A REVIEW ON ENHANCING ACADEMIC ACHIEVEMENT THROUGH MACHINE LEARNING: MOTIVATIONS AND IMPLICATIONS

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Abstract: Academic achievement is a critical indicator of educational success, with significant implications for individual and social development. Machine learning has emerged as a transformational technology in a wide range of domains, with the potential to enhance academic achievement in educational settings significantly. This study examines the integration of machine learning into enhancing academic achievement, focusing on its motivations and practical implications for educational institutions. The study analyzed a range of primary studies and identified key motivations behind integrating machine learning in education into two categories: identifying at-risk students and providing personalized learning. The study also explores the practical implications and potential benefits of these technologies for future research and development in education. The review of the study reveals that machine learning has the ability to significantly improve academic achievement by providing educational institutions with targeted interventions and adaptive learning solutions.

Keywords: Machine learning; Academic achievement; Student performance; Academic success

1. INTRODUCTION

The education sector landscape is rapidly evolving, with technology playing a crucial role in delivering, assessing, and optimizing learning (Khaustova & Petrykiva, 2023; Rajarshi Roy Chowdhury & Arun Kumar Singha, 2023). Machine learning (ML) has emerged as a powerful tool that has the potential significantly enhance academic achievement (Sharma & Rajput, 2023). ML applications in education range from predicting student performance (Baig et al., 2023) and identifying at-risk students (Fauszt et al., 2023) to personalizing learning experiences (Essa et al., 2023) and automating administrative tasks (Samigova, 2023).

Utilization ML in education is crucial to improve learning outcomes and address diverse challenges faced by students and educators. Traditional educational models struggle to meet individual needs, leading to academic imbalance (Onyema et al., 2022). ML offers a promising solution by developing personalized learning systems that adapt to each student's unique needs (Essa et al., 2023). Additionally, it also provides educators with powerful tools to predict and intervene in cases of underperforming students, offering timely and targeted support (Elsaid Khoudier et al., 2023).

ML is being used in education for personalized learning, resource management, and practice improvement. By analyzing large student data, ML algorithms can identify patterns and insights that inform instructional strategies and curriculum design (Hilbert et al., 2021). This data-driven approach enhances teaching effectiveness, supports institutional decision-making, and maximizing student success (Aldriwish, 2024).

However, the integration of ML in education faces challenges such as data privacy, algorithmic bias, and equitable distribution of educational opportunities (Umer et al., 2021). These issues highlight the need for a critical examination of the motivations behind ML adoption and its implications for stakeholders like students, educators, and policymakers.

This review examines the motivations behind ML integration in education and its impact on academic achievement. The study also explores how ML is transforming the educational landscape and its influence and contributions to academic excellence.

2. METHODS AND DATA ANALYSIS

This review analyzed primary studies on the application of ML in enhancing academic achievement across multiple academic databases including Scopus and IEEE Xplore, using keywords such as "machine learning," "academic achievement," "academic success," and "student performance". Based on publication date, quality, and topic relevance, a total of 18 studies were selected.

Key information was extracted from these studies, including ML methods, educational context, and outcomes measured. The selected studies were analyzed to identify common themes, methodologies, and overall effectiveness of ML approaches in improving academic achievement. The review aimed to explore the potential of ML in enhancing academic achievement, including its motivations, contributions, and practical implications for educational institutions.

3. RESULTS AND DISCUSSIONS

The review of the study revealed several key findings regarding the application of ML to enhance academic achievement. Firstly, the study highlighted a range of motivational factors driving the integration of ML in educational settings. We identified and classified the key motivations of the selected primary studies into two distinct categories: (1) Identification of At-Risk Students (2) Personalized learning.

3.1 Identification of At-Risk Students

The application of ML techniques in identifying students at-risk is a concerning factor in educational environments such as virtual learning and has a significant impact on students' learning and academic achievement (Rose & Mary, 2022). Additionally, ML technology can help in the early identification of students who are at risk of academic failure or dropout (Gallego et al., 2021), allowing for timely or early interventions to be taken (Nimy et al., 2023).

A total of 11 primary studies focused on motivation to identify at-risk students. Based on their studies' contributions, we identified and categorized the selected primary studies into a group, namely the development of predictive models. Thus, the summary of studies contributions to the development of predictive models and their practical impacts for educational institutions in Table 1.

Table 1
Summary of studies on predictive model development and practical impacts in education

Key contribution	Practical impacts	Reference
Development of Predictive Models	efficacy of ML in accurately classifying students' academic outcomes, predicting academic success, and addressing retention issues in decision-making.	(Guanin-Fajardo et al., 2024)
	proposed early warning system (EWS) has achieved over 99.5% accuracy in identifying at-risk students, focusing on socio-cultural, structural, and educational factors affecting dropout rates, aiding in educational planning and decision-making.	(Skittou et al., 2024)
	developed ML-based system to predict student performance and identify at-risk students using a dataset of grades and behavior during specific tasks.	(Latif et al., 2023)
	proposed a framework using ML algorithms for predicting student performance, combining academic and non-academic features for improved accuracy.	(Waheed et al., 2023)
	utilized ML to predict at-risk students, reducing their educational failure and providing targeted support, with a hybrid model enhancing prediction accuracy.	(Pek et al., 2023)
	ML models are being utilized for early detection of at-risk students and for predicting student dropouts in higher education institutions.	(Martins et al., 2023)

	ML model predicts at-risk students early, identifying factors contributing to low performance, aiding in interventions to improve academic performance and reduce dropout rates.	(Albreiki et al., 2022)
	proposed ML model enhances student performance prediction using temporal and overall data, improves learning behavior analysis with visual aids, enhances online education performance prediction, and aids in identifying at-risk students for timely intervention.	(Tieyuan et al., 2022)
	ML is used to predict at-risk students, improve academic decision-making, and identify low performance, late graduates, and campus capacity.	(Brdesee et al., 2022)
	ML techniques are used to predict student dropout risk, provide personalized monitoring, and assist academic managers in preventive actions.	(Tamada et al., 2022)
	provides practical insights into early prediction for at-risk students in introductory programming courses and suggests reconsidering registration requirements for educational institutions.	(Jamjoom et al., 2021)

The stated summary in Table 1 focused on study contributions, and their practical impacts for education institutions. The review of previous studies indicated that, with regard to the identification of at-risk students with ML, it can be concluded that the main concern for study motivation is developing predictive model that support for practical implications in early identify and predict at-risk student, improving academic decision-making, addressing retention issues in decision-making and aiding in interventions to improve academic performance and reduce dropout rates.

3.2 Personalized Learning

Personalized learning is a strategy that customizes educational experiences to each student's strengths, weaknesses, interests, and pace. By using advanced ML technology, it significantly enhances academic achievement, fosters deeper understanding, engagement, and motivation, and addresses unique learning needs.

In this category, the study analyzed seven studies focusing on personalized learning and their contribution mostly to developing innovative technologies and methods-based ML The summary of the study's contributions to innovative technology and methodology and their practical impacts for educational institutions is shown in Table 2.

Table 2
Summary of studies on innovations in technology and methodology and practical impacts in education

Key contribution	Practical impacts	References
Innovations in Technology and Methodology	developed framework enhances student learning outcomes through personalized feedback and collaboration among educators, administrators, and learners.	(Sharif & Uckelmann, 2024)
	developed ML-based framework for accurate student mark and grade prediction, improving educational planning through data analysis, and enhancing administrative and teaching staff in academic organizations.	(Hussain & Khan, 2023)
	utilized ML, graph analysis, and personalized plans for academic advice, highlighted the importance of high-quality data, and identified key factors influencing student grades.	(Atalla et al., 2023)
	developed system improves student academic performance prediction by identifying emotional factors and influencing factors for personalized advice.	(Kukkar et al., 2023)
	proposed framework using ML algorithms for predicting student performance that incorporates both academic performance and social relationship features.	(Alhazmi & Sheneamer, 2023)
	developed adaptive consultation framework predicts student performance early and offers personalized actions for improvement, applicable to various courses beyond introductory programming.	(Khan et al., 2021)
	proposed AI model for personalized training in colleges and universities, designing training plans for new students, and adapting the AI model for career planning.	(Xiao & Yi, 2021)

The summary in Table 2 focused on study contributions, and their practical impacts for education institutions. The review of previous studies indicated that, with regard to the integration of ML in personalized learning, it can be concluded that the main concern for study motivations is developing innovative technology and methodology that provide great support for practical implications in developing ML-based models and frameworks that enhance student learning outcomes and personalized actions, identify the influencing factors for personalized advice, and improving educational planning in academic organizations.

4. CONCLUSIONS

This review examines the potential of ML in enhancing academic achievement by examining its motivations, contributions, and practical implications for educational institutions. The findings highlight that ML offers benefits in two key areas: identification of at-risk students and personalized learning.

The findings show that the primary motivation behind studies on identifying at-risk students using ML is the development of predictive models that support early identification and intervention. These models are crucial for improving academic decision-making, addressing student retention issues, and enhancing academic performance while reducing dropout rates in educational institutions. While the integration of ML into personalized learning aims to develop innovative technologies and methodologies for enhancing student learning outcomes, providing personalized actions, identifying key influencing factors for personalized advice, and improving educational planning within academic organizations.

The integration of ML in education institutions has been increasingly driven by the need to address diverse learning needs, improve student retention, and optimize resource allocation. Furthermore, ML is promising to be a powerful tool for data-driven insights that can transform traditional educational practices. In conclusion, ML offers potential for improving academic outcomes, but its effectiveness depends on its application and evaluation. Future research should explore how to effectively utilize these technologies to meet diverse educational needs and enhance academic achievement.

5. ACKNOWLEDGEMENT

This research was not funded by any grant.

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