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Research Article

Predicting the Effect of Mobile Phone on Student Academic Performance Using Machine Learning

Shuaibu Yau[1*], Abdulsalam Abdulganiyu Ishola[2], Abdu Ibrahim Adamu[3]

[1,2]Dept. of Computer Science, Faculty of Science, Federal University Birnin Kebbi, Nigeria
[3]School of Electrical Engineering, College of Engineering, UiTM Shah Alam Selangor, Malaysia

Corresponding Author: shuaibuauna@gmail.com

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Abstract— The study aimed to predict the effect of mobile phones on students' academic performance using Machine Learning, focusing on the Faculty of Science at the Federal University Birnin Kebbi (FUBK). With the increase in the prevalence of mobile phone usage among students, there is concern about its effect on academic performance. A total of 227 students partakes in the research, with a gender balance of 57.3% male and 42.7% female. Online Questionnaire was distributed for data collection among students from 200Level to 400Level, and responses were cleaned and preprocessed to ensure consistency and accuracy. Analysis was conducted using Python, employing two models: Random Forest (RF) and Decision Tree (DT). However, the results indicated that DT achieved an R^2_score of 57%, whereas RF achieved an R^2_score of 63% in predicting students' grade point averages based on their mobile phone usage. Other models, like Linear Regression, K-Nearest Neighbor (KNN), and Neural Network Regression, could also be explored for prediction purposes. This study recommends that universities consider implementing predictive models to inform students about their expected grade point averages, aiding them in focusing on their studies. Additionally, universities should encourage students to engage in meaningful tasks, providing additional data points for predictive models and improving their accuracy. Lastly, it is advised that universities be mindful of the ethical implications associated with the use of predictive models.

Keywords— Academic performance, Semester grade point, Machine learning, Regression analysis, Mobile phone, FUBK

1. Introduction

Advancements in technology have significantly transformed the landscape of education, offering students unparalleled access to information and resources through technological gadgets such as mobile phones, laptops, and tablets [1]. However, concerns have emerged regarding the potential negative impact of mobile phone use on academic performance. Excessive dependence on mobile phones may hinder critical thinking skills, disrupt attention spans, and impede traditional learning methods [2]. Today, technology has become deeply ingrained in daily life, influencing various aspects including communication, entertainment, and education [3, 4]. Mobile phones have evolved into multifunctional devices known as smartphones, offering not only communication capabilities but also access to a wide array of educational resources [5]. With smartphones becoming increasingly affordable and ubiquitous, they have become indispensable tools for individuals of all ages [6]. The integration of mobile phones in educational contexts has transformed learning, providing students with immediate access to academic resources, digital libraries, and online educational tools [7]. This technology enables self-directed learning, offering students the opportunity to enhance their knowledge outside of traditional classroom settings. Studying the impact of mobile phone use on academic outcome is crucial for understanding whether these devices genuinely aid learning or if their distractions outweigh their benefits. Such a study helps discern the fine line between productive and unproductive usage, offering a basis for educational policies that maximize benefits. As mobile phone usage among students continues to increase, there is a noticeable shift in study habits, information processing, and communication. Research on the effect of mobile phones on academic outcome can provide valuable insights into these behavioral shifts. Recognizing how the presence of a mobile device alters the attention span, time management, and study routines will allow educators and policymakers to develop strategies that foster a more conducive learning environment, balancing technological advantages with effective study practices. Mobile phones have also brought about significant improvements in digital literacy, an increasingly valuable skill in modern academia and the workforce. Students who learn to navigate digital resources through mobile phones often perform better on research-based projects, assignments, and presentations. However, it is critical to assess whether increased screen time due to mobile device usage inadvertently hampers academic success. By studying this dynamic, institutions can promote balanced, responsible mobile phone usage that supports academic goals rather than detract from them. As technology advances, mobile phones are likely to become more integral to education. Understanding their current impact on academic performance can help to prepare educational institutions for future trends. As universities move toward more digital and hybrid learning models, studying mobile phone usage patterns among students provides foundational knowledge that can guide the development of future educational frameworks. This research can help institutions create policies that embrace technological advancements while maintaining rigorous academic standards, ensuring that students gain the maximum benefit from both digital and traditional resources. This work studies the effect of mobile phone usage on the academic outcome of students in the Faculty of Science, FUBK, Nigeria, using machine learning techniques. The outcomes aid vital insights into the relationship between phone usage and students' academic outcomes, hence, shedding light on the potential distractions and benefits associated with mobile phone usage. The outcomes of this work will inform educators, policymakers, and parents about the need for guidelines and regulations governing mobile phone use in academic settings. By identifying the indicators that influence students' academic performance, this work can contribute to the development of strategies to minimize distractions and maximize the educational benefits of mobile technology. Ultimately, this study aimed to enhance student learning outcomes, improve academic performance, and bridge the digital divide, ensuring that students harness the potential of technology to support their educational goals without compromising their cognitive skills and overall academic success.

1.1 Problem Statement

The prevalent use of mobile phones among students pursuing higher education raises concerns regarding their potential impact on academic performance. Excessive engagement with mobile devices for non-academic activities, including social media and gaming, can lead to distractions, reduced study time, and lower retention of information, ultimately resulting in poor academic outcomes [8]. As mobile phone usage becomes increasingly pervasive among students, there is a need to investigate its correlation with academic performance [9]. This work aimed to ascertain the extent to which mobile phone usage influences students' academic performance.

1.2 Research Hypotheses

This work proposes the following hypothesis as per below:

H1: There is a relationship between regular mobile phone usage and face-to-face social interaction among students.

H2: The amount of time spent on mobile phones correlates with students' academic outcome.

H3: The purpose of mobile phone usage affects students' academic performance.

H4: Multitasking, such as using mobile phones for non-academic tasks during lectures, is associated with decreased attention span.

1.3 Background

Technology is commonly understood as the application of scientific knowledge to enhance human life, often involving modification and manipulation of the human environment [10]. This field of study encompasses the creation and utilization of technical media, exploring their interconnectedness with various aspects of life, society, and the environment, spanning topics such as industrial art, engineering, applied science, and pure science [11]. Despite its potential benefits, modern technology can impede learning [12]. For instance, students who excessively rely on computers may witness a decline in their math scores. However, when utilized judiciously, modern technology can positively affect learners' educational outcomes. For example, computers offer personalized instruction, autonomy, and self-paced learning opportunities, broadening educational horizons, particularly for children in isolated rural communities or those facing limitations due to disability or illness. The widespread adoption of modern technologies, especially mobile phones and computers has led to concerns about their adverse effects on students' cognitive skills and academic performance [13]. Today, students lack analytical skills, creativity, and perseverance more than ever before [14]. Additionally, a digital divide has emerged with unequal access to technology based on factors such as wealth, race, gender, and geography [15]. In particular, mobile phones have been identified as a significant cause of lecture-room distractions [16]. Often likened to students' "lollipops," mobile phones have become ubiquitous, impacting concentration and reducing the time spent on academic activities. Despite being primarily used for communication, mobile phones serve multifunctional purposes, akin to a mobile computer, enabling tasks such as file storage and Internet browsing [17]. Although integrating technology into lecture rooms has shown promise, there are drawbacks to consider [18]. Although technology promotes student readiness, engagement, and improvement in learning, its unchecked use can lead to adverse effects. For instance, excessive reliance on modern technology may alter cognitive skills and basic psychology, affecting student development in the lecture room [19]. Additionally, studies have struggled to establish a definitive causal relationship between internet use and student achievement, highlighting the contentious nature of this issue [20, 21].

1.4 Potential Benefits and Detriments of Operating Mobile Phones in Lecture Rooms

Research suggests that mobile phones in lecture rooms offer various benefits, including increased motivation, relevance for future work, pedagogical innovation support, and enhanced interactivity [21]. Moreover, mobile phone use facilitates content creation, assessment, instruction differentiation, and reflection. However, studies have also identified the potential disadvantages associated with mobile phone use in lecture rooms. For instance, one study found that banning mobile phones in classrooms led to improved standardized test scores, particularly among low-achieving students, suggesting that banning phones could mitigate educational inequalities [22]. Additionally, there is evidence of a negative association between mobile phone use and the self-reported grade point average (GPA), with unstructured mobile phone use in class adversely affecting learning and grades.

2. Related Work

Numerous works have studied the prediction of students' academic performance by utilizing machine learning methodologies to elucidate various factors influencing educational outcomes. In their research, [23] developed a model that incorporated student demographic characteristics and semester-long activity metrics. Employing a Gradient Boosting Machine (GBM) classification model, they identified previous academic performance and attendance as critical factors. However, significant economic circumstances were not considered, as emphasized in [24]. Comprehending the global challenge of academic achievement necessitates accounting for its complex relationship with economic development, employment, and overall societal well-being.

Nevertheless, research on this topic frequently relies on traditional statistical methods applied to survey data [24]. By leveraging 16 demographic characteristics, including age, gender, and class attendance, they employed machine learning techniques, like Random Forest, Logistic Regression, k-nearest neighbors, and support vector machines (SVM), achieving prediction accuracies ranging from 50% to 81%. Another study [25] identified the key indicators affecting school academic outcome and proposed a learning-based model to elucidate their relationships. Their findings emphasized factors such as school size, competition, and parental pressure, with a regression tree analysis highlighting the pivotal role of school size and sex ratio in predictive accuracy. However, their model was specific to secondary schools in Tunisia. Moreover, [26] proposed a machine-learning-based model to identify students at risk of academic underperformance, yielding a classification accuracy, up to 85%. However, unlike the present study, their focus was primarily on student retention rather than the influencing factors. While [27] introduced a learning model by considering learning methods, social support, demography, health, and academic performance indicators, their findings may not be generalized to developing countries, such as those in Africa, which face unique challenges. Additionally, [28] studied the correlation between college students' Internet usage behavior and academic outcome, achieving high accuracy in predicting student outcomes. They suggested that Internet usage plays a crucial role in students' academic performance. However, their study is specific to the Chinese context. Furthermore, [29] examined the efficacy of learning management system logging in predicting student success. Accurately predicting student academic outcome requires a holistic understanding of student performance and its influencing factors. Various features, such as course performance, student participation, demographics, and psychomotor skills contribute to academic outcomes [30]. Meanwhile, [31] analyzed parental influence on academic performance, highlighting attributes such as family size, parental education, and home Internet access as significant predictors. Similarly, [32] assessed the academic performance of students in private institutions, emphasizing environmental characteristics and academic context as influential factors. Their findings underscore the importance of predicting academic performance to enhance education quality and support at-risk students. In their research, [33] explored the relationship between app usage and students' academic performance, focusing particularly on grade-point averages. They concluded that high and low performance is strongly related to app usage behavior, highlighting the need for further research on individual social media apps. However, this study contends that this relationship was not evident in our findings. Additionally, [34] conducted a systematic review, revealing that most methods in contemporary literature still rely on statistical approaches. This aligns with [35, 36, 37], where [36] investigated the effect of phone usage on students' achievement in public schools in Nigeria, utilizing chi-square for hypothesis testing and simple percentages for research questions. Similarly, [37] employed the mean, standard deviation, and t-tests to analyze their study.

In summary, the review of the existing literature highlights numerous issues faced by the education sector in developing countries that contribute to a decline in student performance. There is a need to comprehensively investigate the latent factors influencing student performance because current models often lack flexibility in analyzing multiple academic and non-academic factors. Moreover, reliance on statistical methods, particularly in our context, poses limitations and the datasets used may not be universally applicable. Further research is essential to address these gaps and provide comprehensive insights into the factors influencing student performance, especially by leveraging learning models.

3. Research Approach

The objective of this work is to propose predictive models capable of accurately forecasting the effect of mobile phone usage on students' academic outcome. To achieve this, Decision Tree (DT) and Random Forest (RF) models were proposed, as shown in Figure 1.

The conceptual framework of this work illustrates the correlation between mobile phone usage and academic achievements. The framework posits that mobile phone usage (independent variable) affects academic performance (dependent variable) through mediating factors, such as face-to-face social interactions and the purpose of mobile phone use. The model suggests that regular mobile phone usage influences students' social interactions, which, in turn, affects their academic performance.

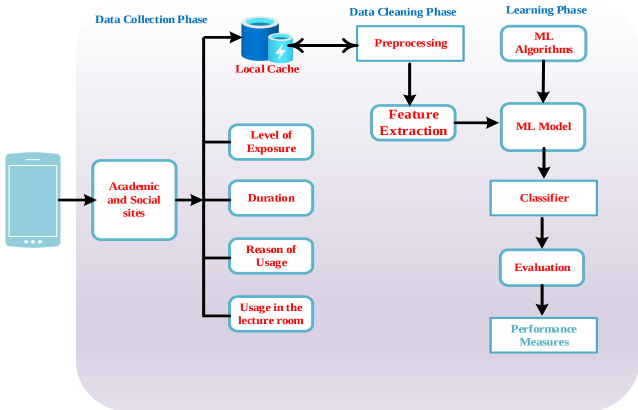

Figure 1. Conceptual framework

Additionally, the time spent on mobile phones and the purpose of use (e.g., academic or non-academic) also correlate with academic performance. Multitasking, particularly during lectures, is hypothesized to decrease attention span, ultimately affecting academic outcomes. The DT and RF algorithms will be applied to the questionnaire data to test the research hypotheses (H1-H4) and validate the conceptual framework.

4. Experimental Method

4.1 Decision Trees (DTs)

Decision trees are predictive models of supervised learning, known not only for their indisputable usefulness in many applications, but also for their ease of understanding and robustness. This supervised learning technique is a non-parametric method applicable to both classification and regression problems. The structure of a decision tree commences with a root node, from which branches extend to form internal nodes, also known as decision nodes.

According to the available functionality, all the types of nodes perform evaluations, yielding homogeneous subsets known as a leaf or terminal nodes. The leaf nodes represent all possible outcomes in the dataset. Fig 2 shows a decision tree.

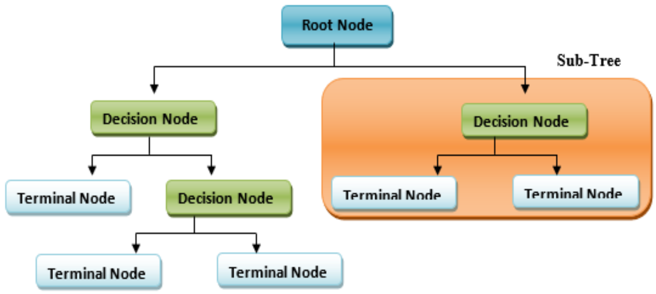

Figure 2. Decision Tree (DT).

4.2 Random Forest

The Random Forest is a commonly used machine learning algorithm pioneered by Leo Breiman and Adele Cutler, which combines the output of multiple decision trees to obtain a single result. It is used to overcome the problem of decision tree overfitting. The random forest consists of many trees, each of which independently predicts its own classification, and the final decision is made according to the model based on the maximum number of votes of the trees. RF is vital because the training process is faster than that of other algorithms, and the accuracy of RF regression is high. It works well with large datasets.

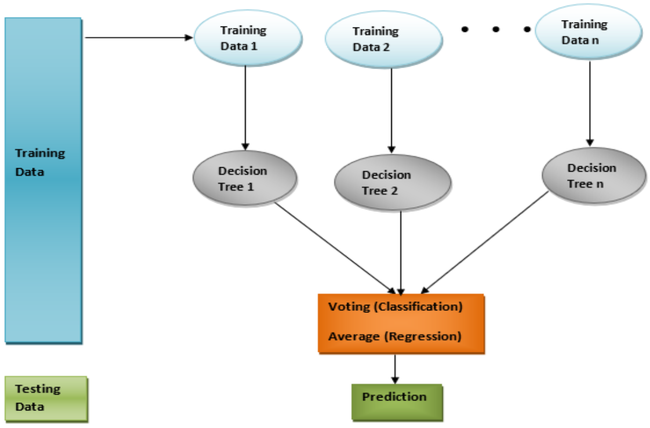

Figure 3. Random Forest

4.3 Survey form

The Figure below (fig 4) shows the questions that are used to obtain the data from the students from 200L to 400L. The link to the survey form:
https://docs.google.com/forms/d/1l6AqzrexC6oFSX32SBYkL97VLyDnRx1NqrUuAacia6g.

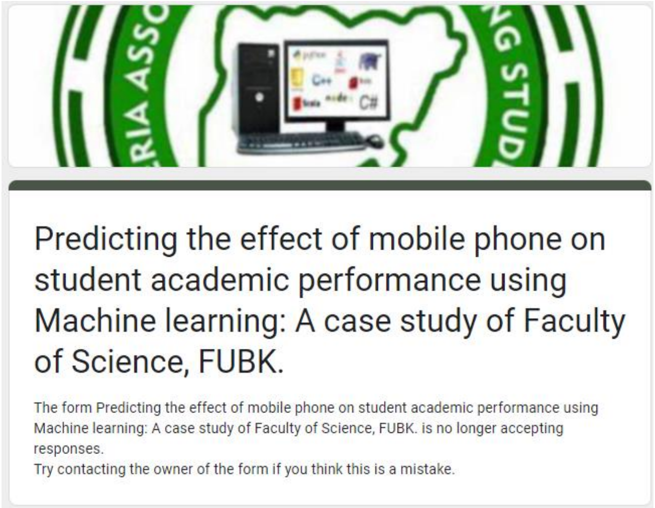

Figure 4. The Survey form

5. Results and Discussion

5.1 Results

This work used a dataset of 227 students. Relevant libraries were imported, and the data underwent cleaning, visualization, pre-processing, and fitting to the model, yielding the following findings:

H1: Mobile phone usage has a discernible impact on social interactions among students [1].

H2: Students who spend less time on their mobile phones tend to achieve better grade point averages, indicating a correlation between mobile phone usage duration and academic performance [8].

H3: The nature of mobile phone usage influences student performance [9].

H4: The presence of mobile phones in the lecture room is associated with decreased attention spans among students, suggesting a distracting influence [16]. The study used an online questionnaire and employed Python programming language to analyze the data using two models: Decision Tree Regressor and Random Forest Regressor.

Table 1. DT Results

DECISION TREE REGRESSOR	
MSE	0.3161
MAE	0.3805
R^2_SCORE	0.5704
RMSE	0.5622

The results indicate that DT achieved an R^2_score of 57% in predicting students' grade point averages based on their mobile phone usage, whereas RF achieved an R^2_score of 63% in predicting students' grade point averages based on their mobile phone usage.

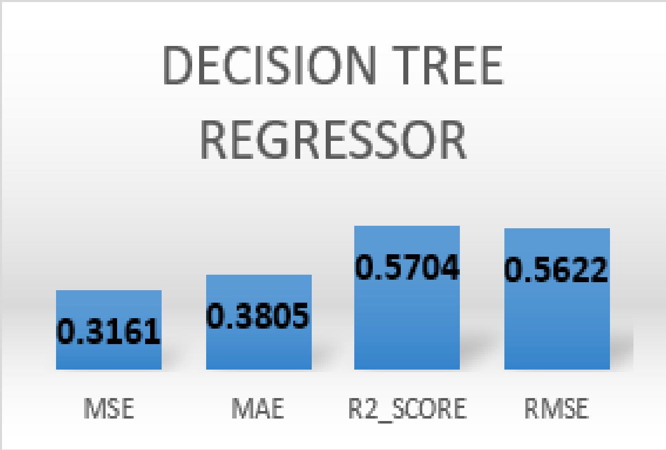

Figure 5. The Decision Tree Regressor Results

The evaluation metrics for both models are presented in Tables 1 and 2, and Figures 5, 6, and 7, respectively.

Table 2. RF Results

RANDOM FOREST REGRESSOR	
MSE	0.2681
MAE	0.3429
R^2_SCORE	0.6357
RMSE	0.5177

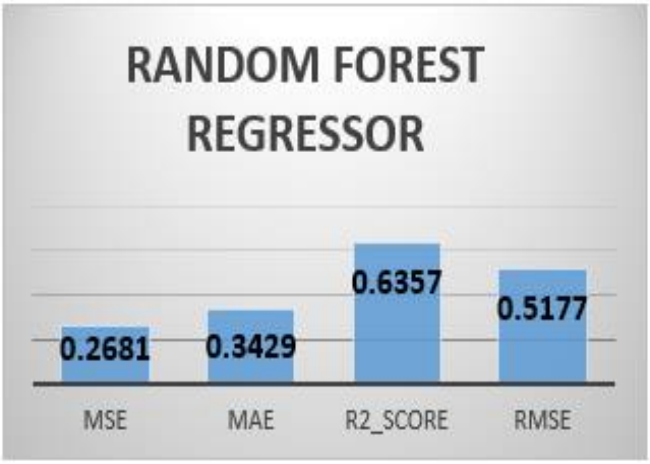

Figure 6. The Random Forest Regressor Results

5.2 Evaluation Metrics

This section offers a comprehensive analysis of the decision tree and Random Forest models, evaluating their performance using four key metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared (R^2), and Root Mean Squared Error (RMSE).

5.2.1 Mean Squared Error: The decision tree model exhibited an MSE of 0.3161, whereas the RF model achieved a lower MSE of 0.2681. MSE calculates the average squared difference between the predicted and actual values, with lower scores indicating higher accuracy. The lower MSE of RF suggests that it outperforms the Decision Tree in prediction accuracy, particularly in minimizing substantial errors, which is vital for applications sensitive to errors.

5.2.2 Mean Absolute Error: The Decision Tree model yielded an MAE of 0.3805, whereas the RF model attained a lower MAE of 0.3429. The MAE measures the average absolute difference between the predictions and actual target values. Unlike MSE, MAE does not have square errors, making it less affected by outliers. The lower MAE of the RF indicates that its predictions are generally closer to actual values, offering more accurate results than the Decision Tree model.

5.2.3 R-squared: The DT model achieved an R^2 score of 0.5704, while the RF model recorded a higher R^2 of 0.6357. The R^2, known as the coefficient of determination, signifies how much of the variation in the dependent variable is accounted for by the independent variable(s). As R^2 approaches unity, it indicates an increasingly precise fit of the model to the observed data. The Decision Tree's R^2 value of 0.5704 suggests that it accounted for 57.04% of the target variable's variance, while the Random Forest model explained 63.57%. This implies that the Random Forest model better captures the underlying patterns and relationships within the data.

5.2.4 Root Mean Squared Error: The Decision Tree model had an RMSE of 0.5622, whereas the Random Forest model produced a lower RMSE of 0.5177. RMSE, the square root of MSE, is obtained in the same units as the target variable, enhancing interpretability. As RMSE penalizes larger errors more heavily, the lower RMSE of Random Forest indicates improved prediction consistency and reduced deviation from actual values compared to the Decision Tree model.

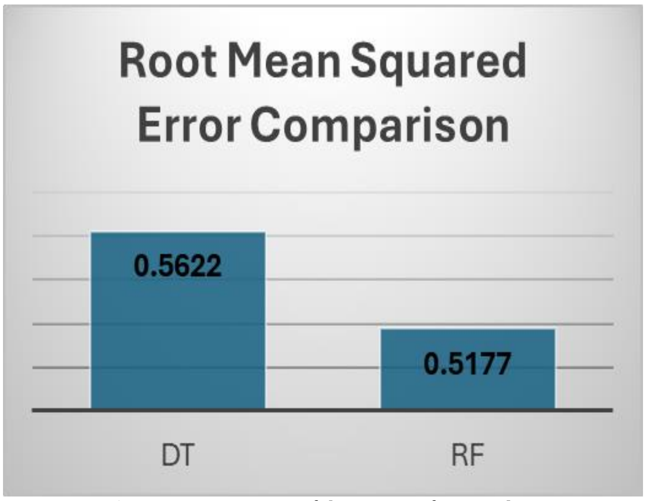

Figure 7. Comparison of the RMSE of DT And RF

5.3 Discussion

This research corroborates that mobile phone usage, particularly social networking sites (SNS) usage, has impact on students' academic outcome, which is in line with previous studies [1]. Excessive use of mobile devices can lead to distractions, decreased study time, and reduced retention, resulting in poor academic outcomes [8]. These findings are consistent with earlier research that identified a negative relationship between mobile phone use and academic performance [22]. The role of mobile phone use is crucial; engaging in multiple tasks during studies diminishes concentration, rendering mobile devices both beneficial educational instruments and potential distractions on their application. Moreover, students who devoted more time to SNS typically achieved lower grade point averages, validating that SNS engagement can interfere with the student focus and reduce efficiency. An evaluation of Decision Tree and Random Forest algorithms revealed that RF surpasses DT in forecasting student academic achievement based on mobile phone habits [27]. The RF model metrics, MSE (0.2681), MAE (0.3429), R^2 (0.6357), and RMSE (0.5177), exhibited superior predictive precision and resilience. In contrast, the DT model, with an MSE of 0.3161, MAE of 0.3805, R^2 of 0.5704, and RMSE of 0.5622, proved to be less effective, presumably owing to overfitting. The enhanced performance of RF illustrates the advantages of ensemble learning, where multiple decision trees are integrated to generate more generalized predictions, making RF more dependable in practical applications [29]. These discoveries have significant implications for educators and policymakers, emphasizing the necessity of considering mobile phone usage and SNS involvement when assessing student performance [6]. Future studies should investigate additional factors influencing academic outcomes and develop tactics to mitigate the adverse effects of mobile phone use on learning [28]. Through the implementation of machine learning techniques, this study contributes to an expanding body of knowledge on the connection between mobile phone use and academic performance. The RF model's superior predictive accuracy demonstrates the potential of advanced algorithms to enhance the understanding of behavioral patterns and academic results [29].

6. Conclusion and Future Scope

This study compared two predictive model approaches for estimating students' grade point average based on their mobile phone usage patterns, device type, and time spent using it. Analysis of real-world data yielded promising results. The predictive model approach provides students with a dependable forecast of their potential GPA, offering valuable insights into how their mobile phone activities affect their academic performance. This model can be utilized as an effective tool for students to make informed choices regarding allocating time to mobile devices. By comprehending the relationship between their usage habits and GPA, students can modify their behavior to enhance their academic outcomes. Considering the importance of GPA in university environments, this predictive model has the potential to positively affect student success. However, this study had certain limitations. A significant constraint was its exclusive focus on mobile phone usage habits, disregarding other factors that might influence GPA, such as SNS usage, study practices, and individual differences. Moreover, the study used self-reported data, which could be biased and inaccurate. Furthermore, the findings may not be applicable to all student populations as the sample was limited to a specific university context. Future research could benefit from exploring predictive models that specifically examine student SNS usage. Given the substantial impact of SNS use on academic performance, further investigation is warranted. As contemporary students spend considerable time on social networks, understanding their effects on GPA could provide valuable insights into academic support and intervention strategies. Consequently, the research findings from this study are expected to be beneficial for learners, caregivers, and educators to understand technology usage and its impact.

Data Availability
Datasets analyzed during the current study are available within the research team but cannot be shared publicly because of confidential agreements with participants. Participants' privacy and confidentiality were ensured through signed agreements, which prohibited the sharing of raw data. However, the aggregate data and summary statistics are available upon request from the corresponding author.

Conflict of Interest
There is no conflict of interest whatsoever.

Funding Source
None.

Authors' Contributions
We equally wish to state that the Conceptualization and Methodology of this work was done by Abdulsalam Abdulganiyu and Shuaibu Yau, Draft writing was carried out by Abdulganiyu Abdulsalam while Shuaibu Yau and Abdu Ibrahim Adamu reviewed and edited the manuscript.

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AUTHORS PROFILE

Shuaibu Yau is a PhD candidate at the Department of Computer Science, Chiang Mai University, Thailand. Prior to that he received the B.Sc. degree in computer science from the Kano University of Science and Technology, Nigeria and the M.Sc. degree in Computer Science from Bayero University Kano, Nigeria. He works as a lecturer at the Department of Computer Science, Federal University Birnin Kebbi, Nigeria. His research interests include Cloud and Edge Computing, Optimizations, Machine Learning, Multimedia Streaming, and intelligent systems.

Abdulsalam Abdulganiyu Ishola Graduated with a First Class Degree in Computer Science from the Federal University Birnin Kebbi. His research interest is around Machine Learning.

Abdu Ibrahim Adamu Completed an Msc in computer science at the Universiti Teknologi Mara, Shah Alam, Selangor, Malaysia and currently a PhD Candidate at the School of Electrical Engineering, College of engineering of the same University. Prior to that, he received the B.Sc. degree in computer science from the Kano University of Science and Technology, Nigeria. He works as a lecturer at the Department of Computer Science, Audu Bako College of Agriculture, Kano State, Nigeria. His research interests include Machine Learning and Wireless Sensor Networks.