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ANALYZING THE EFFECT OF LEARNING MANAGEMENT SYSTEMS POWERED BY ARTIFICIAL INTELLIGENCE ON TEACHING AND LEARNING IN HIGHER EDUCATION

Asma Abdulmana Alhamadi[1*]
[1*]King Khalid University

Asma Abdulmana Alhamadi
*Corresponding Author:

Abstract
Learning Management Systems (LMSs) driven by artificial intelligence are causing a transformative change in the educational sector. This study aims to explore their impact on the teaching and learning processes inside higher education. The study deploys a mixed method of qualitative and quantitative approaches to understand the current applications and AI-LMS advantages. This research uses qualitative analysis to discover key themes in student performance, learning problems, and interventions. Quantitative analysis will be conducted using the Paradis corpus consisting of naturalistic language samples from 25 children learning English, using descriptive, category, correlation, and inferential statistics. Machine learning algorithms will be utilized to classify and predict student performance. The study's novelty lies in the combination of quantitative and qualitative methods to provide evidence-based suggestions for addressing challenges detected in student performance. The study suggests deploying advanced algorithms for machine learning and qualitative interviews to improve the accuracy of predicting models for student achievement. This might include engaging an extensive range of participants from varying origins and educational contexts.
Keywords: Learning Management Systems, Artificial intelligence, Teaching, Learning, Higher Education, student performance.

1. INTRODUCTION

Personalized learning experiences, as well as the ability to customize instruction, assessments, and suggestions to the specific requirements of each student, have been made possible by Learning Management Systems (LMSs) that are driven by Artificial Intelligence (AI). Using these tools, everyday tasks are automated, which enables teachers to concentrate on developing more personalized relationships with students and improving their teaching methods. A further benefit of using AI algorithms is that they provide useful insights into the development and performance of students, which helps teachers modify their instructional methods. Moreover, AI-learning management systems provide improved accessibility and flexibility, making it possible to accommodate a wide range of learners, including those with impairments, and allowing learning to take place at any time and in any location, according to the lives of modern learners. The context of education has experienced extensive change over the past century and it is characterized by the growth of technology (Burbules et al., 2020). LMSs which have been integrated with AI are establishing themselves as sources that are transforming the processes of learning and teaching process, especially within higher education (Turnbull et al., 2020;

George & Wooden, 2023). This is one of the most important advancements. These systems, which AI drives, represent an innovation since they provide personalized techniques that can be adapted to the specific requirements of each learner (Kabudi et al., 2021). This revolutionizes the conventional techniques of teaching and enables instructors to go further into personalized instructional techniques (Alshahrani, 2023).

When it comes to current educational environments, there are major problems involved in both comprehending and resolving the wide range of elements that influence the academic achievement of students. There is a need for a complete analysis that combines quantitative evaluations from accessible datasets with qualitative perspectives collected from current literature. Although previous research provides insights into these elements, there is still a need for such an analysis. Quantitative and qualitative methods were used to fill a research gap in the fields of education technology and pedagogy. It sought a comprehensive knowledge of how AI-driven LMSs affect higher education teaching, learning, and achievement among students. The study synthesized quantitative predictions with qualitative experiences to enhance decision-making and provide evidence-based views regarding effective methods, measures, and regulations. It also suggested adaptive measurements and strategies establish accessible, equitable, and productive learning environments by recognizing significant concepts, challenges, and strategies.

The study used quantitative and qualitative methods to bridge the research gap provide a thorough knowledge of AI-driven LMSs in higher education and establish the groundwork for practical solutions and policy. Previous research has thoroughly examined the separate effects of AI-LMS on teaching methods and student learning experiences. However, there is an apparent absence of comprehensive studies that combine both qualitative and quantitative evaluations. The lack of research that combines rigorous quantitative evaluations from datasets with qualitative insights from current literature limits the development of a comprehensive knowledge of the many impacts of AI-LMS in higher education. Hence, there is a need for research that tactically combines various techniques to provide a detailed and all-encompassing perspective on the impact of AI-powered LMSs on student performance, teaching methods, and the broader educational environment.

The rest of the paper is structured as follows. In section 2 a literature review of the application of LMS, Advancements, Challenges, and Implications for Academic Performance and Learning Outcomes in Diverse Contexts is presented. In section 3, the methodology used is described. The findings are explained in section 4 and the discussion of the results and their limitations are presented in section 5. Section 6 depicts the conclusion of the study. Finally, the future works are briefed in section 7.

2. LITERATURE REVIEW

2.1.Application of AI in Learning Management Systems and Higher Education

AI has become an essential component of daily life across several industries, including the field of education. Manhiça et al., (2022) investigated the use of AI in LMS in higher education. It analyzed 356 articles spanning the period of 2010 to 2022. Among them, a total of 33 were selected for the final analysis. The data suggested that Moodle is the most often utilized LMS for AI solutions in education. AI is mostly used for assessing student performance using techniques such as decision trees, Support Vector Machine, Neural

Networks, K-means, Naive Bayes, and Random Forest. The report emphasized the increasing significance of AI in streamlining educational processes. Al-Ansi & Fatmawati, (2023) examined the incorporation of ICT into higher education at Thamar University in Yemen. A total of 264 participants, staff members, and learners completed questionnaires. The findings indicated that ICT components such as the internet, structures, and LMS had a beneficial influence on the integration of ICT in higher education. Conversely, the policies of educational institutions had an adverse effect. The report also identified a dearth of backing from institutions and government officials for e-learning throughout the COVID-19 epidemic, indicating the need for more financing as well as instruction for those involved in education. The COVID-19 epidemic has highlighted the significance of AI in LMS. Ali et al., (2023) conducted with mass communication students from two public sector institutions in Pakistan revealed that AI plays a crucial role in LMS, where Natural Language Processing (NLP) and Reasoning are closely interconnected. NLP greatly enhances the utilization of LMS by students, while Reasoning plays a vital role in mediating the connection between AI and LMS. An AI-powered LMS improves learning experiences and offers systematic answers for intricate inquiries.

2.2. AI and its Impact on Educational Innovation and Online Learning

AI is revolutionizing the methods of education and instruction, as it plays a crucial role in the realms of research, innovation, and progress. It is especially beneficial for the development of an adaptive learning-based E-Learning Management System Technology (ELMST), which can transform traditional classroom learning into digital material. ELMST improves pedagogical techniques by using visual depictions, animations, and digital materials. Data Mining classifies learner behavior using clusters, while AI aids in the identification of pupils based on their learning aptitudes (Laxmaiah et al., 2022). Overseeing innovation in education is crucial in the age of globalization and technological advancements, as it establishes dynamic learning environments. However, this task requires a deep understanding of various factors, including student needs, resources, scientific advancements, and societal influences. The management process of innovation involves identifying, developing, implementing, and assessing novel approaches to enhance education quality, student competitiveness, efficiency, and inclusivity. However, practical implementation often faces opposition, resource constraints, technical challenges, and administrative hurdles. The integration of AI has transformed traditional educational approaches, facilitating personalized learning experiences, improved efficiency, and data-driven development. However, obstacles like infrastructure development, personnel training, data privacy protection, and cultural transformation have emerged. A participatory approach, involving all stakeholders, has been successful in addressing these challenges while maximizing the benefits of AI technology in higher education (Nuzli et al., 2023). The rapid expansion of the education sector and the emergence of data-driven business models have prompted a transition to data-driven pedagogical approaches. Nevertheless, the extent to which AI and learning analytics (LA) are employed by organizations to deliver customized educational experiences is limited. The motivations and obstacles that impact data-driven pedagogical and curricular pathways within EdTech companies are the subject of this study. The traditional objective of education and the innovative concept of knowledge sharing and instruction are opposed. An imperfect understanding of data, ambiguity, and a lack of data sovereignty impede the development and implementation of pertinent solutions. The discourse surrounding AI-based learning systems is nevertheless propelled by the need for customization and adaptation (Alam & Mohanty, 2022).

2.3. AI Applications in Online Higher Education and Educational Administration

Ouyang et al., (2022) investigated the roles, effects, and implications of AI applications within online higher education. From the initial pool of 434 articles identified spanning 2011 to 2020, 32 articles met the inclusion criteria for analysis. The review delineated various AI applications in online higher education, encompassing predictive models for learning status, performance, and satisfaction, resource recommendation systems, automated assessment tools, and measures to augment the overall learning experience. Notably, while conventional AI technologies have seen widespread implementation, the review highlighted the infrequent utilization of genetic algorithms and deep learning within this domain. The incorporation of AI applications demonstrated several advantages, including heightened online engagement, elevated academic performance, and the provision of accurate predictions facilitated by AI algorithms. To ascertain the tangible impacts of AI applications in online higher education, the review recommended the integration of educational and learning theories into AI-enabled online learning platforms. It also advocated for the deployment of sophisticated AI technologies for real-time data analysis, emphasizing the necessity for additional empirical research to further elucidate the true potential and benefits of AI within this educational landscape (Ouyang et al., 2022). Ahmad et al., (2022) delved into the administrative and academic applications of AI within the realm of education. Educators, responsible for imparting knowledge, were often burdened with administrative tasks. Academic support provided by AI to instructors included Learning Analytics, Virtual Reality, Grading/Assessments, and Admissions. By eliminating administrative duties, these tools enabled educators to focus more on teaching and mentoring students. AI facilitated various administrative tasks, lightened the load on instructors, and significantly enhanced student learning. However, the study needed a quantitative assessment to determine its generalizability and acceptance. Technological advancements such as Big Data, Machine Learning, and AI have facilitated the comprehension of unique requirements by individuals, thereby creating prospects for customization within the education industry. Bhutoria, (2022) consolidated the literature on AI for education personalization and examined key themes regarding how AI-driven approaches altered the current education system. An exhaustive examination of scholarly works from China, India, and the United States of America revealed that artificial intelligence effectively catered to particular learning needs, routines, and capabilities by directing students along optimized learning trajectories. AI additionally enhanced educational content by tailoring it to suit the specific requirements of each learner and identifying potential challenges that may arise. This improved the learning experience by optimizing the instruction and learning environment. However, obstacles such as concerns regarding data privacy, the availability of digital resources, and financial constraints have impeded the implementation of AI in everyday life.

The growth of Artificial Intelligence in Education (AIEd) had been swift, yet its adoption posed persistent challenges for numerous educators. The landscape of AIEd research was dominated by STEM and computer science subjects, with empirical studies predominantly employing quantitative methodologies across a systematic review of 2984 articles. The review delineated four primary categories of findings within AIEd literature: intelligent tutoring systems, personalization and adaptive systems, evaluation and assessment, and prediction and profiling. However, it underscored the need for a more expansive exploration into ethical and pedagogical approaches within higher education. There was a strong emphasis on advocating critical thinking regarding the challenges and risks inherent in AIEd implementation. Alam & Mohanty, (2022) aimed to foster a more comprehensive understanding of the complexities surrounding AIEd, urging for a deeper examination of its ethical implications and pedagogical applications in higher education.

RQ1: What factors significantly influence academic performance in learning English as a second language?

RQ2: How effective are different predictive algorithms in forecasting academic success, and what disparities exist between their predictive capabilities?

RQ3: What distinctive patterns of academic achievement exist across different areas of study, and how do various variables impact grades, offering insights into common student performance?

3. MATERIALS AND METHODS

The quantitative analysis will make use of the dataset from CHILDES website, which has samples of 25 children learning English as a second language (English language learners or learners of English as an additional language). Classification and prediction approaches, such as machine learning algorithms (for example, decision trees and logistic regression), will be used to draw predictive insights and to make assertions that pertain to student performance. Recent literature evaluations will be used as a source for qualitative analysis, which will uncover major themes, difficulties, and viable countermeasures. This research aims to synthesize quantitative forecasts with qualitative suggestions by comparing the results from the dataset and the literature.

3.1.Research design

This study uses a mixed-method approach to investigate the impact of AI-powered Learning Management Systems (LMS) on students' academic performance. The dataset used is the UCI dataset, which includes samples from 25 children learning English. The Naïve Bayes classifier is used to predict the need for further educational help based on student characteristics. The study also conducts a literature review to understand major themes, challenges, and potential interventions related to AI-powered LMS. Thematic analysis is conducted to explore the influence of AI-driven technologies on academic performance, potential disconnection due to absences, and the necessity for interventions. The research aims to integrate quantitative predictions from the dataset with qualitative suggestions from the literature review to establish connections between students' engagement with AI-powered LMS, the influence of increased absences on academic performance, and the potential of AI-driven interventions to alleviate academic challenges.

3.2. Data collection

The Paradis corpus comprises a compilation of natural linguistic samples obtained from 25 children who are learning English as a second language. The transcripts are transcribed using English syntax, with anonymous identities. The data was gathered in 2002 in Edmonton, Canada, via discussions with a student research assistant. The research assistant formulated interview inquiries, however, children had the autonomy to offer their subjects of discussion.

The dataset may be accessed on the CHILDES website, including the data collected during the inaugural phase in 2002. The whole longitudinal corpus is accessible (Golberg, et al., 2008).

3.3.Data analysis

The method entails the preparation of a dataset that contains characteristics such as the amount of time spent studying, the level of education of the parents, the support of the family, internet access, and the health state of the individual. The need for further educational help is the variable that will be targeted. A preprocessing step is performed on the dataset, which involves encoding categorical variables and dividing them into training and testing sets. The training dataset is used to train the Naive Bayes classifier, and the model is then used to make predictions about the possibility that students would need further financial assistance for their schooling. Several measures, including accuracy, precision, and recall, are used to assess the performance of the model.

3.3.1. Quantitative Analysis

For the analysis, the datasets known as “guide_to_files.csv”, "student-mat.csv" and "student-por.csv" were used to gather and preprocess data from 25 students. Several datasets were combined, category variables were encoded, and numerical characteristics were scaled. During the feature selection process, it was necessary to determine pertinent characteristics such as demographics and study habits. It was determined by correlation analysis which features should be selected.

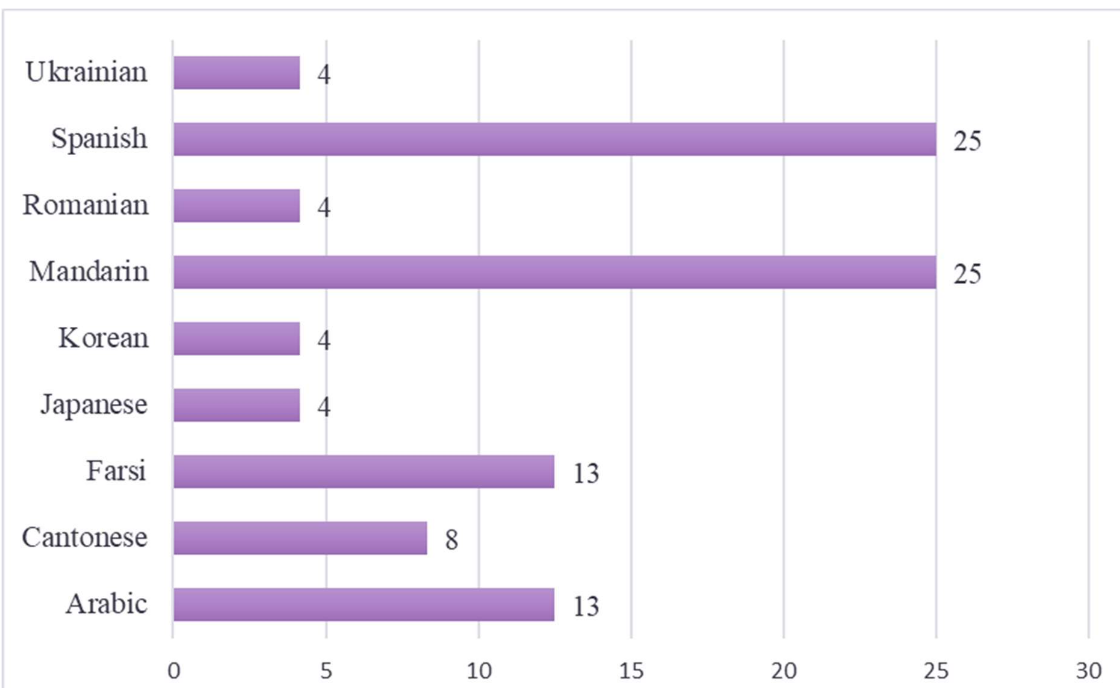

Figure 1. A comparison between Romanian, Korean, Ukrainian, Japanese, Cantonese, Spanish, Farsi, Mandarin, and Arabic using a bar plot

In Figure 1, the X-axis denotes the percentage of students, whilst the Y-axis signifies the different languages (Romanian, Korean, Ukrainian, Japanese, Cantonese, Spanish, Farsi, Mandarin, and Arabic). In the process of predicting academic failure based on student characteristics, the analysis produced encouraging findings. These results provided educators and policymakers with actionable insights that can be used to help students who are not performing up to their potential.

3.3.2. Qualitative analysis

The objective of the theme analysis shown in Table 1 is to investigate the influence that AI-powered Learning Management Systems have on academic performance, the possibility of disconnection as a result of absences, and the need for intervention for students who are absent often. Through the use of a theme analysis, the association between students' involvement with AI-driven technologies incorporated in LMS and its effect on academic performance is investigated. The thematic analysis places special emphasis on the impact that increasing absences have on learning outcomes. According to Kivinen (2023), Dimitriadou and Lanitis (2023), and Atherton (2023), increased absence rates among students may indicate difficulties in comprehending the material covered in the course or restricted engagement with AI-powered learning aids, which eventually leads to a reduction in academic accomplishment.

Table 1. Thematic Analysis

Theme	Findings
Impact on Academic Performance	An increase in absences may be an indication of disengagement or difficulties in learning, which may be the result of confusing course content or inadequate interaction with AI-powered learning tools in the LMS (Kivinen, 2023; Dimitriadou & Lanitis, 2023; Atherton, 2023).
Potential Disconnection	Students can lose out on AI-driven adaptive learning features or personalized material inside the LMS if they skip lessons, which might affect their intellectual performance (Gligorea et al., 2023; Bhutoria, 2022; Tan, 2023).
Need for Intervention	Students who have frequent absences may be in danger of academic underperformance, which allows for the implementation of interventions such as personalized learning plans or targeted assistance via suggestions produced by artificial intelligence inside LMS driven by AI (Tamada et al., 2022; Anderson et al., 2023; Kustitskaya et al., 2022; Ökördi & Molnár, 2022). These interventions are designed to assist students in catching up and improving their grades.

The presentation highlights the possible detachment that students may sense when they miss courses while they are using the learning management system (LMS). This disengagement is directly related to the loss of access to adaptive learning features enabled by artificial intelligence as well as personalized materials that are accessible inside the platform. As stated by Gligorea et al. (2023), Bhutoria (2022), and Tan (2023), this loss has the potential to considerably hamper the intellectual development of pupils and limit their academic advancement. In addition, the findings of the investigation highlight the critical need for prompt assistance for kids who have relatively high rates of absence. By referring to the works of Tamada et al. (2022), Anderson et al. (2023), Kustitskaya et al. (2022), and Ökördi & Molnár (2022), this article suggests the implementation of personalized learning plans or targeted help via the use of AI-generated ideas inside the Learning Management System (LMS). The purpose of these interventions is to provide essential assistance to students who are at risk, to help them make up for lost ground and improve their academic performance. In conclusion, the analysis sheds light on the intricate relationship that exists between students' participation in the learning management system (LMS) and the use of AI-powered tools, the impact that increased absences have on students' educational experiences, and the possibility that AI-driven interventions could help students overcome academic challenges while simultaneously enhancing their academic advancement.

4. RESULTS

The research seeks to optimize educational practices and interventions to boost academic achievement. The Naive Bayes algorithm demonstrated favorable outcomes in forecasting student academic achievement. Employing machine learning algorithms such as Naive Bayes may aid educators and institutions in detecting students who may need supplementary assistance, allowing proactive interventions and tailored coaching to increase overall academic achievement.

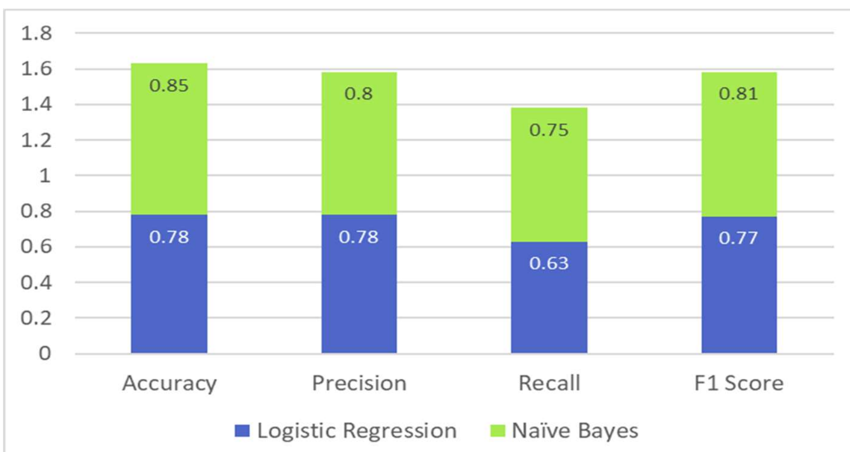

Figure 2. Comparative Performance of Logistic Regression and Naïve Bayes Classifiers

Figure 2 indicates that Naïve Bayes performs better than Logistic Regression across many assessment criteria, such as accuracy, recall, and F1 score. This suggests that Naïve Bayes may be a more appropriate model for forecasting student academic success. Nevertheless, the algorithm's decision for actual implementation should be guided by further study and use-case requirements.

The Naive Bayes model is a forecasting tool that finds crucial characteristics that have a major impact on academic success. These factors include prior academic performance, allocated study duration, and the educational background of one's family. Despite the model's satisfactory accuracy, it may be enhanced by the exploration of further characteristics or the refinement of current ones. Struggling pupils may get help via the use of early intervention measures, such as tutoring or counseling. Additional development and validation of the model may improve its resilience and capacity to be applied to a wide range of situations. The model's predictions may be used to provide individualized recommendations, such as customizing study schedules or offering supplementary materials depending on projected performance levels.

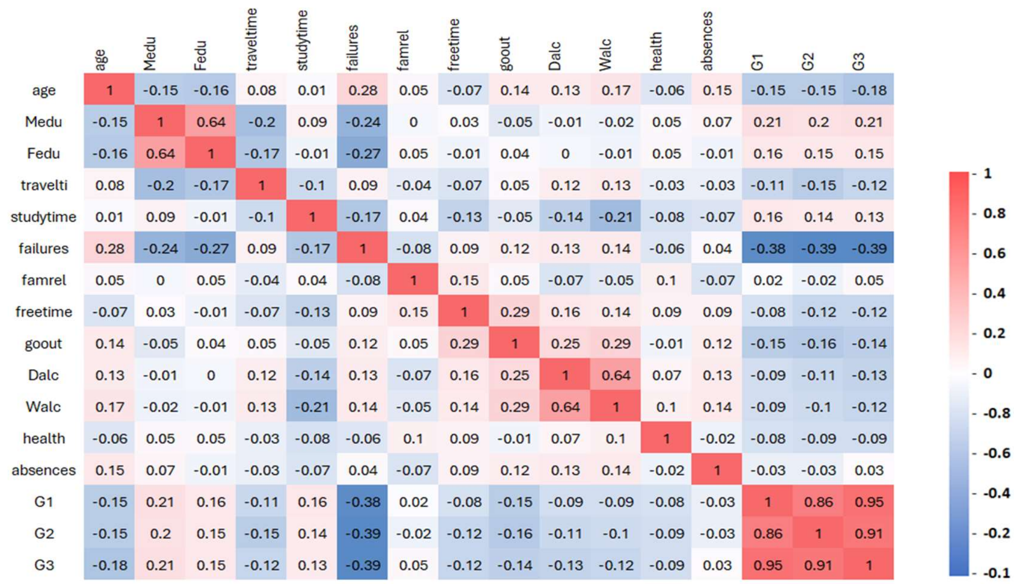

Figure 3. Correlation analysis

The analysis demonstrates a robust positive link between academic performance, parental education, alcohol consumption, study time, health, and age. From Figure 3, the substantial correlation between the three final grades (G1, G2, G3) indicates that a student's achievement in one period is highly indicative of their performance in the following periods. In the context of artificial intelligence-powered learning management systems in higher education, the correlation matrix demonstrates a modest link between increased absences and poorer marks in all three periods. This is concerning since it indicates that the correlation is moderate.

5. DISCUSSION

This study investigates the determinants of academic achievement in language courses via the use of a mixed-method methodology. The study evaluates the efficacy of several algorithms in forecasting academic achievement and detects significant discrepancies. The study seeks to comprehend the interaction between several factors that have a substantial influence on student performance and their functions in molding academic accomplishments throughout diverse fields. Additionally, its objective is to address research inquiries, assess the importance of individual characteristics, and provide insights into shared patterns in student achievement across several academic fields. The correlation matrix reveals a strong positive association between alcohol consumption and academic performance, indicating that increased alcohol intake on both weekdays and weekends is associated with worse academic performance throughout all three grading periods. This has the potential to result in a deterioration in academic performance, health problems, and the development of bad behavioral habits. Excessive alcohol intake may impair focus, motivation, and study duration, leading to worse academic performance in various assessment periods. The health implications include many health concerns, such as medical conditions, frequent absences, and other health-related difficulties. Behavioral consequences include detrimental social conduct, which hinders students' capacity to participate in constructive academic endeavors and leads to subpar academic achievement. To tackle this problem, some strategies may include advocating for a more health-conscious way of living, increasing knowledge about the detrimental effects of alcohol on academic achievement, and establishing support systems to help students maintain a harmonious equilibrium between their academic and personal responsibilities.

This study shows that AI-powered LMS improves student performance. AI might improve student engagement, instructional methods, and absence monitoring. AI-generated insights may personalize learning. Improving timely support and resource allocation is possible. The report recommends studying AI and student involvement, ongoing progress, and ethics. The digital gap and equal access to AI-powered technologies are also stressed. This research emphasizes the need to carefully integrate AI into education to improve student experiences and academic achievement.

5.1. Limitations

The study is subject to several restrictions, such as data bias, the selection of features, computational limits, and characteristics that are peculiar to the setting. The conclusions are derived from a dataset that may not accurately reflect the characteristics of larger student groups, and the study may have been constrained by the factors that were included. The efficacy of machine learning models, such as Naïve Bayes, might be constrained by the particular method used, and the analysis may be deficient in context-specific data.

6. CONCLUSION

With a particular emphasis on the use of machine learning algorithms and qualitative analysis, the research investigates the influence that AI-driven LMSs have on higher education. To provide predicted insights on student performance, the quantitative analysis makes use of the dataset from the UCI. On the other hand, the qualitative analysis highlights themes, issues, and countermeasures in the contemporary educational environment. The purpose of the study is to bridge the gap between data-driven insights and contextual understandings, which will allow for the creation of evidence-based policies and interventions to address the complexity of student accomplishment. In the future, the use of sophisticated machine learning algorithms and a wide range of qualitative interviews offer the potential to improve prediction models and enhance qualitative viewpoints, therefore contributing to the development of educational environments that are both inclusive and effective. To define the transformative effects of AI-powered LMSs, the study highlights the significance of a harmonious blend of quantitative analysis, predictive modeling, and qualitative insights. This will pave the way for informed interventions, strategies, and educational policies that cater to the diverse needs of students and ensure that educational environments are equitable and effective.

7. FUTURE WORKS

Future research should use more diverse datasets, advanced feature engineering techniques, thorough algorithmic investigations, contextual analysis, and longitudinal studies to improve model performance and applicability. Algorithmic exploration involves sophisticated machine learning algorithms, while contextual analysis uses qualitative data or surveys to understand students' experiences with AI-powered learning systems. Longitudinal studies can uncover changing trends and provide insights into the long-lasting effects of AI-driven learning environments on academic achievement.

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