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REVIEW

Early Prediction of Students' Performance Through Deep Learning: A Systematic and Bibliometric Literature Review

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ABSTRACT
Early prediction of student performance is a critical and challenging task in the field of Educational Data Mining (EDM), encompassing all levels of education. Although there is extensive literature on student performance within EDM, studies specifically focused on early prediction are limited and mostly rely on traditional machine learning methods. However, in recent years, the importance and use of deep learning (DL) methods have increased due to their ability to process large datasets. This systematic literature review focuses on the early prediction of student performance using DL techniques. A total of 39 articles selected from the Scopus and Web of Science databases were analyzed using systematic and bibliometric methods. The review addresses five key research questions, including the distribution of studies by publication year, type, and education level; the datasets and features used; DL models and techniques; the timing of early predictions; and the challenges, limitations, and opportunities encountered. The bibliometric analysis, conducted with the VOSviewer program, visualized relationships between keywords, authors, and articles. Overall, this review provides a comprehensive synthesis of existing research on the early prediction of student academic performance using DL, offering valuable insights into trends and opportunities for researchers, educators, and policymakers.

Keywords: Education, Educational data mining, Early prediction, Student performance, Deep learning, Bibliometric literature review, Systematic literature review

1. Introduction

Educational data mining (EDM) is an interdisciplinary field that focuses on extracting meaningful insights from educational data to enhance learning and teaching processes [1]. The International Educational Data Mining Society emphasizes that EDM aims to analyze educational data types, predict student performance, and develop innovative methods to improve learning outcomes. With the advent of deep learning (DL) techniques, EDM has gained significant momentum, enabling more accurate and early predictions of student performance compared to traditional machine learning (ML) approaches. EDM combines social science methods such as psychometry, psychology, and broad-based mathematical methods from statistics, artificial intelligence, and machine learning (ML) to deep learning (DL) [2].

Early prediction is defined as implementing predictive models utilizing key variables to accurately forecast student failure or dropout as early as possible [3], [4]. It involves leveraging technological information to detect potential or actual academic problems. Detecting at-risk students promptly allows for timely interventions, support, and preventative strategies, aiming to prevent academic setbacks. Student information sources for early predictions are diverse, encompassing questionnaires, activities, events, log files, demographic data, evaluation results, behavior data, grades, affective variables, and more. The challenge of early prediction is amplified in the EDM field due to numerous factors influencing a student's final status. This challenge holds critical implications globally across all educational stages (primary, secondary, and tertiary education), necessitating early identification of at-risk students to implement adequate preventative measures and interventions [5].

Previous research in EDM has extensively explored various aspects of student performance prediction, including machine learning [6] – [9], student dropout [10], learning analytics [11] – [13], and data mining [12], [14], [15]. While traditional ML

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methods such as Decision Trees (DT), Random Forests (RF), and Support Vector Machines (SVM) have been widely used, recent studies highlight the superior performance of DL techniques in handling complex and large-scale educational data [29]. However, a comprehensive comparison of DL and ML models regarding computational cost, training time, and prediction accuracy remains underexplored. This gap necessitates a deeper analysis of the trade-offs between these approaches.

Researchers have written numerous articles in predicting student performance in EDM. These literature studies by researchers focus on machine learning [6], [7], [8], [9], student dropout [10], learning analytics [11], [12], [13], data mining [12], [14], [15], student performance predictions [16], [17], [18], e-learning [19], computer-supported collaborative learning [20], student retention [21], feature selection [22], affecting factors [23], classroom learning (Khan and Ghosh, 2021), predicting academic success [24], early prediction [25], [26], and big data [27], [28] topics. While traditional ML methods such as Decision Trees (DT), Random Forests (RF), and Support Vector Machines (SVM) have been widely used, recent studies highlight the superior performance of DL techniques in handling complex and large-scale educational data [29]. However, no one specifically focuses on early student performance prediction through DL techniques.

Previous literature studies emphasized the need for a literature review to examine the impact of DL methods on early prediction of student performance. In this study, we aimed to conduct a literature review that encompasses these two research areas. The contributions of this literature review article are as follows:

- Provides an overview of DL techniques and algorithms in early student performance prediction.
- Identifies existing uses of DL for early student performance prediction through a systematic literature review.
- Identifies gaps in the literature and highlights future research areas to enhance early prediction of student performance with DL.
- A bibliometric literature review explains relationships between keywords, authors, and articles and presents these relationships visually.

This review article is divided into six sections. Section 2 explains the steps of the review methodology used. Search results are presented in Section 3. Section 4 provides a systematic literature analysis of selected articles. Bibliometric analysis is introduced in Section 5. Section 6 presents the conclusion of the current literature.

2. Literature Review Methodology

This literature review is divided into two sections: Systematic and Bibliometric Review. The details of the review steps are presented in the following subsections.

2.1. Systematic Review

This study adopts a systematic literature review approach, adhering to the guidelines proposed by Kitchenham for software engineering researchers [30]. The primary objective is to analyze the current landscape of DL techniques and algorithms for predicting students' performance early, providing insights into existing studies and identifying gaps for future research. The systematic literature review procedure is outlined as follows.

1. Research Questions: The study addresses the following research questions (RQs):
    - RQ1: What is the distribution of studies by publication year, publication type, education type, and level?
    - RQ2: What datasets, attributes, and predicted attributes are used for early prediction?
    - RQ3: What DL models and techniques are employed for early prediction, and what are the performance evaluation methods?
    - RQ4: How early can student academic performance be predicted with an acceptable level of accuracy?
    - RQ5: What are the main challenges, limitations, and research opportunities identified in previous studies?
2. Search Process The systematic analysis encompasses studies from Scopus and Web of Science library databases until December 20, 2023. The search utilizes five key terms: "educational data mining," "data mining," "machine learning," "deep learning," and "early prediction of student performance." The search terms are structured for both Scopus and Web of Science databases. The search used the following search query:
    - Scopus: TITLE-ABS-KEY (("educational data mining" OR "data mining" OR "machine learning" OR "deep") AND ("deep learning" OR ("deep" AND "Neural Network")) AND student AND performance AND early)

- Web of Science: (ALL= (((“educational data mining” OR “data mining” OR “machine learning” OR “deep”)))) AND AB= (((“deep learning” OR (“deep” AND “Neural Network”)) AND student AND performance AND early))

3. Inclusion and Exclusion Criteria The review includes DL techniques and algorithms for early prediction of students’ performance, published until December 20, 2023. Excluded topics do not involve early prediction of student performance and DL, lack appropriate abstracts and keywords, must be in English, or have inaccessible full texts.
4. Quality Assessment Research papers from active scholarly journals in the specified databases are considered of sufficient quality, while those outside these databases are excluded from the Review.
5. Data Collection Relevant data was extracted for the selected articles and organized into an electronic spreadsheet. The information includes article details, type and level of education, datasets and attributes, DL/ML models, evaluation methods, early prediction status, limitations, contributions, and future research suggestions.
6. Data Analysis The collected data is analyzed by defined research questions. The analysis results are synthesized, and common themes are identified by comparing findings related to each research question.

2.2. Bibliometric Review

Bibliometric Review incorporates a research approach involving bibliometric analysis, which quantitatively assesses publications in scientific literature and their interconnections. This investigation aims to comprehend scientific production, publication trends, significant researchers, highly cited works, and institutional contributions within a specific subject, field, or discipline. Bibliometrics provides the methods and indicators commonly employed in these analyses. The outcomes of bibliometric reviews are typically represented through graphs, diagrams, and maps.

In this article, we utilized VOSviewer (Visualization of Similarity), a widely adopted tool for visualizing and conducting network literature analysis. This tool integrates text mining and network analysis techniques to identify crucial concepts and connections within literature. Such a tool proves beneficial for researchers and information professionals in pinpointing significant focal points within a field, focusing on specific topics, or monitoring developments in a particular subject.

Bibliometric data, obtained from the Scopus website, where all information of the 39 selected studies was found at the end of the systematic literature review process, were exported in CSV format. Using this dataset, an analysis was conducted in the VOSviewer program to comprehend and visually represent relationships among keywords, authors, and articles.

2. Search Results

Two hundred seventy-eight articles published in the Web of Science and Scopus databases up to November 2023 were obtained from the abovementioned search process. Of these articles, 69 were found to be duplicates present in both databases, and one was excluded. Consequently, a unique set of 209 articles was reached. Of these, 113 were journal articles, 61 were from international conferences, 21 were conference reviews, and 13 were of different types such as books, book chapters, meetings, proceedings papers, and Reviews. Each article’s abstract was meticulously examined, and 142 articles were excluded at this stage. Among the excluded articles, 116 were unrelated to student performance prediction and deep learning, 24 lacked free access and full-text availability, and two needed to be in English. A selection process involving reading the full texts was applied to the remaining articles, and 28 articles not related to student performance prediction and deep learning were also excluded. As a result, 39 articles were chosen.

The remaining 39 articles addressed five main research questions and conducted bibliometric analysis in the VOSviewer program. In the discussion sections (Sections 5 and 6), the obtained results were detailed and discussed, providing a comprehensive overview of the literature on the subject.

4. Systematic Analysis of Deep Learning in Early Prediction of Academic Performance Within EDM

This section of the systematic literature review discusses the findings obtained in response to the identified research questions.

4.1. RQ1. What is the Distribution of Studies by Publication Year, Publication Type, Education Type, and Level?

Table 1 presents the critical details of the selected 39 studies. These studies were published between 2017 and December 20, 2023. All the studies comprise journal and conference publications, with journal studies accounting for 65% of the total (24 studies).

Table 1. Distribution of Essential Information for Selected Studies

Ref.	Year	Type	Cited by	Scopus	WoS	Source Title	Publisher	Education Types			Education Levels		
								F	B	E	S	U	All
[31]	2022	J	8	✓	✓	Complex and Intelligent Systems	Springer	✓				✓	
[32]	2023	J	1	✓		Revue d'Intelligence Artificielle	IIETA	✓			✓		
[33]	2023	C	1	✓		ITIKD 2023	IEEE Inc.			✓		✓	
[34]	2023	J	0	✓	✓	Applied Sciences	MDPI			✓		✓	
[35]	2022	C	1	✓		IC3SIS 2022	IEEE Inc.			✓			✓
[36]	2023	J	5	✓		Expert Systems with Applications	Elsevier Ltd			✓		✓	
[37]	2023	J	1	✓		SN Computer Science	Springer	✓				✓	
[38]	2022	C	0	✓		TALE 2022	IEEE Inc.			✓		✓	
[39]	2023	J	2	✓		Heliyon	Elsevier Ltd			✓		✓	
[40]	2023	C	0	✓	✓	COMPSAC	IEEE Computer Society	✓				✓	
[41]	2023	J	1	✓		IEEE Access	IEEE Inc.		✓			✓	
[42]	2023	J	1	✓	✓	IEEE Access	IEEE Inc.		✓			✓	
[43]	2022	J	6	✓	✓	Applied Sciences	MDPI			✓		✓	
[44]	2021	J	20	✓		IEEE Access	IEEE Inc.		✓			✓	
[45]	2018	C	14	✓		INAPR 2018	IEEE Inc.	✓				✓	
[46]	2020	J	242	✓	✓	Computers in Human Behaviour	Elsevier Ltd			✓		✓	
[47]	2019	J	45	✓		Sustainability	MDPI			✓		✓	
[48]	2021	J	2	✓		Sustainability	MDPI			✓		✓	
[49]	2021	J	1	✓		JATIT	Little Lion Scientific	✓			✓		
[50]	2020	C	8	✓		EDM 2020	IEDMS			✓			✓
[51]	2022	J	6	✓	✓	iJET	IAOE			✓			✓
[52]	2021	J	16	✓	✓	iJET	IAOE	✓					✓
[53]	2018	C	29	✓		EDM 2018	IEDMS			✓			✓
[54]	2019	J	17	✓		Computing	Springer			✓			✓
[55]	2020	C	12	✓	✓	Lecture Notes in Computer Science	Springer			✓		✓	
[56]	2021	C	8	✓	✓	Lecture Notes in Computer Science	Springer	✓			✓		
[57]	2019	C	33	✓	✓	ISET 2019	IEEE Inc.		✓			✓	
[58]	2021	J	4	✓	✓	Optical Memory and Neural Networks	Pleiades journals			✓			✓
[59]	2020	C	25	✓		EDM 2020	IEDMS			✓		✓	
[60]	2020	J	51	✓	✓	Journal of Learning Analytics	UTS ePRESS			✓		✓	
[61]	2019	C	23	✓	✓	ICPS	ACM	✓				✓	
[62]	2019	J	53	✓		International Journal of Intelligent Systems	John Wiley and Sons Ltd			✓		✓	
[63]	2017	C	65	✓		EDM 2017	IEDMS			✓			✓
[64]	2020	J	18	✓	✓	IEEE Access	IEEE Inc.			✓	✓		
[65]	2021	J	9	✓	✓	IEEE Access	IEEE Inc.	✓				✓	
[66]	2021	J	10	✓		JOIV	Politeknik Negeri Padang			✓		✓	
[67]	2021	J	41	✓	✓	IEEE Access	IEEE Inc.	✓				✓	
[68]	2021	J	70	✓	✓	IEEE Access	IEEE Inc.			✓		✓	
[69]	2021	J	48	✓	✓	Sustainability	MDPI	✓			✓		

F: face-to-face education; B: hybrid (blended) education; E: e-learning; S: secondary school; U: university

The sources with the highest number of publications are listed in Figure 1. Twenty-three studies, approximately half of the total, were published by six different sources. Notable among these sources are IEEE Access (7 studies), International Conference on Educational Data Mining (ICEDM) (4 studies), Sustainability (3 studies), Applied Sciences (2 studies), The International Journal of Engineering Technologies (IJET) (2 studies), and Lecture Notes in Computer Science (LNCS) (2 studies).

The publishers with the highest number of publications are listed in Figure 2. Furthermore, 31 studies, constituting 79% of the total, were published by six different publishers. Prominent publishers include IEEE Inc. (12 studies), Multidisciplinary

Digital Publishing Institute (MDPI) (5 studies), Springer (5 studies), the International Educational Data Mining Society (IEDMS) (4 studies), Elsevier Ltd (3 studies), and the International Association of Online Engineering (IAOE) (2 studies).

The selected studies have been classified according to the type of education system and education level. As shown in Figure 3, the studies encompass e-learning (23 studies, 59%), traditional face-to-face education (12 studies, 31%), and hybrid (blended) education (4 studies, 10%). Upon evaluation of these studies, as seen in Figure 3, it was determined that 26 out of 39 studies (67%) were conducted with university students, 5 out of 39 studies (13%) focused on secondary school students, and the remaining 8 out of 39 studies (21%) were related to e-learning courses at all education levels. The predominant reasons for conducting studies primarily at the university level include data accessibility, ease of data collection, and the widespread use of computer-assisted education. Additionally, it was observed that studies at the higher education level were predominantly carried out at the undergraduate level. No studies were conducted at the graduate level or in primary schools.

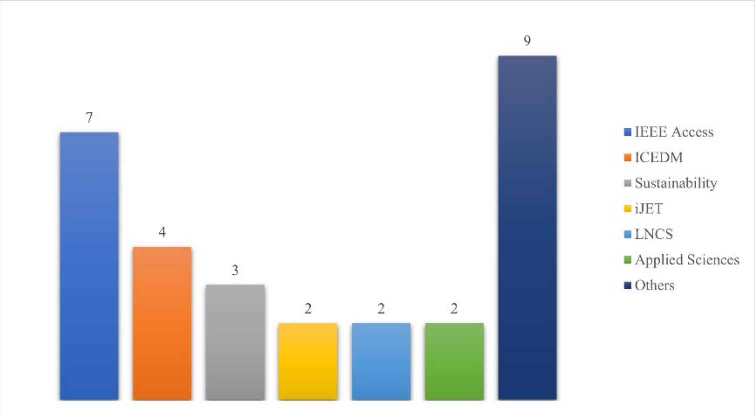

Figure 1. The Sources with the Highest Number of Publications

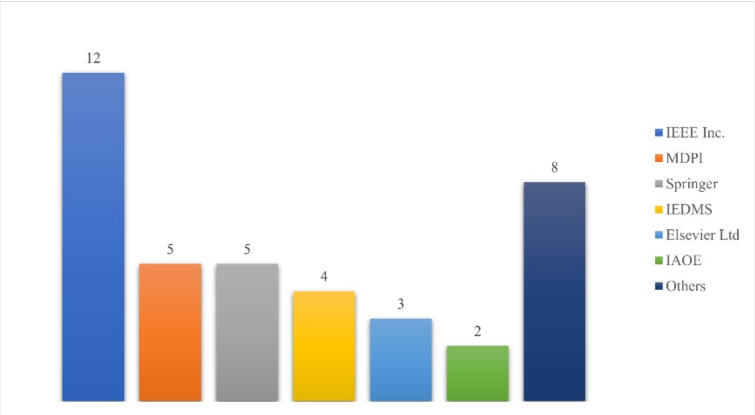

Figure 2. The Publishers with the Highest Number of Publications

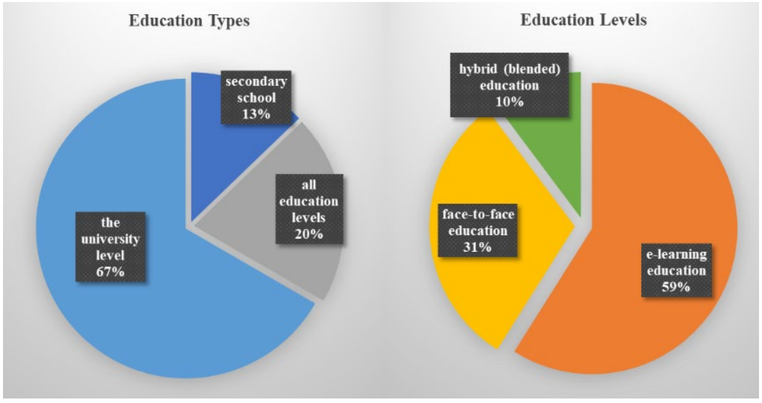

Figure 3. Education Types and Levels

Upon analyzing citation counts, it was determined that an average of 23 citations were obtained for each study. The citation counts, totals, and averages by year are presented in detail in Table 2.

Table 3 presents the researcher density in the selected articles. Authors are weighted based on the number of contributors to each paper. For example, in a paper with n authors, each author contributes to their country with a weight of 1/n.

The table indicates that the People's Republic of China is the most active country in this field, followed by the United States of America, Saudi Arabia, Pakistan, India, Indonesia, Taiwan, Canada, Egypt, Bahrain, Philippines, Japan, Yemen, and Malaysia. Among other countries, South Korea, Brazil, Oman, United Kingdom, Kerala, Australia, Spain, Tunisia, Nigeria, and Germany are noteworthy for their substantial contributions to this field.

Table 2. The Citation Counts, Totals, and Averages by Year

Year	Count of Cited by	The sum of Cited by	Average of Cited by
2017	1	65	65
2018	2	43	22
2019	5	171	34
2020	6	356	59
2021	11	229	21
2022	5	21	4
2023	9	12	1
Total	39	897	23

Table 3. The Authors' Countries Distribution

Country	Count	Score	References
China	10	8.9	[31], [35], [40], [41], [51], [54], [55], [59], [64], [69]
United States	7	5.3	[50], [53], [56], [61], [63], [64], [66]
Saudi Arabia	7	3.3	[36], [47], [52], [62], [65], [69]
Pakistan	6	3	[36], [47], [62], [68], [69]
India	4	2.8	[32], [35], [37], [59]
Indonesia	3	2.6	[42], [43], [46]
Taiwan	2	1.4	[43], [48]
Canada	2	1.1	[60], [69]
Egypt	2	1.1	[65], [67]
Bahrain	1	1	[33]
Yemen	1	1	[39]
Japan	1	1	[38]
Philippines	1	1	[57]
Malaysia	1	1	[49]
South Korea	1	1	[66]
Other	8	3.6	[35], [36], [37], [44], [46], [53], [56], [69]

4.2. RQ2. Datasets, Attributes, and Outcomes Used for Early Prediction of Student Performance

The datasets used for early student performance prediction vary widely regarding type, structure, and quality. The distribution of these datasets is detailed in Table 4.

Upon evaluating Table 4, as seen in Figure 4, it was observed that 63% of the studies (25 studies) were associated with Massive Open Online Courses (MOOCs), Virtual Learning Environments (VLEs), Learning Management Systems (LMSs), and Intelligent Teaching Systems (ITSs), with VLEs prominently featured among these datasets. Additionally, open datasets were generally employed in 25% of the studies (10 studies). Among these, the Open University Learning Analytics Dataset (OULAD) VLE general dataset, encompassing weekly VLE activity information for students, was utilized in ten studies. As seen in Figure 4, specifically 15 studies, one-third of the selected studies constitute general datasets. Among these general datasets are OULAD (10 studies), The edX open dataset (1 study), Udacity Data (1 study), xAPI-Edu-Data (1 study), and UCI Machine Learning Repository (4 study). These general datasets have unique advantages and limitations. The Open University Learning Analytics Dataset (OULAD) provides rich data on student interactions but can negatively impact model performance due to imbalanced class distributions. Similarly, datasets from MOOC platforms like edX are large-scale but often lack detailed behavioral information. These limitations can be addressed through data augmentation or advanced preprocessing techniques, which can enhance the reliability and accuracy of predictive models.

The categorization of attributes and predicted features for the early prediction of student performance is also detailed in Table 4. Accordingly, it was observed that the most frequently used attributes include student demographic information (age, gender, region, address, family size, mother's education, father's education, mother's job, father's job, current health status, etc.), evaluation results, activity data, LMS log data, and behavioral information. Other attributes such as student grades, grade points, test scores, learning outcomes, student details, and snapshot data were noteworthy. In evaluating the research, it was noted that 67% of the studies (26) aimed to predict final scores and grades. Other outcomes encompass grade point averages (GPAs), learning outcome scores, post-test scores, application scores, quiz performance scores, learning behavior, lecture grades, dropouts, and snapshot grades.

Table 4. Datasets, Features, and Estimated Attributes Distribution

References	General / Specific	Types	Datasets	Features							Estimated Attributes							
				Demographics	Academic	Events	Assessments	Behaviors	Log files	Others	Final Grades	Final Scores	GPAs	Dropouts	Graduation	The GPAs	Learning	Other
[31]	S	Other	The datasets of the university in Beijing	✓				✓								✓		
[32]	S	Other	The government and self-financed engineering colleges dataset	✓	✓		✓						✓					
[33], [34], [36], [39], [42], [46], [47], [59], [62], [68]	G	VLE	OULAD	✓	✓	✓	✓				✓							
[35]	S	MOOCs	MITx and Harvard X courses							✓				✓				
[37]	S	Other	The publicly accessible data source		✓	✓	✓											✓
[38]	S	Other	M2B Learning systems							✓	✓							
[40]	S	LMS	A sophomore course from the School of Computer Science and Engineering			✓	✓		✓			✓						
[41]	S	Other	The dataset of the university	✓	✓	✓	✓	✓				✓						
[43]	S	LMS	Moodle LMS			✓				✓		✓						✓
[44]	S	Other	The CS1 course is compulsory for 16 STEM degrees at the Federal University of the Amazonas.			✓					✓							
[45]	S	Other	The data used in this experiment are from computer science at Bina Nusantara University.				✓						✓					
[48]	S	LMS	A general education course at a university in northern Taiwan.			✓	✓		✓			✓						
[49], [56], [58], [69]	G	ITSs	UCI Machine Learning Repository	✓	✓	✓	✓	✓			✓							
[50]	S	ITSs and Other	Pyrenees and iSnap							✓								✓
[51]	G	MOOCs	The edX open dataset							✓							✓	
[52]	S	Other	Two data sets are mathematics and Portuguese language courses.	✓	✓	✓	✓				✓							
[53]	G	MOOCs	Udacity Data			✓									✓			
[54]	S	Other	The datasets are from two real e-learning system	✓	✓	✓	✓	✓	✓		✓							

Table 4. (Continued)

[55]	S	Other	Datasets from 505 university students			✓		✓				✓						
[57]	S	LMS	Moodle LMS			✓		✓			✓							
[60]	S	LMS	Moodle LMS			✓	✓		✓		✓							
[61]	S	Other	A dataset from University X				✓									✓		
[63]	S	MOOCs	Code.org							✓								✓
[64]	S	LMS	The Blackboard LMS			✓	✓	✓	✓		✓							
[65]	S	Other	The university dataset				✓						✓					
[66]	S	LMS	The Cyber University LMS system	✓	✓	✓			✓				✓					
[67]	S	Other	Students' grades				✓											✓
[69]	G	LMS	xAPI-Edu-Data	✓	✓	✓				✓	✓							

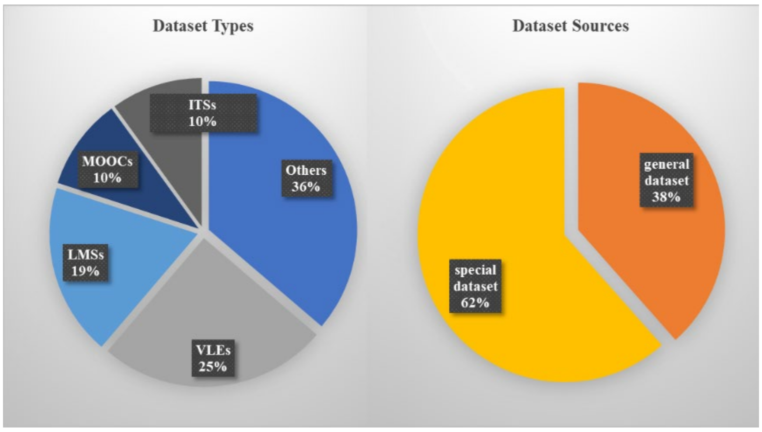

Figure 4. Dataset Types and Sources

4.3. RQ3. Proposed Models, Compared Models, and Performance Evaluation Methods for Early Prediction of Student Academic Performance

The distribution of the proposed models, compared models, classification, and evaluation methods are presented in Table 5. Figure 5 illustrates the proposed DL models in the selected articles. Long Short-Term Memory (LSTM), Deep Feed Forward Neural Networks (DFFNN), Bidirectional LSTM (BLSTM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Deep Belief Network (DBNN), Deep Neural Networks (DNN) DL, and Hybrid DL techniques were used. Among these techniques, it has been observed that many LSTM techniques were used.

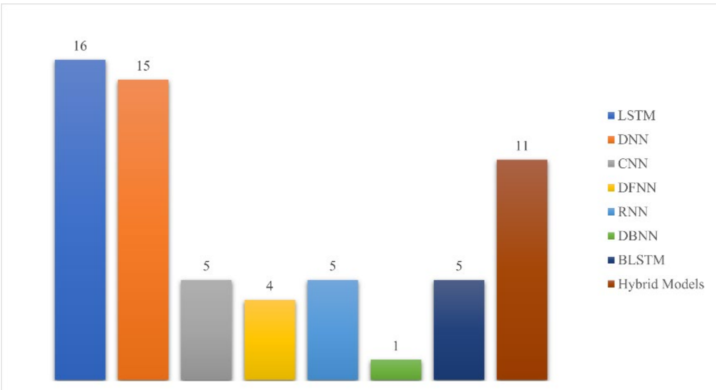

Figure 5. Proposed DL Models

It was observed that hybrid DL techniques were used in nine studies, and they were CNN-LSTM [31], [32], [43], [55], Levy Flight Rock Hyraxes Swarm Optimization (LFRHSO)-RNN [37], Atom Search Optimization (ASO)-DBN [58], BLSTM + the Condition Random Field (CRF) [65], DNN- Integrated Framework Based on Latent Variational Autoencoder (LVAEPre) [64], and LSTM-ANNs [39].

Among these studies, Chen et al. (2022) proposed a hybrid intelligent framework comprised of CNN and LSTM models to address the issue of unstable data distribution and predictability in VLE [43]. Li et al. (2020) Introduced the Sequential Prediction Based on Deep Network (SPDN) model, consisting of CNN and LSTM DL models, to predict students' 13-week course performance using online learning records and blog data from the university campus network [55]. In another study, Li et al. (2022) suggested an end-to-end hybrid DL model that combines CNN and LSTM models to automatically extract features from multi-source heterogeneous four-day behavioral data of students [31].

Table 5. The Distribution of The Proposed Models, Compared Models, Classification, and Evaluation Methods

References	Reg. / Class.	Classification	Proposed Model								Compared Models										Evaluation Methods						
			LSTM	Deep ANN	CNN	DFNN	RNN	DBN	BLSTM	Hybrid	SVM	RF	LR	DT	KNN	NB	ANN	GBM	AdaBoost	Others	Accuracy	F1 score	Precision	Recall	ROC-AUC	RMSE	Others
[31]	C	3								✓		✓	✓	✓					✓	✓	✓	✓	✓	✓			
[32]	R C	4	✓	✓						✓	✓	✓						✓		✓	✓	✓	✓	✓		✓	
[33]	C	2		✓							✓					✓	✓			✓	✓						
[34]	C	4				✓					✓	✓	✓			✓					✓	✓	✓	✓			
[35]	C	2		✓								✓	✓		✓	✓				✓	✓		✓				
[36]	C	2	✓								✓		✓	✓	✓		✓			✓	✓	✓	✓	✓	✓		✓
[37]	C	2		✓	✓		✓	✓		✓					✓						✓			✓			✓
[38]	C	2	✓									✓			✓	✓		✓		✓		✓	✓	✓			
[39]	C	4	✓			✓	✓			✓										✓	✓	✓	✓	✓			
[40]	C	2							✓												✓				✓		
[41]	C	3		✓	✓						✓			✓	✓					✓	✓	✓		✓			
[42]	C	2	✓																	✓	✓	✓					✓
[43]	C	2	✓							✓	✓		✓								✓	✓	✓	✓			
[44]	C	2		✓								✓								✓	✓	✓	✓	✓	✓		
[45]	R C	2		✓									✓	✓							✓					✓	
[46]	C	2		✓							✓		✓								✓		✓	✓			✓
[47]	C	2	✓								✓		✓				✓				✓		✓	✓			✓
[48]	C	2	✓		✓		✓													✓	✓	✓	✓	✓			
[49]	C	2		✓								✓						✓		✓	✓			✓			✓
[50]	C	2	✓										✓							✓	✓	✓	✓	✓	✓		
[51]	C	5		✓							✓		✓	✓		✓						✓	✓	✓			
[52]	C	2		✓							✓	✓									✓	✓	✓	✓			
[53]	C	2							✓											✓					✓		
[54]	C	2	✓	✓			✓				✓	✓								✓	✓	✓					
[55]	C	2							✓	✓		✓	✓	✓		✓					✓	✓			✓		
[56]	C	5			✓						✓	✓	✓	✓					✓	✓	✓						
[57]	C	2				✓															✓				✓		
[58]	C	3								✓	✓				✓		✓					✓	✓				✓
[59]	C	4	✓								✓		✓									✓		✓			
[60]	C	2	✓								✓	✓	✓	✓	✓	✓	✓	✓							✓		
[61]	R C	2	✓																	✓	✓	✓					✓
[62]	C	2	✓										✓				✓				✓		✓	✓			✓
[63]	C	2	✓										✓									✓	✓	✓			

Table 5. (Continued)

[64]	C	2		✓						✓				✓					✓		✓	✓	✓	✓			✓
[65]	C	2							✓	✓	✓	✓	✓	✓		✓	✓				✓	✓	✓	✓			
[66]	C	2		✓							✓	✓		✓							✓	✓	✓	✓	✓		
[67]	C	2		✓							✓	✓	✓	✓	✓			✓			✓	✓					✓
[68]	C	4				✓					✓	✓			✓		✓	✓	✓	✓	✓	✓	✓				
[69]	C	6	✓		✓		✓		✓		✓	✓	✓		✓	✓					✓	✓	✓	✓			

Venkatachalam and Sivanraju (2023) proposed a hybrid Student Achievement Prediction Model Using the Distinctive Deep Learning (SADDL) framework, which includes three modules: LSTM, CNN, and Multilayer Perceptron (MLP). The SADDL model has demonstrated superior performance to other machine learning models when utilizing the students' physiological, academic, and demographic data to achieve results [32]. Sayed et al. (2023) presented a method to predict student performance using the suggested hybrid model (LFRHSO-RNN) and a large student, administrator, and teacher data dataset. Additionally, they compared the proposed model with different hybrid models such as Grey Wolf Optimizer (GWO)-RNN, Fire- fly Algorithm (FFA)-RNN, Bat algorithm (BAT) -RNN, and Particle Swarm Optimization (PSO)-RNN [37]. Surenthiran et al. (2021) proposed a hybrid model based on DBNN, supported by ASO, which has been utilized to categorize students according to their historical performance [58]. Uliyan et al. (2021) reported high accuracy in examining students' retention status using a hybrid DL technique consisting of BLSTM and CRF [65].

Du et al. (2020) proposed an integrated framework, LVAEPre, based on latent variational autoencoder (LVAE) with DNN to alleviate the imbalanced distribution of the dataset and provide early warnings for students at further risk [64]. Al-azazi and Ghurab (2023) proposed a hybrid ANN-LSTM model consisting of Artificial Neural Network (ANN) and LSTM models to predict students' performance on a day-wise multi-class basis [39].

It has been observed that the proposed DL models were primarily compared with basic ML models such as Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), k-Nearest Neighbors (KNN), Artificial Neural Network (ANN), Gradient Boosting Machine (GBM), Adaptive Boosting (AdaBoost), and Naive Bayes (NB). Some studies compared the proposed models with the LSTM, CNN, RNN, and DNN DL models. Figure 6 illustrates the ML models in the selected articles that were compared.

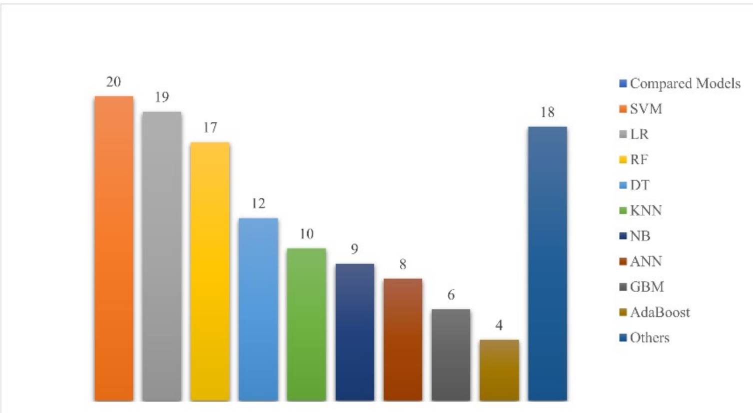

Figure 6. Compared ML Models

Consequently, the proposed DL models obtained the same or better results than the compared ML and DL models, demonstrating their effectiveness in early student performance prediction. In particular, hybrid DL models that integrated multiple architectures, such as CNN-LSTM and ASO-DBN, showed notable improvements in prediction accuracy, robustness, and generalizability across different datasets. These findings highlight the advantages of utilizing deep learning techniques over traditional machine learning methods, especially in handling complex, high-dimensional educational data and capturing intricate patterns in students' learning behaviors.

Figure 7 illustrates the classification types in the selected articles. It was observed that while regression models were performed in only two studies [45], [61], other studies were interested in classification. Considering all the studies that have been classified, Outcomes in 72% of them were divided into two classes, with the remaining 28% predicted by three classes, four classes, five classes, and six classes. In binary classification, pass-fail, true-false, passed-withdrawn, successful-unsuccessful, and at risk-not at risk can be given as examples. As several models are usually built, evaluating them and selecting the best-performing model is crucial. Figure 7 illustrates the evaluation methods in the selected articles. Root Mean Square Error (RMSE) was used in regression studies, while accuracy, precision, recall, F1 score, and Area Under the Curve (AUC) performance evaluation methods were used in classification studies.

4.4. RQ4. Early Prediction of Student Performance

Considering all the studies selected for the early prediction of student performance, it was observed that the early prediction times varied depending on the course length. In some studies, information regarding the length of the educational process was not provided [32], [37], [41], [44], [45], [49], [51], [52], [58], [61], [63], [64], [65], [66], [69]. The course length, prediction frequency, and early prediction time are given in Table 6.

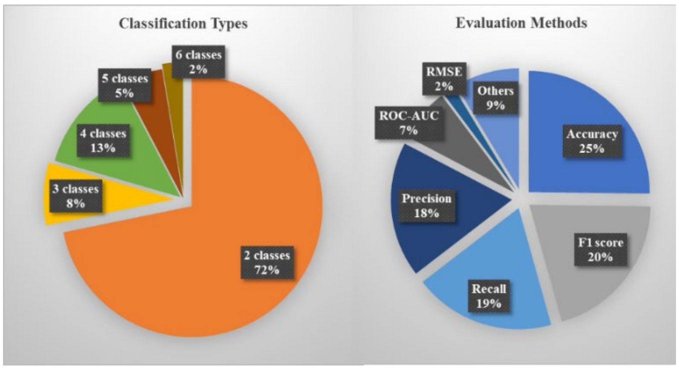

Figure 7. Classification Types and Evaluation Methods

Table 6. Distribution of Early Prediction Time

References	Course Length	Prediction Frequency	Early Prediction Time
[35]	5 Weeks	Weeks 1-5	Week 1
[38]	7 Weeks	Weeks 1-7	Week 7
[53]	8 Weeks	Weeks 1-8	Week 3
[55]	13 Weeks	Weeks 1-13	Week 7
[60]	16 Weeks	Weeks (6,8,10,12,16)	Week 6
[48]	17 Weeks	Weeks (3,6,9,12,18)	Week 9
[40]	21 Weeks	Weeks 1-12	Week 8
[34], [68]	40 Weeks	The sequence length (10,20,30,40,50,60,70,80,90,100)	20% sequence length
[47]	40 Weeks	Weeks (5,10,20,30,40)	Week 10
[62]	40 Weeks	Weeks (5,10,15,20,25)	Week 10
[46]	40 Weeks	Quarter 1-4	Quarter 1
[36]	40 Weeks	Weeks (5,10,20,30,38)	Week 20
[59]	40 Weeks	Weeks (5,10,15,20)	Week 20
[39]	40 Weeks	Days (0 and 270)	First 90 days
[33]	40 Weeks	Days (0,7,14,30,45,60)	First 0 days
[42]	40 Weeks	Days (0,20,40,60,80,100,120,140)	First 140 days
[31]	145 Days	The sequence length (5,10,15,20)	20% sequence length
[60]	70 Days	Days (28,42,56,70)	First 28 days
[51]	48000 Volumes	The volume of data (8000, 16000, 32000, 40000, 48000)	8000 Volumes
[67]	14 Academic years	Academic years	First two academic years
[50]	20 Minutes	Minutes (2,4,6,8,10,15,20)	First 10 minutes
[57]	3 Months	Midterm and final	The first month
[63]	12 Timesteps	Timesteps 1-12	Timestep 5

When Table 6 is assessed, it is observed that student performance is predicted earlier in the first quarter and midway through the prediction interval. This prediction interval varies from 20 minutes [50] to 14 academic years [67]. Additionally, an improvement in predicting student performance is observed as the predicted time interval increases. The best prediction results are generally obtained at the end of the prediction interval.

Figure 8 presents the highest accuracy values of studies conducting week-based early predictions using the 40-week OULAD general dataset [36], [46], [47], [62]. As the figure shows, prediction accuracy generally improves as the prediction interval progresses. For instance, models achieved accuracy rates ranging from 69% to 80% in the fifth week, which increased to 85%-97% by the 40th week. This trend provides a clear perspective on how prediction accuracy evolves, demonstrating a consistent improvement as more weeks of data become available.

4.5. RQ5 Limitations of Studies, Contributions to Literature, and Future Research Studies

4.5.1. Limitations of Studies

The limitations of studies were reported generally about datasets. These limitations have been listed as follows: the imbalanced distribution of the dataset [33], [34], [36], [39], [42], [46], [47], [48], [52], [59], [60], [62], [67], [68], the small sample size [50], [60], it does not structure [50], the dataset was limited [32], [37], [40], [64], short training period (Mao et al, 2020), the general dataset [33], [34], [36], [39], [42], [46], [47], [51], [53], [56], [59], [62], [68], considering only essential features (Yousafzai et al, 2021), insufficient enrolment [47], and same types of data [38], [45], [61], [65], [67].

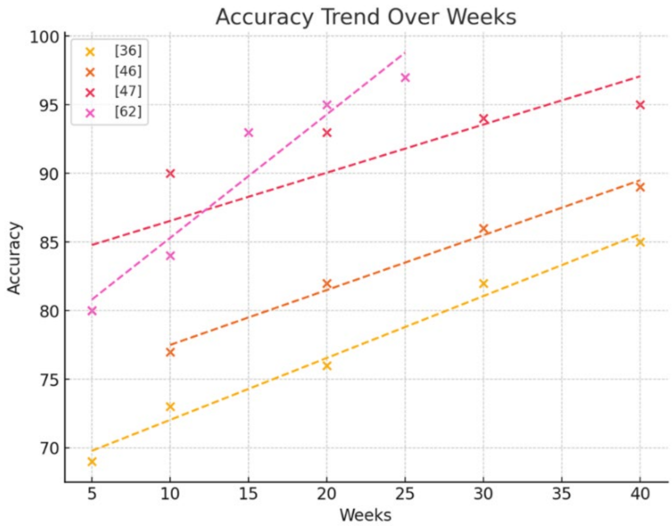

Figure 8. Accuracy Trend in 40-Week OULAD Studies

4.5.2. Contributions of Studies

When the selected studies are evaluated, they have contributed to the literature by developing new algorithms to address the following issues: examining behavioral data [44], [54], [55], [55], [56], [64], [68], predicting learning outcomes [50], [51], addressing the imbalanced distribution of the dataset [33], [34], [35], [43], [52], [60], enhancing the interpretability of prediction results [39], [43], integrating feature selection [51], [69], and tackling time series sequential classification problems [31], [36], [38], [40], [47], [53], [55], [59], [60], [62]. Additionally, the studies have addressed other significant problems, including focusing on multi-step exercises with unlimited solutions [50], [63], making predictions in a blended learning environment [57], forecasting dropouts [35], and predicting graduation [53].

4.5.3. Future Research Suggested by the Studies

The suggestions for future research from the reviewed studies were divided into two classes: data and models. Regarding the elimination of data limitations, solving the data imbalance problem [33], [36], [59], [60], [67], analyzing the data sparsity problems [59], [68], and expanding the data set to eliminate its limitations [31], [32], [36], [37], [38], [41], [43], [47], [48], [49], [52], [53], [55], [62], [64], [67], [69] have been left to future studies. Regarding the development of the models, it has been observed that the research of time-sensitive models [39], [50], the use of different models [32], [66], improving the proposed model [34], [40], [65], the use of natural language processing techniques [46], [47], [64], [68], and the dynamic estimation of the interpretability of DL models [31] have been left to future studies.

5. Comprehensive Science Mapping Analysis

This section presents bibliometric analysis results of the selected 39 articles downloaded from the Scopus database using VOSviewer. Figure 9 illustrates the periodic distribution of the total number of articles.

As shown in Figure 9, there is an increasing trend in the number of articles, with a year-over-year growth. The initial studies were only published as conference proceedings in 2017 and 2018. After 2019, the number of articles significantly increased. Moreover, there was a notable surge, particularly in 2021, where 11 works were published, including ten articles. Therefore, there is a growing interest in the subject. In this regard, more researchers are focusing on the topic.

5.1. Keyword Analysis

Table 7 displays the “Author Keywords Occurrence” and “Total Link Strength” for the top ten author keywords with a minimum keyword occurrence of 3 in the selected studies using the VOSviewer program. “Author Keywords Occurrence” indicates how often a specific keyword appears, while “Total Link Strength” represents the frequency and strength of co-occurrence between two keywords.

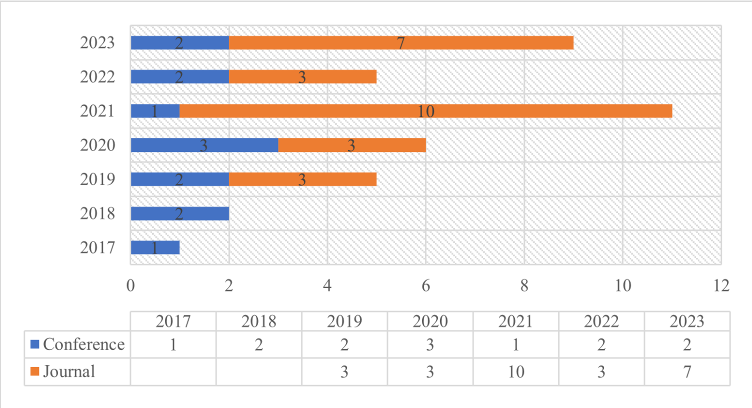

Figure 9. The Annual Number of Articles

Table 7. The Occurrence and the Total Link Strength of Author Keywords

Order	Keyword	Occurrences	Total link strength
1	deep learning	16	22
2	machine learning	12	18
3	educational data mining	8	11
4	early prediction	6	10
5	learning analytics	7	10
6	long short-term memory (LSTM)	3	8
7	virtual learning environment (VLE)	3	8
8	student performance prediction	5	6
9	deep neural networks	4	5

As shown in Table 7, deep learning is the most frequently occurring and highest total link strength keyword among the top ten keywords, based on a minimum keyword occurrence of 3. The other significant keywords are “machine learning,” “educational data mining,” “early prediction,” and “learning analytics.” The visual analysis presented by VOSviewer, shown in Figure 10, helps us understand the popularity of keywords and the connections between them. These visual analyses can assist in better understanding trends in literature and relationships between topics.

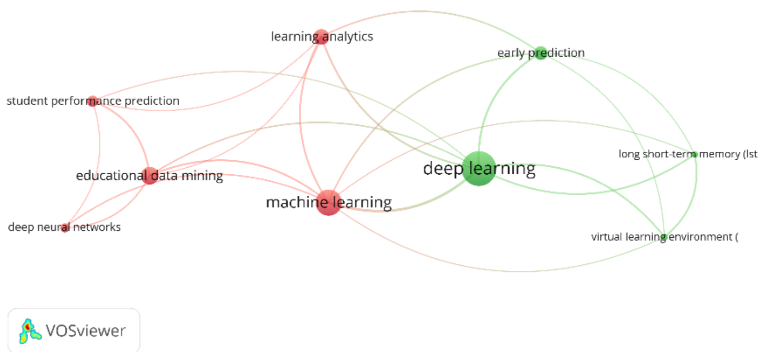

Figure 10. Network Visualization Maps of Co-Occurrence for Keywords

5.2. Co-Authorship for Country Analysis

VOSviewer's Co-authorship Analysis by Country is utilized to understand and visualize the collaboration frequencies and partnership relationships among authors operating in a specific country. Figure 11 presents the Country Collaboration Network Visualization Map provided by the VOSviewer program. As evident from Figure 11, two distinct groups are noticeable. The first group includes authors from China, the United States, and Egypt, while the second group encompasses authors from Saudi Arabia, the United Kingdom, and Pakistan. There are prominent collaboration relationships among authors from countries within both groups.

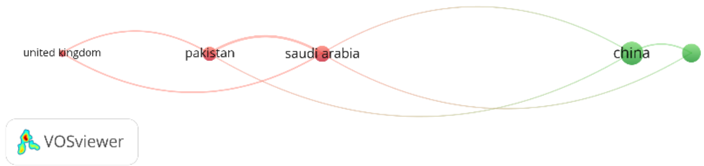

Figure 11. Network Visualization Maps of Co-Authorship for Country

5.3. Citation for Country Analysis

VOSviewer's Citation for Country Analysis features maps and visualizes the citation relationships of scientific publications produced in a specific country. This analysis helps understand the level of interaction of research outputs in the country, relationships with other countries, and international citation networks. These visualizations can give researchers important insights into understanding trends and networks in scientific knowledge production, identifying potential collaborations, and observing interdisciplinary interactions. Figure 12 presents the Network Visualization Map for country-based citation analysis provided by the VOSviewer program. As seen in Figure 12, two distinct groups are notable, similar to the analysis conducted by authors. The first group includes China, the United States, and India, while the second group encompasses Saudi Arabia, the United Kingdom, Indonesia, and Pakistan. There are evident citation network relationships among countries within both groups.

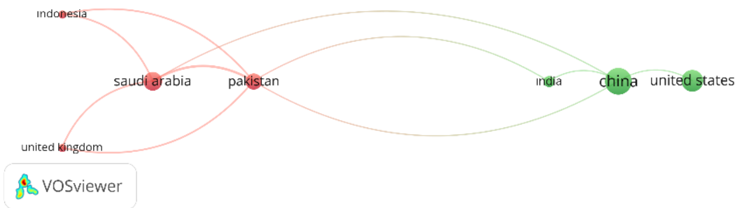

Figure 12. Network Visualization Maps of a Citation for The Country

5.4. Bibliographic Coupling for Sources Analysis

The Bibliographic Coupling for Sources Analysis in VOSviewer analyzes and visualizes connections between scientific sources. This analysis evaluates the similarity of sources in scientific articles and identifies strong relationships among these sources. Bibliographic coupling is based on two separate articles having the same reference. In other words, the connection between two articles is based on referencing the same sources. This analysis is used to identify scientific sources that work on similar topics or focus on similar research subjects and understand the connections between these sources. VOSviewer presents these bibliographic connections by creating network maps and visualizing relationships between sources. This visual analysis can help researchers understand important sources within a specific topic or discipline and the intense interactions between these sources. Figure 13 presents the network map of bibliographic connections for sources VOSviewer provides. As shown in Figure 13, four source groups are highlighted with red, blue, green, purple, and yellow lines. The purple lines, indicating IEEE Access and other blue sources, represent the most robust connections.

5.5. Sources Analysis

The source analysis was conducted based on the number of publications and the average citation count for each source, as illustrated in Figure 14. In terms of average citation count, "Computers in Human Behavior" has the highest average citation count. Regarding the number of publications, "IEEE Access" has the highest published articles.

6. Conclusion

This literature review offers an in-depth examination of the current advancements in deep learning (DL) methodologies applied to early predicting student performance in Educational Data Mining (EDM). The study systematically addressed five central research questions, delving into the distribution of existing research, the types of datasets and attributes utilized, the DL models proposed, the timing of early predictions, and the challenges and future directions highlighted in prior studies.

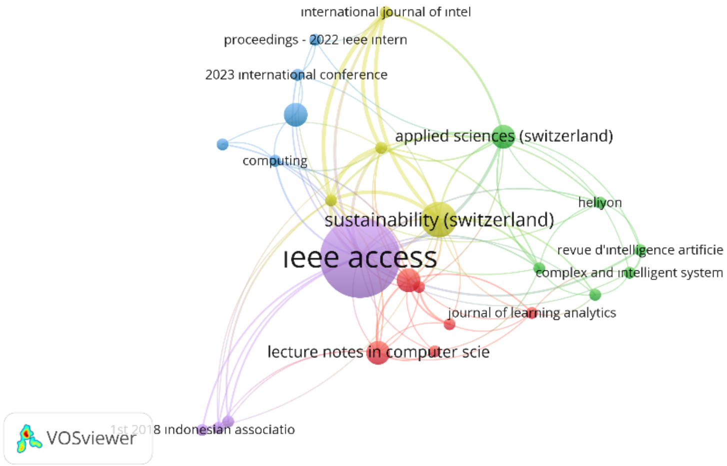

Figure 13. Network Visualization Maps of Bibliographic Coupling for Sources

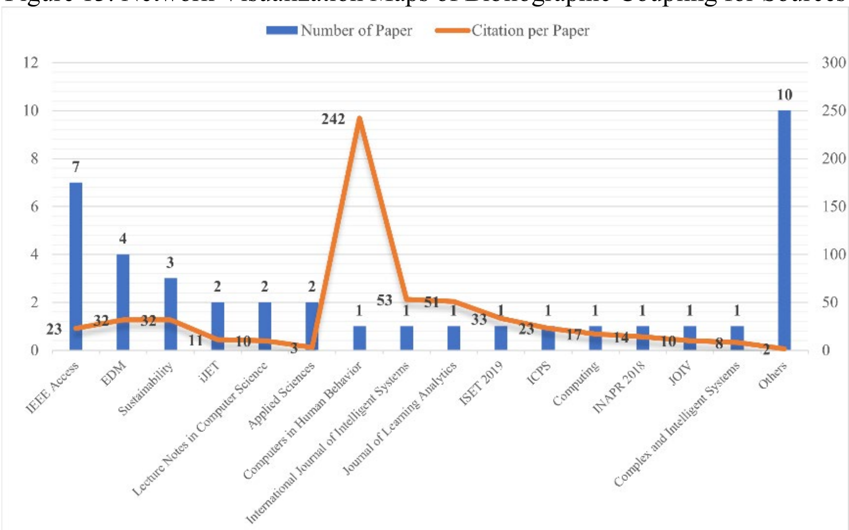

Figure 14. The Number of Publications and The Average Citation Count for Each Source

The results demonstrate that DL approaches, especially Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), outperform traditional machine learning (ML) techniques in managing intricate and voluminous educational datasets. Hybrid DL models have also gained traction as a viable solution, delivering enhanced accuracy and reliability in forecasting student outcomes. Nevertheless, persistent issues such as dataset imbalances, restricted sample sizes, and the demand for greater transparency continue to hinder the broader implementation of these methods.

The review emphasizes the critical role of early prediction in detecting at-risk students and enabling timely support mechanisms. The evaluation of prediction timelines reveals that while early forecasting is achievable, prediction accuracy increases as additional data is accumulated. This finding highlights the necessity for ongoing monitoring and adaptive predictive systems capable of adjusting to the evolving nature of student learning processes.

Future studies should prioritize overcoming the limitations outlined in this review, particularly concerning dataset quality and the interpretability of models. Broadening dataset diversity to include more representative samples and incorporating natural language processing (NLP) techniques could significantly improve the predictive power of DL models. Furthermore, creating time-sensitive models and investigating dynamic feature selection approaches present promising directions for further exploration.

In summary, this review underscores the transformative potential of DL in EDM for early student performance prediction. Researchers and educators can create more effective tools to improve student outcomes by addressing current challenges and leveraging emerging opportunities. The increasing research interest in this field indicates a promising future for DL in reshaping educational support and understanding.

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Authors Contributions
Authors contributed equally to the study.

Conflict of Interest Notice
There is no conflict of interest to declare

Ethical Approval and Informed Consent
The ethics committee approval was not required as the study.

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