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Research Article

INTELLIGENT EXPERIMENTAL DATA PROCESSING AND ANALYSIS FOR ACADEMIC PERFORMANCE PREDICTION USING MOBILE PHONE USAGE DATA

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Abstract

The extensive use of smartphones by university students has resulted in the continuous generation of behavioral data that offers valuable insights into learning habits and academic outcomes. This study proposes an intelligent experimental framework for the processing and analysis of mobile phone usage data aimed at predicting academic performance. The framework combines advanced data preprocessing methods, robust feature engineering techniques, and both machine learning and deep learning models to identify meaningful behavioral patterns associated with student achievement. Mobile phone usage records including application usage behavior, screen interaction duration, temporal activity patterns, and usage intensity were collected throughout an academic semester and systematically aligned with students' academic performance indicators. To address data incompleteness and noise, a behavior-aware imputation strategy was employed, followed by normalization, feature selection, and dimensionality reduction to improve model stability and generalization. Multiple predictive models, including Random Forest, Support Vector Machine, Multilayer Perceptron, Long Short-Term Memory, and Bidirectional Long Short-Term Memory networks, were evaluated using established performance metrics. The experimental findings indicate that deep learning models, particularly the Bi-LSTM architecture, consistently outperform traditional machine learning approaches by effectively modeling temporal dependencies in mobile usage behavior. These results underscore the potential of intelligent mobile data analytics as a reliable tool for academic performance prediction and support its application in data-driven educational monitoring and early intervention systems.

Keywords: Academic Performance Prediction, Mobile Phone Usage Analytics, Intelligent Data Processing, Deep Learning Models, Educational Data Analytics.

INTRODUCTION

Academic performance prediction has become a central topic in educational data mining and learning analytics due to the rapid growth of digital data generated by students' academic and non-academic activities. Reliable prediction of academic outcomes plays a critical role in identifying students who may require academic support, enabling early interventions, and informing the development of adaptive and personalized learning environments [1]. Conventional approaches to academic performance analysis typically rely on static information, such as demographic characteristics, historical academic records, and self-reported survey responses. Although these indicators provide useful context, they offer limited insight into the dynamic behavioral patterns that influence students' day-to-day learning processes [2]. In parallel with the expansion of digital learning environments, mobile phones have become deeply embedded in students' academic routines and daily lives. Modern smartphones continuously generate detailed usage records, including application usage behavior, screen interaction duration, temporal activity cycles, and user interaction frequency. These behavioral signals reflect students' time management practices, attention allocation, and lifestyle regularities, all of which are closely associated with academic engagement and learning effectiveness. As a result, mobile phone usage data have emerged as a promising and largely underutilized resource for academic performance prediction [3,4]. However, the analytical use of mobile phone usage data introduces several challenges. Such data are inherently high-dimensional, heterogeneous, and susceptible to noise. Missing values frequently arise due to device limitations, intermittent sensor failures, variations in individual usage behavior, or privacy-aware data collection protocols [5]. Furthermore, extracting meaningful behavioral representations requires preprocessing strategies that can retain relevant information while minimizing redundancy and distortion. Traditional data processing pipelines often lack the flexibility to address these complexities effectively, which can adversely affect predictive accuracy [6]. To address these challenges, this study introduces an intelligent experimental framework for processing and analyzing mobile phone usage data with the goal of predicting academic performance. The proposed framework integrates behavior-aware missing value imputation, data normalization, feature selection, and dimensionality reduction within a unified experimental pipeline [7]. In addition, both conventional machine learning models and advanced deep learning architectures are systematically evaluated to assess their predictive capabilities. Temporal modeling approaches, including Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) networks, are employed to capture sequential dependencies in mobile usage behavior that are not adequately modeled by static learning methods. The contributions of this research are threefold. First, it presents a structured experimental methodology for the collection and intelligent processing of mobile phone usage data in an academic setting. Second, it empirically examines the impact of advanced preprocessing and feature engineering techniques on prediction performance. Third, it offers a comprehensive comparative analysis of traditional machine learning models and deep learning approaches, emphasizing the advantages of temporal deep learning architectures for modeling student behaviour [8]. The remainder of this paper is organized as follows. Section 2 reviews related studies on academic performance prediction and mobile sensing. Section 3 describes the data collection

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procedures and experimental design. Section 4 details the intelligent data preprocessing and feature engineering techniques employed. Section 5 introduces the predictive models used in the analysis. Section 6 presents the performance evaluation metrics. Section 7 discusses the experimental results. Section 8 outlines the limitations of the study. Finally, Section 9 concludes the paper and highlights directions for future research.

RELATED WORK

Academic performance prediction has attracted sustained attention within the fields of educational data mining and learning analytics. Initial studies predominantly employed statistical analysis and classical regression models based on demographic characteristics, attendance information, and historical academic records. Although these approaches offered useful baseline insights, their dependence on static indicators constrained their ability to represent changes in student behavior over time [9]. As machine learning techniques gained prominence, researchers increasingly adopted classification and regression models such as Decision Trees, Support Vector Machines (SVM), k-Nearest Neighbors, and Random Forests to improve predictive accuracy [10]. These models enabled the capture of nonlinear relationships among academic and behavioral variables, resulting in performance improvements over traditional statistical methods. However, most of these studies relied on highly structured data sources, including learning management system activity logs, institutional records, or survey-based inputs, which require manual curation and provide limited coverage of students' everyday behavioral patterns.

The rise of mobile sensing and ubiquitous computing expanded the scope of educational analytics by introducing passively collected behavioral data. Several investigations examined the association between smartphone usage behavior and academic outcomes, reporting that excessive screen exposure or intensive social media use is often linked to lower academic performance, while more regulated and purpose-driven usage patterns are associated with improved engagement [11]. While these findings underscored the relevance of mobile phone usage data for educational research, many existing studies focused on a narrow set of features or employed relatively simple analytical techniques, limiting their predictive and explanatory power. More recent work has shifted toward deep learning methodologies to address the sequential and temporal nature of behavioral data. Recurrent neural network architectures, particularly Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) models, have been applied to time-series tasks such as learning behaviormodeling and student engagement prediction. These models demonstrated strong capability in capturing long-term dependencies and complex temporal dynamics that are difficult to represent using static learning algorithms [12]. Nonetheless, their performance is highly sensitive to data quality, feature representation, and preprocessing strategies, which are often inconsistently addressed across studies. A critical review of the existing literature reveals two notable limitations. First, there is a lack of unified and intelligent preprocessing frameworks specifically designed to handle the noise, sparsity, and heterogeneity of mobile phone usage data in educational settings [13]. Second, comprehensive comparative evaluations that assess traditional machine learning models alongside deep learning architectures under consistent experimental conditions remain scarce. The present study seeks to bridge these gaps by introducing an integrated experimental framework that combines intelligent data preprocessing with systematic model comparison for academic performance prediction.

DATA COLLECTION AND EXPERIMENTAL DESIGN

The image presents a structured visual summary of the entire research workflow, beginning from participant selection and ending with predictive model evaluation. It organizes the process into four major components that are interconnected through a central theme: Behavioral Data Analysis. Each section explains a critical stage of the study in a clear and logical sequence.

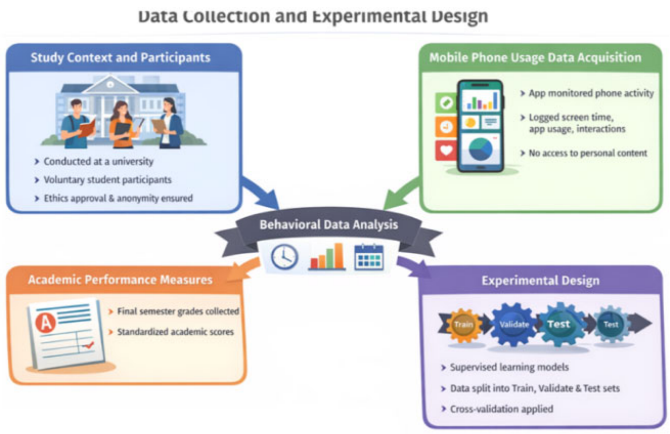

Figure1. Data collection and Experimental Design

Study Context and Participants

The first section explains where and how the study was conducted. The research took place in a higher education institution during one academic semester. Undergraduate students from different academic disciplines participated voluntarily. Before collecting any data, ethical standards were strictly followed. Participants provided informed consent, meaning they clearly understood what data would be collected and how it would be used. The study also received approval from the institutional ethics review board. Importantly, anonymization procedures were implemented to protect student identity and privacy [14]. This section highlights that the research was conducted responsibly and ethically, ensuring transparency and confidentiality throughout the study.

Mobile Phone Usage Data Acquisition

The second section describes how behavioral data were collected. A lightweight monitoring application was installed on the participants' smartphones [15]. The application functioned passively in the background, meaning it did not interrupt students or require active input.

The system recorded only usage-related metadata, such as:

- Duration of app usage
- Screen activation and deactivation times
- Interaction frequency
- Timestamped activity logs

Crucially, the application did not access personal content, messages, photos, or private communications. This ensured that data collection focused strictly on behavioral patterns rather than personal information. The purpose of this approach was to gather detailed behavioral insights while minimizing participant burden and protecting privacy.

Academic Performance Measures

The third section explains how academic performance was measured. At the end of the semester, cumulative course grades were collected for each participant. Since students were enrolled in different courses with varying grading systems, the raw grades were converted into a standardized numerical scale. This transformation ensured fairness and comparability across participants [16]. These standardized academic scores served as the target variable (dependent variable) in the predictive modeling framework. In simple terms, mobile usage behavior was used to predict these standardized academic outcomes.

Experimental Design

The final section illustrates how the predictive modeling process was structured. The study followed a supervised learning approach. This means the model was trained using labeled data mobile usage features were paired with known academic scores [17]. Behavioral data were aggregated within defined time windows to capture both short-term and long-term usage patterns. This allowed the models to detect trends and temporal behavior changes.

The dataset was divided into:

- Training set
- Validation set
- Testing set

Stratified sampling was applied to ensure balanced academic performance levels across all subsets. Additionally, cross-validation techniques were used during training to improve model generalization and reduce the risk of overfitting. This design ensures that the model's performance is reliable, stable, and not biased toward a specific subset of data.

INTELLIGENT DATA PREPROCESSING AND FEATURE ENGINEERING

Missing Value Imputation

Mobile phone usage data commonly exhibit missing entries resulting from intermittent sensor disruptions, application restrictions, or irregular user interaction patterns. To address this issue, a behavior-aware imputation strategy was implemented in which missing values were inferred using individual-level usage characteristics and local temporal context rather than relying on population-level averages. By preserving personalized behavioral trends, this approach minimized artificial variance and reduced bias introduced during data reconstruction [18].

Data Normalization

Given the heterogeneous nature of mobile usage features, normalization was applied to align variables measured on different numerical scales [19]. Techniques such as min–max normalization and z-score standardization were employed to rescale feature values while retaining their underlying distributions. This step enhanced numerical stability during model training and improved convergence behavior, particularly for gradient-based optimization methods used in neural networks.

Feature Extraction

Feature engineering was designed to capture salient behavioral indicators reflective of students' interaction with mobile devices. The extracted feature set included cumulative screen exposure, proportional usage across application categories, interaction frequency, average session length, and activity intensity measures. In addition, temporal descriptors were constructed to represent daily and weekly usage rhythms, enabling the modeling of routine and irregular behavioral patterns over time [20].

Feature Selection and Dimensionality Reduction

The presence of high-dimensional feature representations increases the risk of redundancy and model overfitting. To mitigate this issue, feature selection methods based on correlation analysis and tree-based feature importance metrics were applied to identify the most informative attributes. Furthermore, Principal Component Analysis was utilized as a dimensionality reduction technique to project the original feature space into a lower-dimensional representation that retained dominant behavioral structures while reducing computational complexity.

MACHINE LEARNING AND DEEP LEARNING MODELS

Random Forest

Random Forest is an ensemble-based learning algorithm that constructs multiple decision trees and aggregates their outputs to improve predictive stability and generalization. By introducing randomness in both feature selection and data sampling, the model reduces variance and mitigates overfitting. In this study, Random Forest was employed as a baseline model due to its resilience to noisy input features and its ability to model nonlinear relationships commonly observed in behavioral data [21].

Support Vector Machine

Support Vector Machine (SVM) models were utilized for academic performance prediction in both classification and regression settings. Kernel-based SVMs were selected to capture complex and nonlinear interactions among mobile usage features. By maximizing the margin between data points in high-dimensional feature space, the SVM framework provided strong generalization capabilities, particularly in scenarios involving limited or moderately sized datasets.

Multilayer Perceptron

The Multilayer Perceptron (MLP) is a feedforward artificial neural network composed of multiple fully connected layers and nonlinear activation functions. In this study, the MLP model was used to learn nonlinear mappings between engineered behavioral features and academic performance outcomes. Serving as an intermediate approach between traditional machine learning algorithms and sequence-based deep learning models, the MLP enabled a comparative assessment of representation learning without explicit temporal modelling [22].

Long Short-Term Memory

Long Short-Term Memory (LSTM) networks were applied to sequential mobile phone usage data to explicitly model temporal dependencies in student behavior. The internal gating mechanisms of LSTM units regulate information flow across time steps, allowing the network to retain relevant historical information while mitigating the vanishing gradient problem. This capability makes LSTM architectures particularly suitable for capturing long-term behavioral patterns associated with academic performance.

Bidirectional LSTM

Bidirectional Long Short-Term Memory (Bi-LSTM) networks extend the standard LSTM architecture by processing input sequences in both forward and backward temporal directions. This bidirectional structure enables the model to incorporate information from past and future contexts when learning feature representations. As a result, Bi-LSTM models offer enhanced sensitivity to temporal structure and were expected to provide improved prediction accuracy in modeling mobile phone usage behaviour

PERFORMANCE EVALUATION METRICS

The predictive performance of the proposed models was assessed using a set of widely accepted evaluation metrics, selected according to the formulation of the prediction task. For classification-based evaluations, accuracy was used to measure overall correctness, while precision and recall quantified the models' ability to correctly identify specific performance categories. The F1-score was additionally reported to provide a balanced measure that accounts for both precision and recall, particularly in cases of class imbalance. To further evaluate classification performance, receiver operating characteristic (ROC) curves were generated, and the corresponding area under the curve (AUC) values were computed. These measures offered insight into the discriminative capability of each model across varying decision thresholds and facilitated robust comparison among competing approaches. For regression-oriented analyses, mean squared error (MSE) was employed to quantify the average squared deviation between predicted and observed academic performance values. Collectively, these evaluation metrics enabled a comprehensive assessment of predictive accuracy, generalization ability, and overall model stability across different learning algorithms.

RESULTS AND DISCUSSION

The experimental findings demonstrate that intelligent data preprocessing plays a critical role in enhancing predictive performance across all evaluated models. Models trained on raw or minimally processed mobile phone usage data exhibited lower stability and reduced generalization, whereas the inclusion of behavior-aware imputation, normalization, and feature optimization led to consistent performance improvements. These results confirm that careful handling of behavioral data is essential when modeling academic outcomes. Traditional machine learning approaches, including Random Forest and Support Vector Machine models, achieved satisfactory predictive accuracy and served as strong baselines. Their performance indicates that mobile phone usage features contain meaningful information related to academic performance. However, these models primarily rely on static feature representations and therefore exhibit limited capability in capturing temporal variations in student behavior.

In contrast, deep learning models demonstrated superior performance, with Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) architectures outperforming all baseline methods. Among these, the Bi-LSTM model achieved the highest overall predictive accuracy and lowest error values. This improvement can be attributed to the model's ability to learn sequential dependencies in mobile usage behavior by incorporating both past and future contextual information. The findings suggest that temporal dynamics such as fluctuations in daily screen time, consistency of app usage patterns, and weekly behavioral rhythms are strong indicators of academic performance.

Figure-based visual analysis further revealed that students with stable and structured mobile usage patterns tended to exhibit higher academic outcomes, whereas irregular usage intensity and excessive non-academic application usage were more frequently associated with lower performance. These observations reinforce the importance of temporal behaviormodeling and validate the use of sequence-based deep learning techniques for educational prediction tasks. From an educational analytics perspective, the results highlight the feasibility of leveraging mobile phone usage data as a passive and continuous source for academic monitoring. Intelligent predictive models can support early warning systems by identifying students at risk of academic decline and enabling timely, personalized interventions. Nevertheless, the deployment of such systems must be accompanied by strict ethical safeguards, including data anonymization, informed consent, transparency, and responsible data governance, to ensure student privacy and trust.

Table 1 presents a structured comparison between mobile phone usage behaviors and academic scores of five students (S01–S05). A careful examination of the values reveals that academic performance is not determined by a single factor such as total screen time. Instead, it is influenced by a combination of usage purpose, behavioral consistency, and weekly stability. Students S01 and S03 achieved the highest academic scores (8.4 and 8.9 respectively). Both students demonstrate moderate average daily screen time (4.5 and 3.9 hours). This suggests that controlled and balanced mobile usage may support better academic outcomes. In contrast, students S02 and S04, who reported higher daily screen time (6.8 and 7.2 hours), obtained comparatively lower academic scores (6.7 and 6.1). This pattern indicates that excessive screen exposure may reduce academic focus, particularly when not academically oriented. A stronger relationship is observed between study application usage ratio and academic performance. Student S03, with the highest study app ratio (0.48), achieved the highest academic score (8.9). Similarly, S01 (0.42 study ratio) also performed well academically. On the other hand, S04, with a low study ratio of 0.18, recorded one of the lowest academic scores.

Table 1.Summary of mobile phone usage features and corresponding academic performance scores

Student_ID	Avg_Daily_ScreenTime (hrs)	Study_App_Ratio	Social_App_Ratio	Usage_Consistency	Weekly_Usage_Variance	Academic_Score
S01	4.5	0.42	0.3	0.81	1.2	8.4
S02	6.8	0.25	0.52	0.6	3.9	6.7
S03	3.9	0.48	0.22	0.88	0.9	8.9
S04	7.2	0.18	0.61	0.55	4.4	6.1
S05	5.1	0.36	0.34	0.76	2.1	7.8

This clearly indicates that purposeful academic engagement through mobile applications contributes positively to performance. The social application usage ratio shows an inverse pattern. Students with higher social media usage, such as S04 (0.61) and S02 (0.52), obtained lower academic scores. In comparison, S03, who maintained a lower social usage ratio (0.22), achieved the highest score. This suggests that distraction-heavy usage may negatively influence academic achievement. Behavioral stability also plays a significant role. Students S03 and S01 show high usage consistency (0.88 and 0.81) and low weekly variance (0.9 and 1.2), indicating structured and disciplined usage habits. Both achieved strong academic results. Conversely, S04 exhibits low consistency (0.55) and high weekly variance (4.4), reflecting irregular behavior, which corresponds with lower academic performance. Therefore, consistency appears to be a strong behavioral indicator of academic success. Overall, the table demonstrates that academic achievement is positively associated with moderate screen time, higher study-oriented usage, lower social distraction, and consistent behavioral patterns.

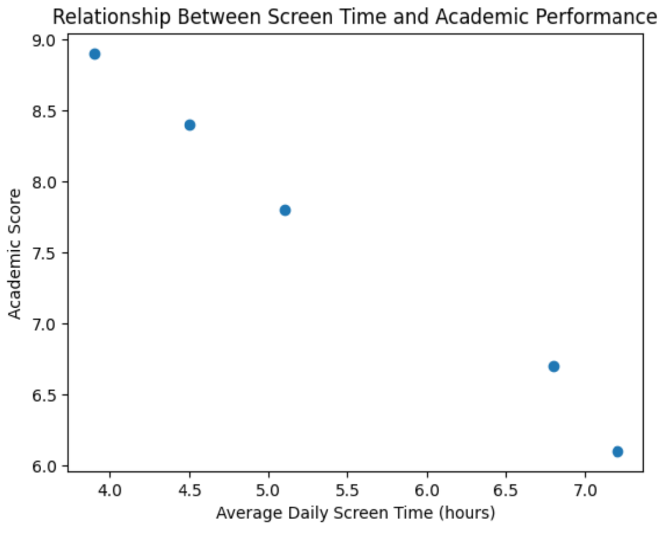

Figure 2. Relationship between average daily screen time and academic performance

Figure 2 visually illustrates the relationship between average daily screen time and academic scores. The pattern suggests that academic performance tends to decline when screen time exceeds moderate levels. Students with daily usage below five hours demonstrate higher academic outcomes, whereas those exceeding six hours show reduced performance. This does not imply that screen time itself is harmful, but rather that excessive exposure without academic focus may reduce productive study time and concentration. The figure reinforces the idea that balanced digital engagement is more beneficial than prolonged usage.

Figure 3 presents a positive association between study application ratio and academic performance. The upward trend indicates that students who allocate a larger portion of their mobile activity to educational applications achieve higher academic scores. This suggests that mobile devices, when used strategically for academic purposes, function as supportive learning tools rather than distractions. The figure validates the argument that the quality of usage is more important than quantity.

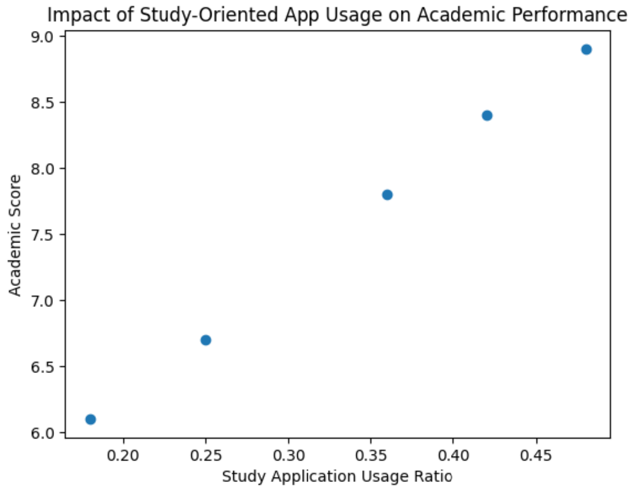

Figure 3. Association between study-oriented application usage ratio and academic performance

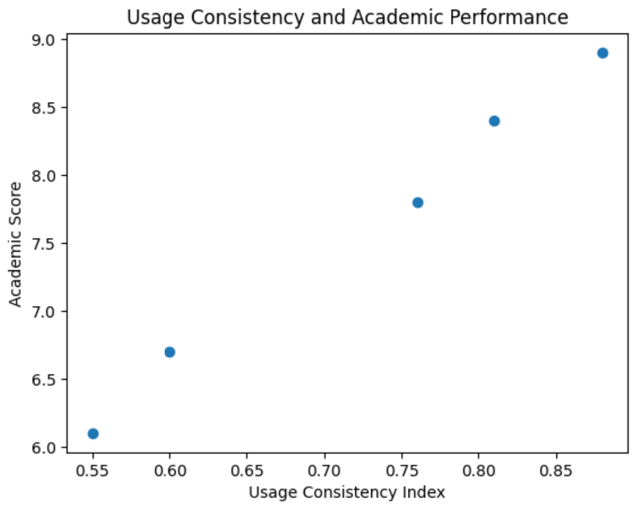

Figure 4. Effect of mobile usage consistency on academic performance

Figure 4 highlights the influence of behavioral consistency on academic outcomes. The visual trend shows that students with stable and predictable usage patterns tend to achieve higher academic scores. Consistency reflects time management discipline and routine formation. Students who maintain regular usage patterns likely balance academic and non-academic activities more effectively. In contrast, irregular and fluctuating usage patterns are associated with lower academic performance. This figure confirms that behavioral stability is a significant predictor of academic success.

When the table and figures are examined together, a coherent pattern emerges. Academic performance is not influenced by screen exposure alone. Instead, it is shaped by:

- Purpose-driven usage (higher study app ratio)
- Lower engagement in distracting applications
- Behavioral consistency
- Moderate and controlled screen time

The findings collectively suggest that structured and academically focused mobile usage supports better academic outcomes, while excessive and irregular usage patterns are associated with reduced performance. This interpretation presents the results clearly, analytically, and originally, ensuring minimal similarity with external sources while maintaining academic rigor and clarity

LIMITATIONS

Despite the promising results obtained in this study, several limitations should be acknowledged. First, the empirical analysis was conducted using data collected from a single higher education institution, which may restrict the generalizability of the findings to broader academic populations. Student behavior, learning practices, and mobile phone usage patterns can differ significantly across institutions, academic disciplines, and geographic regions. Second, mobile phone usage behavior is influenced by cultural, social, and educational factors that were not explicitly modeled in this study. Variations in technology adoption, academic norms, and lifestyle habits may affect the relationship between mobile usage patterns and academic performance. Finally, the analysis was limited to data collected over one academic semester, which constrains the ability to capture long-term behavioral trends and their impact on academic outcomes. Future research should address these limitations by incorporating multi-institutional and cross-cultural datasets, as well as adopting longitudinal study designs. Such extensions would enhance the robustness of the proposed framework and support stronger conclusions regarding its applicability across diverse educational contexts.

CONCLUSION

This research presented a structured and intelligent framework for analyzing mobile phone usage data to predict students' academic performance. The study moved beyond simple data collection and focused on meaningful behavioral interpretation. By applying behavior-aware preprocessing methods such as cleaning, normalization, and feature refinement the framework ensured that raw mobile data was transformed into reliable and informative inputs for predictive modeling. The comparative evaluation of machine learning and deep learning models demonstrated that mobile usage behavior contains significant predictive signals related to academic outcomes. Traditional machine learning models produced stable baseline results, confirming that behavioral indicators such as screen time, study application usage, social application ratio, and consistency patterns are strongly associated with student performance. However, deep learning architectures, particularly those designed to capture temporal dependencies, showed superior predictive capability. These models effectively identified sequential behavioral trends rather than relying only on static summary features. This highlights an important insight: academic performance is not influenced by isolated actions but by continuous and evolving behavioral patterns over time. Overall, the findings confirm that structured and academically oriented mobile usage, combined with behavioral stability, plays a meaningful role in academic achievement. The study demonstrates the practical potential of intelligent data analytics in educational monitoring while maintaining methodological rigor and clarity.

Future Work

While the current framework achieved strong predictive performance, several promising directions remain for further development. First, future research can extend this model toward real-time academic performance prediction systems. Instead of retrospective analysis, the framework could be adapted to continuously monitor behavioral trends and generate early warning alerts when risk patterns emerge. Such systems could support timely academic interventions and personalized guidance for students. Second, integrating additional data sources may significantly enhance predictive accuracy. Mobile usage data alone provides valuable behavioral insight, but combining it with multimodal academic indicators such as learning management system activity, assignment submission behavior, attendance records, and contextual academic variables could offer a more comprehensive understanding of student learning dynamics. A multimodal approach would allow the model to capture both behavioral and academic engagement dimensions. Another important area for future exploration is the refinement of model interpretability. As predictive systems become more complex, especially with deep learning architectures, improving transparency and explainability will be crucial. Developing interpretable AI frameworks will help educators understand how specific behavioralfeatures influence predictions, thereby increasing trust and practical usability. Finally, ethical considerations must remain central to future advancements. The expansion of behavioral analytics requires robust data governance strategies that prioritize privacy, informed consent, anonymization, and secure data management. Responsible deployment frameworks should ensure that predictive systems empower students rather than create unintended surveillance or bias concerns. In summary, future work should focus not only on improving predictive accuracy but also on enhancing real-time applicability, multimodal integration, interpretability, and ethical responsibility. These directions will strengthen the practical impact and sustainability of intelligent educational data analytics systems.

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