VNU Journal of Science: Education Research, Vol. 41, No. 4 (2025) 21-34

VNU Journal of Science: Education Research

Journal homepage: https://js.vnu.edu.vn/ER

Review Article

Approaches to Applying Deep Learning for Early Prediction of Learners' Academic Outcomes

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Received 21st May 2024
Revised 27th August 2025; Accepted 24th September 2025

Abstract: In the context of global digital transformation, the rapid growth of educational data has driven the adoption of advanced technological approaches in educational analytics, particularly the application of deep learning methods for predicting student outcomes. Given its potential to address academic challenges and enhance educational effectiveness, the prediction of student learning outcomes has emerged as a key research area within educational data mining and has attracted increasing scholarly attention worldwide. This article provides an overview of the application of deep learning techniques in educational data analysis, with a particular focus on challenges related to predicting student learning outcomes. In addition, the article highlights emerging research trends in educational science grounded in data-driven analytical methods.

Keywords: Machine learning, deep learning, educational data mining, learning analysis, predicting learners' learning outcomes, 4.0 industrial revolution.

1. Introduction

The advent of the Fourth Industrial Revolution is intricately linked with the realm of data and its analysis. This presents a myriad of challenges for various entities, be it organizations, individual scientists, researchers, or managers, all striving to adeptly navigate the complexities of handling data to enhance operational efficiency and mitigate risks of failure. In the fabric of any agency or unit, data is not merely a resource but a cornerstone, a pivotal component of strategic operations, bestowing immense value upon organizational management and bolstering competitiveness. In the digital age, data exhibits traits of voluminous proportions, intricate structures, and rapid dynamism, necessitating the continual evolution of techniques to meet the exigencies of novel data analysis and transformation.

Efforts are directed towards transmuting data into actionable insights, further metamorphosing these insights into operational strategies, thereby empowering organizational leaders to make pivotal decisions in management and organization. Moreover, data

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https://doi.org/10.25073/2588-1159/vnuer.4967

furnishes scientists and researchers with comprehensive, quantifiable evidence, enabling them to make precise judgments and contribute meaningfully towards resolving persistent research quandaries.

The rapid evolution of advanced learning technology platforms has led to a proliferation of educational data sources, presenting unique opportunities to optimize user engagement on technology platforms, thereby enriching learning experiences [1]. The exponential growth of educational data has catalyzed the emergence of various research trends, including the analysis of educational data to forecast learner behavior and inform educational policy development [2-4]. The field of data analytics in education, born out of the dynamic interaction between learners and educators, has evolved into a multidisciplinary domain, attracting scholars from diverse academic backgrounds [5]. This interdisciplinary nature has spawned a plethora of terms related to the exploration of educational data, such as academic analytics, predictive analytics, and learning analytics. A more recent term, "educational data science," has emerged to encapsulate collaborative research endeavors involving researchers from varied disciplines, united by their shared interest in educational data [6].

Educational data science is an interdisciplinary field that includes many different important components. It involves collecting, synthesizing, meticulously examining, and deeply analyzing data originating from both learners and educators. The overarching goal is to promote a deeper understanding of the learning ecosystem, ultimately leading to enhanced learner performance and optimized instructor effectiveness [7, 8]. Educational data mining and learning analytics are integral to this endeavor, with the prediction of learning outcomes being a significant focus of researchers worldwide.

In recent years, technological advancements have shifted the focus toward leveraging intelligent systems to predict student performance, yielding diverse outcomes [9, 10]. This approach is particularly effective when integrating data-intensive prediction tools such as machine learning, deep learning, and artificial intelligence to mine, analyze, and predict learning outcomes. This article provides an overview of applying deep learning in educational data analysis, with a special focus on the challenge of predicting student learning outcomes, and recommends some research directions for educational research in Vietnam.

The following research questions guide this review:

Research Question 1. What are the recent interdisciplinary research directions in educational data science?

Research Question 2. How is deep learning utilized in educational data analysis and learning analysis, especially in predicting student outcomes?

It commences by elucidating the interdisciplinary nature of educational data science and its primary objective of improving learner performance and instructor effectiveness. Section 2 presents a literature review on the evolution of research from EDM and LA to AI and Deep Learning applications in education. The research methodology is explicated, delineating the approaches utilized for data collection and analysis (section 3). Educational data mining and learning analytics are portrayed as integral components for comprehending learning processes and are introduced as the most popular recent interdisciplinary research directions in educational data science (sections 4 and 5). It is followed by an exposition on deep learning and its pertinence in educational contexts, answering the question of how deep learning is utilized in educational data analysis, with a specific emphasis on predicting student outcomes (section 6). Subsequently, the paper delves into an overview of the application of deep learning for the early prediction of student academic outcomes, showcasing some approaches and methodologies employed in this realm (section 7). A subsequent discussion scrutinizes the implications and challenges associated with integrating deep learning into educational data analysis, specifically in Vietnam (section 7). Finally, the paper concludes by encapsulating key findings and proposing potential future research directions (section 8), underscoring the necessity of continuous evolution and refinement of deep learning techniques in educational settings.

2. Liturature Review

In the context of global digital transformation, the exponential growth of educational data has driven the emergence of Learning Analytics (LA) and Educational Data Mining (EDM) as two foundational pillars of educational data science. In the initial stage (2011–2014), Siemens [7] and Siemens and Long [8] laid the groundwork by defining LA, differentiating it from EDM, and highlighting the strategic role of data in supporting learning, management, and educational policy-making. Concurrently, Bienkowski et al., [11], through a report by the U.S. Department of Education, and Piety et al., [6], with the introduction of the Educational Data Science (EDS) framework, broadened the scope by connecting LA/EDM with data science, thereby shaping both methodological and policy orientations.

From 2015 to 2018, the field entered a stage characterized by the proliferation of comprehensive surveys. Reviews by Baker and Inventado [12], Dutt et al., [13], and Viberg et al., [3] synthesized methods, objectives, data types, and implementations in higher education. These works underscored the growing interest in applications such as learning outcome prediction, dropout prevention, and the design of dashboards to support teaching and decision-making.

Between 2019 and 2023, the domain experienced a significant shift toward Artificial Intelligence (AI) and Deep Learning. Systematic reviews by Chiu et al., [14], Yang et al., [15], Lee et al., [16], and Richter et al., [17] not only explored applications such as Intelligent Tutoring Systems, recommender systems, and online proctoring, but also critically examined challenges of bias, privacy, and fairness. At a more focused level, surveys by Shafiq et al., [18], Zhang et al., [19], and Hashmi et al., [20] emphasized learning outcome prediction and student retention, positioning Deep Learning as a pivotal tool for handling large-scale, imbalanced, and heterogeneous datasets.

In the most recent phase (2024 onward), studies such as Arya et al., [21] illustrate the emergence of critical reviews, drawing attention to ethics, transparency, and fairness in applying AI and EDM in education. Furthermore, the advancement of representation learning [22] has established a robust theoretical foundation for leveraging Deep Learning in educational data analysis.

Overall, a prevailing trend is the application of Deep Learning for predicting student learning outcomes. This direction has evolved into a central research theme in EDM, addressing academic challenges such as dropout, retention, and personalized learning, while simultaneously creating opportunities to enhance both educational quality and equity.

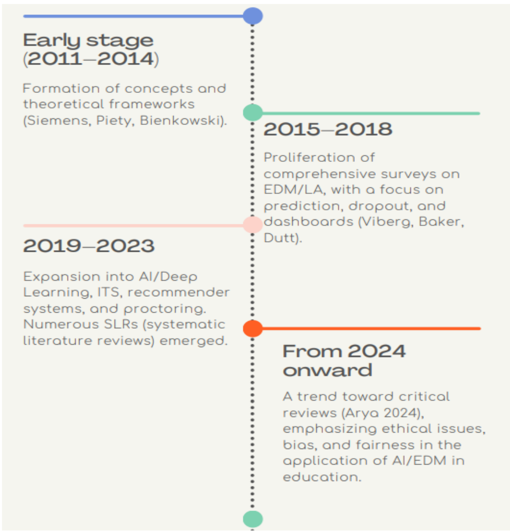

Figure 1. Timeline:
From EDM to AI/Deep Learning Trends.

3. Method

In this article, we employ several general document research methods, including narrative review, descriptive review, scoping review, and systematic review, to evaluate the advantages and disadvantages of the documents. Our goal is to provide a comprehensive understanding of the current state of research on the application of deep learning in educational contexts.

We present findings from the literature on the application of deep learning in analyzing educational data and predicting learning outcomes. Specifically, we examine how deep learning techniques have been used to identify patterns in student performance, provide personalized learning recommendations, and enhance educational interventions.

Various literature review techniques have been implemented in this study. These include rigorous screening processes to select relevant studies, assessing the quality of primary research to ensure reliability, and systematically analyzing and synthesizing data to draw meaningful conclusions. Additionally, we identify gaps in the current research and suggest areas for future investigation to advance the field of educational data analysis using deep learning.

By combining different review methods and thorough analysis, this article aims to offer valuable insights for educators, researchers, and policymakers interested in leveraging deep learning technologies to improve educational outcomes.

For this review, only articles related to the application of deep learning for early prediction of learners' academic outcomes were considered. To identify relevant studies, the author employed a search query based on previous research, focusing on papers containing these terms in the titles, keywords, or abstracts. Only peer-reviewed journal articles published in English were included. The inclusion and exclusion criteria were slightly adjusted for each database to accommodate their specific search functionalities. Specifically, articles selected from Scopus included those in the final stages of publication, while those from WOS were restricted to studies within the field of educational research.

This review adopted and proceeded in three steps: i) article selection; ii) article screening and inclusion; and iii) data coding, extraction, and analysis.

This review exclusively examined articles on the application of deep learning techniques for the early prediction of academic outcomes in learners. To identify the relevant literature, a search query was devised, following the approach of [23]: [("Deep Learning" OR "Academic Outcomes") AND "Prediction"]. This query was designed to capture papers containing these terms in the titles, keywords, or abstracts, published between January 1, 2012, and February, 2025. The search was carried out in Google Scholar, Scopus, and Web of Science (WOS), resulting in 498 initial articles: 268 from Google Scholar, 155 from Scopus, and 75 from WOS. Only peer-reviewed articles in Vietnamese and English were considered. Furthermore, articles from Scopus included those in the final publication stages, while WOS results were limited to educational research studies. After applying the inclusion criteria, 118 articles were selected for further evaluation.

The screening and inclusion process was conducted to select articles for the main analysis. Initially, 10 duplicate articles were removed using the duplication detection feature of EndNote X9. Next, the titles and abstracts of the remaining articles were reviewed to identify empirical studies on deep learning techniques for the early prediction of academic outcomes published in journals. This step led to the exclusion of systematic literature reviews, meta-analyses, conceptual papers, commentaries, editorials, and conference proceedings. As a result, 20 articles were excluded based on these criteria. The full texts of the remaining articles were then examined, and 9 additional duplicates not detected by EndNote were removed, leaving 79 articles. At this stage, a review study and 7 articles that did not focus on deep learning techniques for early academic outcome prediction were also excluded. In the end, 72 articles were retained for the analysis (10 papers in Vietnamese and 62 papers in English).

Research on the application of deep learning in education typically falls into the following categories: educational data mining, learning analytics, deep learning and its applications, and the challenge of predicting learners' academic outcomes. We have classified the reviewed deep learning studies in education based on the roles identified by the authors.

4. Related Works

4.1. Educational Data Mining

Educational data mining (EDM) [11] is emerging as a research field with a system of computational methods and psychological methods, exploiting educational data to understand how students learn, thereby proposing solutions to improve student learning performance as well as innovating processes, ways of managing, and organizing educational activities.

In the dynamic landscape of modern education, the integration of new interactive learning methodologies and computer-supported tools has sparked a paradigm shift [12]. With intelligent, interactive teaching software systems seamlessly linked to broadband internet connectivity, educators now have unprecedented access to a wealth of student data. This transformative capability opens doors to a realm where insights gleaned from data analysis illuminate patterns and trends, fostering the formulation of groundbreaking discoveries and hypotheses about the learning process [24].

EDM utilizes statistical analysis, machine learning, and data mining techniques to analyze complex educational data. Higher education institutions are increasingly adopting data analytics to enhance service delivery and improve student outcomes, including performance and retention rates. Currently, EDM focuses on developing innovative tools to uncover insights within data patterns, operating under the premise that deciphering these patterns can anticipate future events and enable proactive interventions. Several studies have explored these aspects:

i) EDM: Prediction of Students' Academic Performance: This research proposes a machine learning-based model to predict undergraduate students' final exam grades, highlighting EDM's role in forecasting academic performance [25].

ii) EDM in Higher Education: Building a Predictive Model for Graduate Students' Decisions: This study aims to create a model predicting factors influencing graduates' decisions to continue their studies, demonstrating EDM's application in understanding student behaviors [26].

iii) EDM: Employing Machine Learning Techniques and Hyperparameter Optimization to Improve Students' Academic Performance: This research evaluates methods and tools of machine learning and data mining in education, focusing on improving the accuracy of predicting academic achievements [27].

iv) Student Retention Using EDM and Predictive Analytics: A Systematic Literature Review: This systematic review explores the adoption of EDM and learning analytics for knowledge discovery from educational data sources, aiming to improve student retention [18].

These studies collectively illustrate EDM's role in analyzing educational data to predict and enhance student outcomes, thereby enabling proactive interventions to optimize educational processes. EDM traverses various research domains, exploring facets that influence learning activities and educational systems at large. By gaining nuanced insights into student performance, educators can tailor their instructional approaches and implement targeted interventions such as personalized tutoring and tailored assignments. As a systematic literature review on the application of artificial intelligence (AI) in education, the article [14] analyzes the opportunities, challenges, and future research recommendations related to AI in the field of education, with a particular focus on EDM. It highlights how AI and EDM can be used to enhance learning experiences, personalize education, and predict academic outcomes, while also addressing the challenges of data privacy, integration with traditional educational systems, and the need for teacher training in AI tools. The review suggests that future research should explore the effective integration of AI and EDM to optimize teaching and learning processes.

Yet, amidst its potential for transformative impact, EDM encounters notable technical challenges. The interoperability gap among education data systems presents a hurdle, complicating the seamless integration of administrative, survey, and classroom data. Nevertheless, bridging these divides holds promise for enhancing the predictive capabilities of algorithms. By amalgamating diverse data sources from student performance metrics to online engagement indicators educators can gain a comprehensive understanding of student challenges, enabling the design of tailored support mechanisms.

4.2. Learning Analytics

Learning Analytics (LA), as delineated by Bienkowski (2012), epitomizes a vibrant domain integrating both research and practical applications, honing in on academic analytics, action analytics, and predictive analytics [11]. Diverging from EDM, which pioneers the development of novel computational methodologies for data analysis, LA primarily focuses on the application of existing methods and models to tackle pertinent inquiries regarding student learning and organizational learning systems.

At the heart of LA lies an unwavering emphasis on measurement and data collection, deemed indispensable endeavors for educational institutions, alongside rigorous data analysis and insightful reporting. The overarching objective is to empower educators and institutions to tailor educational journeys to the distinctive needs and capabilities of each student, echoing the sentiments echoed in the Horizon Report (2011 Edition) [28].

A pivotal facet of LA is the continuous monitoring and prediction of student performance, with a keen eye on early identification of potential hurdles to enable timely interventions for at-risk students. A myriad of LA models has been meticulously crafted to gauge student risk levels in real-time, striving to elevate student success rates. Notable exemplars encompass Purdue University's Course Signaling system and the Moodog system, seamlessly integrated into the educational fabric of esteemed institutions such as the University of California, Santa Barbara, and the University of Alabama (EDUCAUSE, 2010).

In response to increasing demands for transparency and accountability in student recruitment and retention, higher education institutions are increasingly adopting Learning Analytics (LA). By leveraging LA, these institutions aim to enhance service quality and achieve measurable outcomes such as improved grades and increased student retention rates. [29] indicates that transparency and trustworthiness are crucial for the ethical use of LA and artificial intelligence in promoting social inclusion and equity. Understanding user perceptions of these factors is essential for effective implementation. Additionally, a scoping review reveals that the benefits of LA include predicting and identifying target courses, aiding curriculum development, and improving student learning outcomes, thereby supporting institutional goals related to student success [2]. These studies collectively underscore the role of LA in enhancing transparency, accountability, and measurable improvements in student outcomes within higher education.

Predictive analytics plays a crucial role in forecasting students' academic trajectories, enabling institutions to proactively address potential challenges and enhance educational outcomes. By analyzing diverse data points, such as academic performance, attendance, and engagement levels, predictive models can identify students who may require additional support, thereby improving retention rates and academic success. For instance, a study analyzing the records of 50,095 students from four U.S. universities and community colleges demonstrated that combining macro and meso-level data could predict student dropout with high accuracy, achieving an average Area Under the Curve (AUC) of 78% across various models, with a maximum AUC of 88% [30]. Similarly, research focusing on educational data mining for predicting student performance highlights that such predictive analyses aim to assess students' future grades before they enroll in courses or take exams. This approach is essential for personalized education and has garnered significant attention in the fields of artificial intelligence and educational data mining [19].

These applications underscore the pivotal role of predictive analytics in educational settings, facilitating informed decision-making and proactive strategies to support student success and retention.

4.3. Deep Learning and its Applications

In recent years, advances in computer computing capabilities coupled with the collection of large amounts of data have facilitated significant developments in artificial intelligence (AI) [31]. The field of Machine Learning (ML) has undergone an important advance, opening up a new field known as Deep Learning (DL) [32]. DL has become popular in recent decades, thanks to the access to powerful computational technology of modern computers as well as the availability of large volumes of data (images, sounds, text,...) on the Internet [20]. The relationship between Deep Learning and Machine Learning as well as other related fields can be clearly seen in the image depicted below (Figure 2).

Networks trained using the Deep Learning method are often known as deep neural networks, due to the way they work. The basic property of these networks is their organization into different layers, with each layer taking care of analyzing the input data from different aspects and increasing abstraction by level. The first layers usually perform simple tasks of retrieving information from the data, this information is then passed to the next layers, with more complex tasks, the highest layer in the network will take on the task. solve the problem of the problem. This method helps computers understand complex data through many layers of simple information. Therefore, this method is called Deep Learning.

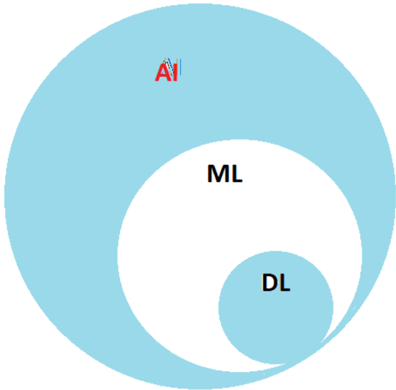

Figure 2. Relationship of deep learning with related fields.

Artificial Neural Network (ANN) is an information processing model designed based on the structure and operation of the nervous system in an organism. It consists of a large number of interconnected neurons that process information. This model, like the human brain, has the ability to learn from experience through training, retaining insights and knowledge from those experiences for use in predicting new data [16]. The applications of artificial neural networks are diverse and widely applied in many fields, including electricity, electronics, economics, military, and many other fields.

When we connect the inputs/outputs of many neurons together, we create a neural network [33]. The process of pairing neurons can follow the principle of freedom and flexibility. A neural network, as an information communication and processing system, is capable of distinguishing between different types of neurons. Neurons have inputs that receive information from the external environment, while other neurons have inputs that connect to other neurons in the network. The distinction between them is usually made through the input weight function vector w. The general structural principle of a neural network includes many layers, each layer contains many neurons with the same function in the network [34]. This structure usually includes:

i) Input layer: Is the layer that receives input information from the environment and transmits it to neurons in the hidden layer;

ii) Hidden layer: Is one or more layers containing neurons that process information and transmit it to the output layer;

iii) Output layer: Is the layer containing neurons that produce the output of the neural network.

Hidden layers help neural networks learn complex features from input data. The presence of multiple hidden layers also increases the ability to learn and represent more complex models.

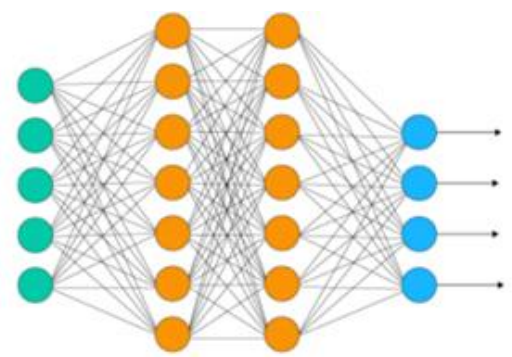

Figure 3. Structure of an artificial neural network [34].

Since its inception in the 1950s by Rosenblatt [34], artificial neural network (ANN) models have represented a cornerstone in computational science. However, it wasn't until around 2006, with the advent of deep learning (DL), spearheaded by Hinton et al. [35], that the field truly burgeoned and captured the imagination of both domestic and international researchers. Deep Neural Networks (DNNs) emerged as a formidable approach within this landscape, featuring multiple hidden layers between the input and output layers [33]. Concurrently, Probabilistic Graph Models (PGMs) integrated probability theory and graph theory to furnish a concise graph-based representation of joint probability distributions, exploiting conditional independence between random variables [36].

Deep learning has unequivocally revolutionized data science, showcasing its prowess across an array of application domains. Notably, a deep learning method set a groundbreaking record in classifying handwritten digits of the MNIST dataset, achieving an error rate of merely 0.21% [13]. Its versatility extends to diverse domains such as image recognition [37, 38], speech recognition [39], natural language understanding [40], acoustic modeling [15], and biotechnology [41].

DL encompasses a spectrum of learning algorithms rather than a singular method, enabling the construction of complex prediction models. These include multi-layer neural networks with numerous hidden nodes [38], convolutional neural networks (CNNs), and refined variants such as Region CNN [21] and Fast RCNN [17]. A defining characteristic of many supervised and unsupervised deep learning model iterations is their incorporation of multiple layers of hidden neurons for learning [42]. Notable deep learning approaches encompass Deep Feed Neural Networks (D-FFNN), Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), Autoencoders (AEs), and Long Short-Term Memory networks (LSTMs), which serve as foundational architectures in contemporary deep learning models and constitute essential tools for data scientists.

5. The Problem of Predicting Learners' Learning Outcomes

In recent years, there has been a concerning increase in the number of students receiving academic warnings or being compelled to drop out of educational institutions. Despite concerted efforts by higher education institutions over the past three decades to improve student retention, retention rates remain disappointingly low [43]. A 2012 report revealed that the average first-to-second-year retention rate stood at a modest 66.5% [43], with nearly one-third of students leaving university after their first year. This trend continues in subsequent academic years, with only 45% of students completing their degree within the expected four to five years [44]. One significant reason behind poor academic outcomes is the mismatch between chosen subjects and individual abilities, coupled with ineffective learning strategies. This disparity often leads to premature departure from academic pursuits or necessitates extended study durations, resulting in wasted time and resources for families, educational institutions, and society at large.

Academic success is pivotal in fostering student persistence in their educational endeavors [45, 46]. As academic achievement rises, the risk of dropout diminishes [47]. Therefore, one strategy to enhance learning persistence and prevent midstream dropout is by improving learning success. This can be achieved through early prediction of learning outcomes, enabling timely interventions to prevent academic failure or premature withdrawal from educational programs, and providing decision support for crafting optimal learning trajectories for students and educators [48]. Predictive analytics empowers students to select courses aligned with their aptitudes and helps administrators and instructors identify students in need of additional support and attention to navigate their academic journey successfully, thereby reducing instances of academic warnings or forced withdrawals due to poor performance. Ultimately, this proactive approach translates into saved time and resources for students, families, educational institutions, and society at large.

Recent research highlights the effectiveness of deep learning models in accurately predicting student learning outcomes. Bendangnuksung (2018) introduced a Deep Neural Network (DNN) model that surpassed other machine learning algorithms, achieving an impressive accuracy of 84.3% [22]. Similarly, Hussain et al., (2019) attained a classification rate of 95.34% using a sequential neural model and the Adam optimization method [49]. Waheed et al., (2020) leveraged a deep artificial neural network, achieving classification accuracies ranging from 84% to 93% in identifying at-risk students [50].

In parallel, Arsad (2013) utilized distinct network models-Markov Networks and Artificial Neural Networks (ANN), respectively-to forecast student learning outcomes [51]. Slim's focus lay on early indicators of student progress, while Arsad delved into the influence of foundational subjects on final learning outcomes. Iatrellis et al., (2021) demonstrated that a clustering approach could offer nuanced predictions of time and student enrollment in postgraduate studies (SEIPS) [52]. Meanwhile, Christou and colleagues (2023) proposed a feature construction and selection method based on grammatical evolution for RBF to forecast student outcomes, outperforming other methods in accuracy across various datasets [53].

Additionally, various deep learning architectures such as Recurrent Neural Networks (RNN) and probabilistic graphical models like Hidden Markov Models (HMM) have been effectively utilized to address the dropout problem [54]. These studies collectively underscore the significant potential of deep learning techniques in enhancing predictive accuracy and informing educational decision-making.

Corrigan and Smeaton (2017) explored Random Forest, RNN, and simple LSTM models to forecast student success within virtual learning environments, highlighting the versatility of deep learning techniques in educational data analysis [55]. Hajra Waheed and colleagues (2019) extended this exploration by deploying a deep artificial neural network to analyze learner interaction data, offering early intervention measures for students at risk of failing-a testament to the practical implications of deep learning in student support systems [50].

Fei and Yeung's investigation (2015) into temporal models like the state space model and recurrent neural network shed light on identifying students prone to dropout, underscoring the importance of predictive analytics in educational settings [54]. Mubarak et al., (2022) contributed further by proposing a

Graph Convolutional Network (GCN)-based model for classifying student engagement patterns, showcasing deep learning's role in behavioral analysis within educational contexts [56]. Additionally, Sarwat et al., (2022) introduced an innovative CGAN-SVM hybrid model, emphasizing the efficacy of combining deep learning techniques for accurate student outcome predictions [57].

Several recent studies have highlighted the efficacy of deep learning models in forecasting student learning outcomes. Hussain et al., (2019) employed a sequential neural model (RNN) with the Adam optimization method, while Waheed et al., (2020) utilized a deep artificial neural network [49, 50]. Sarwat et al., (2022) developed an enhanced Conditional Generative Adversarial Network (CGAN) combined with a deep layer-based Support Vector Machine (SVM) for the effective prediction of student learning outcomes [57]. Son et al., (2021, 2022, 2024) introduced a hybrid architecture incorporating various models, such as LR, LDA, DFS, DNN, CNN, RNN, LSTM, and Transformer, achieving superior performance on real data [58-60]. Sang et al., (2020) have ventured into EDM through deep learning applications [61]. Their study focused on predicting student learning outcomes using deep learning techniques applied to Can Tho University's student management system database. Although their findings represented initial steps, they underscored the growing interest in applying machine learning and deep learning methodologies to enhance educational management practices in local university settings.

In Vietnam, the application of machine learning and deep learning in educational science is an emerging field with promising results. Researchers are exploring various techniques to support student learning and decision-making throughout their educational journeys.

One notable work is Le Xuan Lam's Master's thesis in Information Technology, which focuses on data mining techniques to enhance student learning. Lam's research used the Business Intelligence toolkit of SQL Server 2012 to analyze student learning outcomes, specifically aiding students at People's Security College I in choosing suitable subjects and predicting final learning results. Based on data from 2013 to 2018, the study demonstrated positive results in providing learning consultations [62].

N. Thai-Nghe and colleagues also contributed to this field by presenting analytical models to predict learning outcomes [63]. In 2016, N. T. T. An, N. V. Thanh, D. T. K. Oanh, and N. T. N. Thu examined factors affecting the learning outcomes of first- and second-year students at Can Tho University of Engineering and Technology, highlighting the impact of various elements on student performance [64].

In 2013, Nghe and his team leveraged the advanced capabilities of the Mymedialite system to predict student capacity [65]. They developed a method involving reading, checking, and converting data into a format suitable for prediction algorithms, configuring input parameters, and using pre-built functions to train and predict results. The predicted data was then stored in a database for further application.

Additionally, a 2019 study by Uyen and Tam employed Naïve Bayes and Logistic Regression algorithms to predict learning outcomes and identify students at risk of being forced to withdraw from school [66]. These algorithms effectively pinpointed subjects where students needed to focus more effort to reduce the risk of academic failure.

N. T. Nghe and T. Q. Dinh addressed university admission challenges in 2015 by proposing an intelligent system-based consulting support system for university admissions. This system aimed to enhance the admission process by providing intelligent recommendations and support [67].

Son and co-authors researched applying machine learning techniques to process training and university admission data at Capital University in Hanoi from 2016 to 2020. They analyzed and predicted student learning outcomes based on enrollment data and college learning data (in the first and the second terms), offering recommendations on training policies and enrollment strategies to address university admission issues comprehensively and quantitatively [58, 59].

In a 2023 study, Son and colleagues proposed an architecture deploying various deep learning models, including DNN, CNN, RNN, LSTM, and Transformer, in a neutral environment to predict student learning outcomes. Experimental results on real data from Capital University in Hanoi showed that their model's RMSE, MAE, and R2 metrics outperformed previous models (Son et al., 2023).

Overall, these studies indicate that machine learning, deep learning, and data mining techniques can significantly contribute to educational science by providing insights and tools to improve student learning outcomes and support educational decision-making. Some references can be seen more in the review paper [68].

These studies collectively underscore the potential of deep learning models in predicting student performance, with advanced techniques like attention mechanisms, hybrid architectures, and generative adversarial networks further amplifying their predictive prowess.

6. Discussion

The applications of machine learning, particularly deep learning, and EDM are widespread globally. However, domestic research in Vietnam in this field remains limited. This limitation can be attributed to the relatively slow pace of digital transformation in the education sector compared to other countries. Efforts to collect digital data and digitize educational content are still in their early stages, hindering the availability of comprehensive datasets for research purposes. Additionally, the rapid development of data mining algorithms and machine learning techniques presents challenges in selecting the most suitable algorithms to address educational issues effectively.

Despite these challenges, there is a growing interest among researchers in Vietnam in exploring the application of AI in education. In [69], the authors indicated that AI tools have a significant impact on improving students' learning outcomes. However, students need to be trained on how to use AI optimally to achieve the best results.

The integration of AI technologies holds significant promise for advancing educational practices and improving learning outcomes in Vietnam. By leveraging AI, educators can gain insights from large datasets to enhance teaching methods, develop adaptive learning systems, and provide targeted interventions for students. Moreover, AI-driven analytics can facilitate a more data-informed approach to education policy and planning.

However, to fully realize the potential of AI in transforming the education landscape in Vietnam, further research and investment in digital infrastructure and expertise are needed. Enhancing the digital infrastructure involves upgrading hardware and software systems, improving internet connectivity, and ensuring data security. Additionally, building expertise requires training educators and researchers in AI technologies and fostering collaborations between educational institutions, government agencies, and the tech industry.

Thus, while current limitations present challenges, the increasing interest and ongoing efforts in Vietnam indicate a promising future for the application of AI in education. A study by the United Nations Educational, Scientific and Cultural Organization (UNESCO) reveals that artificial intelligence can enhance the quality of education by offering personalized learning tools and enabling more effective teaching. With sufficient support and investment, AI has the potential to transform the Vietnamese education system into one that is more efficient, inclusive, and responsive to the needs of learners.

7. Conclusion

This article combines different survey methods with thorough analysis to offer valuable insights for educators, researchers, and policymakers interested in using technology and deep learning to improve educational outcomes. Through a review of current research and data analysis, the article not only provides an overview of deep learning's potential for predicting student learning outcomes but also gives specific, actionable recommendations on how to effectively apply these technologies in managing, organizing, and operating educational activities.

The case studies from schools and universities globally illustrate the success of deep learning models in educational settings. The exploration of advanced deep learning techniques such as DNNs, RNNs, LSTMs, GCNs, and Transformers emphasizes their groundbreaking capabilities in educational environments, particularly in personalizing and enhancing the learning experience. These technologies can tailor educational content to meet the needs of individual learners, ensuring more effective engagement and outcomes.

The article further highlights that educators and policymakers should consider practical steps for integrating AI into their systems. Recommendations include: i) Collaborating with AI experts to train faculty and staff in the application of AI-driven tools in teaching; ii) Investing in professional development programs for educators to build familiarity with AI technologies and their educational applications; iii) Encouraging interdisciplinary research to create tailored AI models for specific educational contexts, ensuring that technology is aligned with the unique needs of diverse learner populations; and iv) Implementing pilot projects to test deep learning models in small educational settings, gradually scaling them based on initial success.

These findings open opportunities for innovative teaching methods that better meet the diverse needs of students, promoting personalized learning pathways and facilitating lifelong learning. By adopting deep learning-based solutions, educational institutions can create more adaptive, responsive, and inclusive learning environments, ultimately enhancing educational outcomes on a global scale.

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