that must be overcome. Currently, several resources can be used to increase the understanding of these models. The standard approach is based on a comparison of performance metrics, in which it is possible to identify the best-performing performance and aid the use of graphs to facilitate the understanding of the analysis.

Recently, techniques such as Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) are model interpretation techniques that seek to simplify the interpretation of model results. In LIME, the central objective is to identify the most important features that the original model uses to make its prediction, and for this, a simple linear model is performed based on only one prediction at a time. SHAP is a method that computes the contribution of each variable in the model, which is based on game theory to assign a value to each feature [69–72]. Both methods aim to identify the relevance of independent variables in the final prediction of the initial models. Thus, the best approach to promoting the use of techniques in educational analysis that aim at the design of public policies is to consider the use of these techniques together with performance metrics and with the study of the importance of variables. This approach increases the ability to interpret such models [69–71,73].

The perspective of AI models enables analyses that were previously not feasible in terms of techniques and computational processing. Through this approach, it is possible to process and analyze large amounts of data, allowing the detection of patterns that were previously unidentifiable through traditional statistical methods. Therefore, it is argued that student performance can be better understood thanks to the potential of these techniques, which are already used in several economic sectors, resulting not only in process improvements but also in cost reduction and more efficient allocation of resources.

Several studies were based on surveys collected throughout the country, in which the majority mention the educational system and policy concepts, in terms of time, interventions materialize only in the long term (defined as Macro studies; $N = 40$). On the other hand, many studies focused on a smaller scale, prioritizing the student, the teacher, and the schools, and in which the results of interventions could be perceived in the short term (studies that we define as Micro studies; $N = 30$).

We understand that the use of AI can help in the educational field from a macro perspective: AI modeling can increase knowledge about the processes that manifest themselves in education at the national, state, and local levels, helping to formulate policies and allocate resources to characteristics identified as relevant to educational performance; and from a micro-scale: it would be possible to conduct more specific investigations of individual students, teachers, and schools. In this context, a greater level of personalization of actions would be possible, predicting more immediate results since they would not depend on other governmental spheres. Thus, the analyses can consider the short-term effects of interventions, evaluating the feasibility of pedagogical strategies that have greater adherence in each subject and class [74], probability of failure [44,75] and referring students to an intelligent tutoring system [76,77]. These approaches have already been explored more frequently, possibly due to the ease of implementing interventions when compared with issues on a broader scale, such as the elaboration of public policies.

School dynamics had different levels of datasets, whether in the school or the educational system, it is also relevant to consider the responsibilities of students and effective teaching techniques, the skills of teachers, and classroom management [78]. When thinking about countries with lower educational performance, such as those in LA, interventions must be conducted at the country and school levels, simultaneously, so that the processes of change can result in faster gain of performance.

The analyzes carried out in the included articles were conducted mostly in free software, indicating a trend in the field of analysis that is also observed in other areas of study. The preferred AI models for analysis within classifications and regression were decision trees ($N = 40$), followed by regression models ($N = 27$), Support Vector Machines (SVMs, $N = 27$), and Random Forest ($N = 22$) some of the main methods of supervised learning. We found a strong presence in the analysis of neural network models ($N = 32$), an approach within the domain of Deep Learning.

These models tend to outperform traditional models in terms of performance, which generally contribute to more accurate and assertive predictions. Thus, the use of methods linked to AI can help to detect precise trends in terms of positive or negative correlations between some key factors and academic performance in schools [79]. Therefore, the detection of the relevance of these elements can be calculated (e.g., by calculating the importance of variables), which will help in the selection of characteristics during the elaboration of public policies or local management actions. The following example situation is assumed: the government of a state enacts a law in which all schools must have sports courts; however, the inclusion of complementary activities, which are less costly in financial terms, have a greater impact on the educational performance, this kind of fact should be known by managers, stakeholders, and politicians.

Despite the importance of using AI methods, few studies encourage the application of the findings into practical actions. Only 31.4% (N = 22) of the revised articles mention the elaboration of public policies, considering the results from studies applying AI models [75,79–82]. On the other hand, it is also known that it is a great challenge to identify insights to promote immediate results since data from some surveys take time to be processed [81].

When it comes to the utilization of massive data sets, Martnez-Abad et al. [35] said that Data Mining in education approaches is a major tool for finding patterns in Big Data, which can then be used to transfer knowledge to help the formulation of educational policy [35]. Artificial Intelligence methods offer the ability to efficiently process large amounts of complex and heterogeneous data, making them powerful tools to assist in the elaboration of practical actions in the field of education. By using AI models, it is possible to identify patterns and trends in student performance, as well as in the education system as a whole, which can help the development of policies and interventions tailored to specific needs and challenges.

Finally, the application of more rigorous analyzes can mitigate unfounded discussions, as cited by Cruz-Jesus et al. [56], the classroom size—defined by the total number of students in the class, does not influence the school performance, at least not significantly. Therefore, in times of budget constraints, this finding could help in resource allocation, shedding some light on classroom size, which is recurrent in the educational field [56]. Costa-Mendes et al. [80] defend the use of accurate and robust predictive models as essential in the elaboration of public policies, in which they highlight the relevance of data collection so that there is support for the National Educational System, through the collection of data from long-term academic achievement. In relation to educational research, Brazil stands out as there are numerous surveys that are regularly published. They include the School Census [83], which focuses on school characteristics and is released annually, as well as the Basic Education Evaluation System [84], which is released every three years and evaluates school performance. National school assessment systems are used in LA nations like Argentina, Chile, and others, and they are examined. There is a gap, though, as there are not many in-depth studies conducted despite the data being available.

An important consideration regarding the use of AI models in education is the quality of the data. Insufficient or incomplete data, including the presence of null values, can lead to inaccurate and unreliable patterns. Artificial Intelligence models require large amounts of high-quality data in order to generate accurate and meaningful insights. However, given the limited availability of data at the level of individual public schools, it may be necessary to broaden the scope of analysis to include data from larger geographic areas, such as municipalities or states. This can help ensure that the data used for AI analysis is sufficiently robust and representative of the education system as a whole. As an alternative to the lack of data from governmental and institutional educational surveys, studies can be based on consolidated surveys such as PISA, TIMSS, Laboratorio Latinoamericano de Evaluación de la Calidad de la Educación, and others [85]. Since they have a quantity of data, which can be grouped in several scales considering different aspects of education, they can be considered as a mined source of data [86], which includes valuable information for the administration, elaboration, and school management in the micro and macro scale.

Considering the availability of data, the low popularity of the subject is still more pronounced in LA countries (N = 8): Brazil (N = 5), Mexico (N = 3), and Colombia (N = 1). It is expected that the trend of increasing work considering data in education and AI models will continue to grow, in addition to the increase in popularity, and in fact, there has already been a boom in data generation in recent years. It should be mentioned that the scenario is different when referring to higher education, where a greater number of studies aimed at assessing the impact of AI on various aspects of education can be noted [87].

As a result, various indicators are required to assess the state of the educational systems in developing countries. Enrollment registration stands out as one of the main metrics in quantitative terms as it is a simple statistic that allows for cross-country comparisons.

The number of children in an educational system can indicate a variety of benefits for the country [88], so it is one of the foundations for educational policy research. Although a school year does not always have the same impact in different countries in terms of influencing school performance [89] it is an evaluative measure and, in any case, considered as an indicator of human capital [90].

In addition to PISA, some LA countries participate in studies carried out by Evaluación de la Calidad de la Educación en América Latina [91] that aim to: (i) provide evidence for educational policy; and (ii) develop capacities in educational assessment in LA (UNESCO, 2020). Few countries, such as Brazil and Chile, have specific metrics to monitor the development of the educational system. An increasing concern related to the educational system can be identified by the diversity of indicators that have been used. Currently, access to information makes it possible to assess a series of issues that were previously less explored. Investigations into educational data from these countries are warranted, since this exercise can provide a new perspective on the main difficulties that are imposed and, consequently, have an impact on the low rate of school performance. This type of analysis can help to manage new educational policies aimed at maximizing school performance and structure.

The number of studies in LA that uses AI resources for educational analysis may be low due to a lack of familiarity with the methods, but AI methodologies are becoming more accessible, whether through MOOC courses or platforms like Google Colab, where complex analyses can be performed remotely. Our searches point to Brazil as a separate case in this scenario, as some studies are promoting a new direction for the results obtained via AI [53,75]. Studies from Colombia go in the same direction [92].

Many LA countries lack priority on educational public policy. Without a national development plan or one on the way to being finalized, several countries do not have strategies to increase school performance. The huge expansion in long-distance education, which accompanies the technological advances of the last decades, is given by the insertion of IoT tools, augmented virtual reality, and different learning platforms. There is also an increase in the use of personal computers and cell phones in activities related to education that are not necessarily linked to the modality. Such conditions cross geographical barriers and are certainly present in several countries in LA, so we have a range of datasets to be explored.

Finally, we mention the abrupt necessity to react to the diversities linked with the COVID-19 pandemic, as most schools in LA had to be partially or completely closed, leaving more than 110 million pupils out of school [93]. At this time, inequalities and access to resources have become even more visible, increasing educational challenges in LA, where rapid efforts will be needed to compensate for the losses that happened during the COVID-19 pandemic.

Each day that passes away from face-to-face teaching, the possibility of returning to school becomes reduced. According to UNESCO, around 24 million students, from pre-primary to university levels, may have not returned to school in 2020 after the pandemic [93]. Although the advancements of recent years are clear, education has changed distinctively [94]. Post-pandemic efforts will be vast, and any resources saved will be substantial in the future. With the availability of existing data before the pandemic, it would be feasible to aggregate multiple investigations into the educational system to evaluate the best techniques. Knowledge about the impact of the pandemic has become crucial for the creation of policies that support the restart of educational growth.

8. Future Perspectives

We highlight a few studies that have taken advantage of AI methodologies to comprehend the educational system at geographic scales that allow the design of public policies. This can be reversed. Therefore, it is proposed to utilize techniques that can enhance the interpretability of AI models, such as LIME, SHAP, and others, to mitigate the issue of black boxes in AI. This can be achieved through longitudinal data analysis, which allows for assessing the consistency of predictors and identifying changes resulting from disruptive events, such as the COVID-19 pandemic, for example. Therefore, in future studies, we will focus on analyzing longitudinal data to better understand the patterns in education.

However, the availability of data alone is not enough to generate improvements in education, it is necessary to explore the information so that new knowledge is produced, and insights can be applied in the real world. We emphasize the importance of developing public policies and management actions based on information from analyses carried out with methodologies capable of dealing with a large set of data. This situation has already been observed in several areas of knowledge.

The maximization of investments, better resource allocation, and process optimization have all been noted in the areas where educational performance has already been predicted using computational techniques of machine learning and data mining. It might represent deliberate macro- or micro-management intervention or even educational intervention. By concentrating on areas that are important and linked to students' academic performance, supplying a general interpretation of the data in the context of the classroom can accelerate educational progress.

Future research should investigate a variety of methodologies, the use of traditional survey data as well as data derived from the recent explosion of educational technologies for policy-making. The use of new analysis methodologies should be used to extract pertinent and more individualized information about education. This will open up the possibility for practical actions through subsidies for educational projects that are not linked to partisan plans and exclusively political purposes but rather are based on public demands and the best allocation of resources, allowing educational performance to be maintained and improved over time. Artificial intelligence can promote changes at all levels of education, not being restricted to teaching, but also to school management and administration processes. Thus, at the level of the educational system, there is the possibility of creating more efficient and assertive educational policies.

The use of research, reports, and other documents produced by bodies such as the OECD, The World Bank, Unesco, Unicef, and others are an alternative to performing studies to evaluate education in those countries with limited data. In addition, it is possible to evaluate the data longitudinally and offer a more precise diagnosis of the educational system. Thus, filling in gaps is encouraged by carrying out studies with the already existing range of data, but little explored. The identification of insights can contribute to the development of education in these countries, favoring the accumulation of human capital and sustained economic growth.

The educational policy agenda must be aggressively prioritized as one of the cornerstones of economic development. Actions based on facts will be vital for economic revival, especially in LA countries. The problems imposed by the COVID-19 pandemic further revealed the political and economic vulnerabilities of the countries in this region and the discrepancy between them and the industrialized nations. It is envisaged that the benefits coming from AI technologies can generate fresh perceptions of this circumstance, contributing to more forceful and targeted decision-making.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/world4020019/s1, Table S1. PRISMA Checklist.

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

Appendix A

Table A1. List of articles selected by the review.

Year	Authors	Title	Journal
2008	Liu, X., & Ruiz, M. E.	Using Data Mining to Predict K-12 Students' Performance on Large-Scale Assessment Items Related to Energy	The Journal of Research in Science Teaching
2011	Alsultanny, Y.	Selecting a suitable method of data mining for successful forecasting	The Journal of Targeting, Measurement, and Analysis for Marketing
2012	Şen, B., Uçar, E., & Delen, D.	Predicting and analyzing secondary education placement-test scores: A data mining approach	Expert Systems with Applications
2014	Osmanbegović, E., Agić, H., & Suljić, M.	Prediction of students' success by applying data mining algorithms	The Journal of Theoretical and Applied Information Technology
2015	Dole, L., & Rajurkar, J.	A Decision Support System for Predicting Student Performance	The International Journal of Innovative Research in Computer and Communication Engineering
2015	Kaur, P., Singh, M., & Josan, G. S.	Classification and Prediction-Based Data Mining Algorithms to Predict Slow Learners in Education Sector	Procedia Computer Science
2016	Idil, F. H., Narli, S., & Aksoy, E.	Using Data Mining Techniques Examination of the Middle School Students' Attitude towards Mathematics in the Context of Some Variables	The International Journal of Education in Mathematics, Science, and Technology
2017	Al-Obeidat, F., Tubaishat, A., Dillon, A., & Shah, B.	Analyzing students' performance using multi-criteria classification	Cluster Computing
2017	Chaudhury, P., & Tripaty, H. K.	An empirical study on attribute selection of the student performance prediction model	The International Journal of Learning Technology
2017	Kılıç Depren, S., Aşkın, Ö. E., & Öz, E. [85]	Identifying the classification performances of educational data mining methods: A case study for TIMSS	Kuram ve Uygulamada Egitim Bilimleri
2017	Martínez Abad, F., & Chaparro Caso López, A. A.	Data-mining techniques in detecting factors linked to academic achievement	School Effectiveness and School Improvement
2017	Blasi, A.	Performance increment of high school students using ANN model and SA algorithm	The Journal of Theoretical and Applied Information Technology
2017	Bharara, S., Sabitha, S., & Bansal, A.	Application of Learning Analytics Using Clustering Data Mining for Students' Disposition Analysis	Education and Information Technologies
2018	Al Mazidi, A., & Abusham, E.	Study of general education diploma students' performance and prediction in the Sultanate of Oman, based on data mining approaches	The International Journal of Engineering Business Management
2018	Filho, A. H., Do Prado, H. A., Ferneda, E., & Nau, J.	An approach to evaluate adherence to the theme and the argumentative structure of essays	Procedia Computer Science
2018	Lu, H., & Yuan, J.	Student performance prediction model based on discriminative feature selection	The International Journal of Emerging Technologies in Learning
2018	Masci, C., Johnes, G., & Agasisti, T. [48]	Student and school performance across countries: A machine learning approach	The European Journal of Operational Research

Table A1. *Cont.*

Year	Authors	Title	Journal
2018	Alawi, S. J. S., Shaharanee, I. N. M., & Jamil, J. M.	Analyzing the Oman education data using clustering analysis	The Journal of Advanced Research in Dynamical and Control Systems
2018	Livieris, I. E., Drakopoulou, K., Tampakas, V. T., Mikropoulos, T. A., & Pintelas, P.	Predicting Secondary School Students' Performance Utilizing a Semi-Supervised Learning Approach	The Journal of Educational Computing Research
2019	Aksu, G., & Reyhanlioglu Keceoglu, C.	Comparison of Results Obtained from Logistic Regression, CHAID Analysis, and Decision Tree Methods	The Eurasian Journal of Educational Research
2019	Bulut, O., & Yavuz, H. C.	Educational Data Mining: A Tutorial for the "Rattle" Package in R	The International Journal of Assessment Tools in Education
2019	Barros, T. M., Neto, P. A. S., Silva, I., & Guedes, L. A.	Predictive models for imbalanced data: A school dropout perspective	Education Sciences
2019	Brow, M. V.	Significant predictors of mathematical literacy for top-tiered countries/economies, Canada, and the United States on PISA 2012: Case for the sparse regression model	The British Journal of Educational Psychology
2019	Chung, J. Y., & Lee, S. [35]	Dropout early warning systems for high school students using machine learning	Children and Youth Services Review
2019	Filiz, E., & Öz, E.	Finding the best algorithms and effective factors in the classification of Turkish science student success	Journal of Baltic Science Education
2019	García-González, J. D., & Skrita, A.	Predicting academic performance based on students' family environment: Evidence for Colombia using classification trees	Psychology, Society, and Education
2019	Imran, M., Latif, S., Mehmood, D., & Shah, M. S.	Student academic performance prediction using supervised learning techniques	International Journal of Emerging Technologies in Learning
2019	Lee, S., & Chung, J. Y.	The Machine Learning-Based Dropout Early Warning System for Improving the Performance of Dropout Prediction	Applied Sciences-Basel
2019	Martínez-Abad, F. [83]	Identification of Factors Associated with School Effectiveness with Data Mining Techniques: Testing a New Approach	Frontiers in Psychology
2019	Sokkhey, P., & Okazaki, T.	Comparative Study of Prediction Models for High School Student Performance in Mathematics	IEIE Transactions on Smart Processing and Computing
2019	Sorensen, L. C. [45]	"Big Data" in Educational Administration: An Application for Predicting School Dropout Risk	Educational Administration Quarterly
2019	Swetha, K., & Imtiaz Ur Rahaman, M.	A machine learning practice on NAS dataset: Influence of socioeconomic factors on student performance	The International Journal of Recent Technology and Engineering
2019	Talal, H., & Saeed, S. [36]	A study on the adoption of data mining techniques to analyze academic performance	ICIC Express Letters, Part B: Applications
2019	Timbal, M. A. [44]	Analysis of Student-at-Risk of Dropping Out (SARDO) Using decision tree: An Intelligent predictive model for reduction	The International Journal of Machine Learning and Computing
2019	Fernandes, E., Holanda, M., Victorino, M., Borges, V., Carvalho, R., & Erven, G. Van. [75]	Educational data mining: Predictive analysis of the academic performance of public-school students in the capital of Brazil	The Journal of Business Research
2020	Costa-Mendes, R., Oliveira, T., Castelli, M., & Cruz-Jesus, F. [80]	A Machine Learning Approximation of the 2015 Portuguese High School Student Grades: A Hybrid Approach	In Education and Information Technologies

Table A1. *Cont.*

Year	Authors	Title	Journal
2020	Bozak, A., & Aybek, E. C [78].	Comparison of Artificial Neural Networks and Logistic Regression Analysis in PISA Science Literacy Success Prediction	The International Journal of Contemporary Educational Research
2020	Toprak, E., & Gelbal, S.	Comparison of Classification Performances of Mathematics Achievement at PISA 2012 with the Artificial Neural Network, Decision Trees and Discriminant Analysis	The International Journal of Assessment Tools in Education
2020	Koyuncu, I.	Investigation of Mathematics-Specific Trend Variables in PISA Studies with Neural Networks and Linear Regression	The Journal of Curriculum and Teaching
2020	Filiz, E., & Öz, E. [49]	Educational Data Mining Methods For Timss 2015 Mathematics Success: Turkey Case	Sigma J Eng & Nat Sci
2020	Cruz-Jesus, F., Castelli, M., Oliveira, T., Mendes, R., Nunes, C., Bem-Velho, M., & Rosa-Louro, A. [56]	Using artificial intelligence methods to assess academic achievement in public high schools of a European Union country	Heliyon
2020	Gamazo, A., & Martínez-Abad, F.	An Exploration of Factors Linked to Academic Performance in PISA 2018 Through Data Mining Techniques	Frontiers in Psychology
2020	Gil, J. S.	Predicting Students' Dropout Indicators in Public School using Data Mining Approaches	The International Journal of Advanced Trends in Computer Science and Engineering
2020	Gomes, C. M. A., Lemos, G. C., & Jelihovschi, E. G.	Comparing the predictive power of the CART and CTREE algorithms	Avaliação Psicológica
2020	Güre, Ö. B., Kayri, M., & Erdogan, F.	PISA 2015 Matematik Okuryazarliğini Etkileyen Faktörlerin Egitsel Veri Madenciligi ile Çözümlenmesi	Egitim ve Bilim
2020	Sokkhey, P., Navy, S., Tong, L. Okazaki, T.	Multi-models of Educational Data Mining for Predicting Student Performance in Mathematics: A Case Study on High Schools in Cambodia	IEIE Transactions on Smart Processing and Computing
2020	Karthikeyan, V. G., Thangaraj, P., & Karthik, S.	Towards developing a hybrid educational data mining model (HEDM) for efficient and accurate student performance evaluation	Soft Computing
2020	Márquez, A. H., Poot, A. C., Arenas, A. G., & Luna, G. M.	Ancone: An interactive system for mining and visualization of students' information in the context of planea 2015	Computacion y Sistemas
2020	Martínez-Abad, F., Gamazo, A., & Rodríguez-Conde, M. J. [50]	Educational Data Mining: Identification of factors associated with school effectiveness in PISA assessment	Studies in Educational Evaluation
2020	Musso, M. F., Cascallar, E. C., Bostani, N., & Crawford, M.	Identifying Reliable Predictors of Educational Outcomes Through Machine-Learning Predictive Modeling	Frontiers in Education
2020	Naicker, N., Adeliyi, T., & Wing, J.	Linear Support Vector Machines for Prediction of Student Performance in School-Based Education	Mathematical Problems in Engineering
2020	Rajak, A., Shrivastava, A. K., & Vidushi.	Applying and comparing machine learning classification algorithms for predicting the results of students	The Journal of Discrete Mathematical Sciences and Cryptography
2020	Rebai, S.bemen Yahia, F., & Essid, H. [79]	A graphically based machine learning approach to predict secondary schools' performance in Tunisia	Socio-Economic Planning Sciences

Table A1. *Cont.*

Year	Authors	Title	Journal
2020	Sokkhey, P., & Okazaki, T.	Development and optimization of deep belief networks applied for academic performance prediction with larger datasets	IEIE Transactions on Smart Processing and Computing
2020	Sokkhey, P., & Okazaki, T.	Hybrid machine learning algorithms for predicting academic performance	The International Journal of Advanced Computer Science and Applications
2020	Sokkhey, P., & Okazaki, T.	Study on dominant factor for academic performance prediction using feature selection methods	The International Journal of Advanced Computer Science and Applications
2020	Uyar, S.	Latent class approach to detect differential item functioning: Pisa 2015 science sample	The Eurasian Journal of Educational Research
2020	Yildiz, M., & Börekci, C.	Predicting Academic Achievement with Machine Learning Algorithms	The Journal of Educational Technology and Online Learning
2020	Zaffar, M., Hashmani, M. A., Savita, K. S., Rizvi, S. S. H., & Rehman, M.	Role of FCBF Feature Selection in Educational Data Mining	Mehran University Research Journal of Engineering and Technology
2020	Thangakumar, J., & Kommina, S. B.	Ant colony optimization-based feature subset selection with logistic regression classification model for education data mining	The International Journal of Advanced Science and Technology
2020	Yousafzai, B. K., Hayat, M., & Afzal, S.	Application of Machine Learning and Data Mining in Predicting the Performance of Intermediate and Secondary Education Level Student	In Education and Information Technologies
2021	Aslam, N., Khan, I. U., Alamri, L. H., & Almuslim, R. S. [81]	An Improved Early Student's Performance Prediction Using Deep Learning	The International Journal of Emerging Technologies in Learning
2021	Froud, R., Hansen, S. H., Ruud, H. K., Foss, J., Ferguson, L., & Fredriksen, P. M.	The relative performance of machine learning and linear regression in predicting quality of life and academic performance of school children in Norway: Data analysis of a quasi-experimental study	The Journal of Medical Internet Research
2021	Huang, C., Zhou, J., Chen, J., Yang, J., Clawson, K., & Peng, Y. [47]	A feature-weighted support vector machine and artificial neural network algorithm for academic course performance prediction	Neural Computing and Applications
2021	Hussain, S., & Khan, M. Q.	Student-Performulator: Predicting Students' Academic Performance at Secondary and Intermediate Level Using Machine Learning	Annals of Data Science
2021	Maia, J. de S. Z., Bueno, A. P. A., & Sato, J. R. [53]	Assessing the educational performance of different Brazilian school cycles using data science methods	PLoS ONE
2021	Malini, J., & Kalpana, Y.	Investigation of factors affecting student performance evaluation using education materials data mining technique	Materials Today: Proceedings
2021	Pallathadka, H., Wenda, A., Ramirez-Asís, E., Asís-López, M., Flores-Albornoz, J., & Phasinam, K.	Classification and prediction of student performance data using various machine learning algorithms	Materials Today: Proceedings
2021	Sathe, M. T., & Adamuthe, A. C.	Comparative study of supervised algorithms for prediction of students' performance	International Journal of Modern Education and Computer Science
2021	Yekun, E. A., & Haile, A. T.	Student Performance Prediction with Optimum Multilabel Ensemble Model	Journal of Intelligent Systems

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