International Journal of Informatics and Computation (IJICOM)
Vol. 8, No. 1, 2026
ISSN: 2685-8711, E-ISSN: 2714-5263 DOI: 10.35842/ijicom

Measuring Student Digital Behavior and Academic Performance Using Decision Support System

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Abstract
This study proposes a decision support system for measuring student digital behavior and predicting academic performance using machine learning algorithms. The system analyzes digital activity features, including login frequency, access duration, assignment submission patterns, and learning interaction, to classify students into high-performance, moderate, and at-risk categories. This study implements and compares Random Forest, Support Vector Machine, and Logistic Regression models to identify the most effective predictive approach. We obtain that the Random Forest model achieves the best performance with an accuracy of 0.89, demonstrating superior capability in handling complex and non-linear behavioral data. The selected model is integrated into the proposed decision support system and applied to 200 student records, producing classification results of 31% high-performance students, 49% moderate, and 20% at-risk. Furthermore, the system generates academic recommendations based on the prediction outcomes to support monitoring and early intervention strategies. Feature importance analysis reveals that assignment submission is the most influential factor in predicting academic performance, followed by login frequency and access duration. This study demonstrates that integrating artificial intelligence with decision support systems can produce reliable predictive insights and improve the effectiveness of academic monitoring and educational decision-making.

Keywords:
Academic, Performance, Behavior, Decision Support System

1. Introduction

The rapid growth of digital technology in education significantly changes how students interact with learning systems, academic resources, and online communication platforms. Educational institutions increasingly adopt digital learning environments, artificial intelligence, and online academic systems to support teaching and learning activities. This transformation produces large amounts of behavioral data that reflect student engagement, participation, and academic habits. Educational researchers and institutions now recognize that digital behavior can provide valuable indicators for measuring learning performance and predicting academic outcomes. However, many institutions still struggle to utilize this data effectively due to the absence of integrated decision support systems capable of transforming behavioral information into actionable academic insights. As a result, educational decision-making often relies on conventional evaluations that fail to capture real-time student learning patterns and behavioral trends. [1], [2], [3], [4]

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The increasing adoption of e-learning platforms also introduces new challenges related to monitoring student engagement and academic consistency. Students interact with digital learning systems through login frequency, assignment submissions, discussion participation, online attendance, and resource access patterns. These activities generate digital traces that can reveal students' learning motivation and academic discipline. Nevertheless, educational institutions often analyze academic performance only through examination scores and final grades, while ignoring behavioral indicators that strongly influence learning success. Recent studies show that digital learning behaviors strongly correlate with academic achievement and can support early intervention strategies for students at risk of poor performance. Therefore, measuring student digital behavior becomes essential for developing intelligent academic monitoring systems that support data-driven educational management. [14], [17], [18], [19]

Artificial intelligence and machine learning technologies increasingly support modern decision support systems because they provide efficient methods for analyzing large educational datasets. Machine learning algorithms such as Support Vector Machine (SVM), Random Forest, Logistic Regression, and ensemble learning methods demonstrate strong capability in classification and prediction tasks across multiple domains. In educational environments, these algorithms help identify learning patterns, predict student performance, and support academic recommendations. Researchers report that machine learning models can improve prediction accuracy by analyzing behavioral and academic variables simultaneously. However, many existing systems focus primarily on numerical academic data and provide limited analysis of digital learning behavior generated through online platforms. This limitation reduces the capability of current systems to capture comprehensive student learning characteristics in digital environments. [5], [6], [7], [8], [10]

Decision Support Systems (DSS) continue to evolve as important tools for assisting organizational and educational decision-making processes. In higher education, DSS applications support academic evaluation, student monitoring, curriculum planning, and institutional management. AI-driven DSS frameworks allow institutions to process large datasets efficiently while producing intelligent recommendations for educators and administrators. Previous studies demonstrate that integrating artificial intelligence into decision support systems improves operational efficiency and predictive capability. Despite these advantages, many educational DSS implementations still lack adaptive analytical models that incorporate digital behavior analytics as a central component of performance evaluation. Consequently, institutions often experience difficulties identifying students who require academic intervention at an early stage. [2], [3], [4], [9], [11]

Recent studies in educational data mining and learning analytics emphasize the importance of behavioral analysis in understanding student learning performance. Researchers use digital logs from online learning systems to analyze engagement levels, learning habits, interaction frequency, and time management patterns. These behavioral indicators provide meaningful information regarding student motivation and academic consistency. Several studies reveal that students with higher engagement in digital learning environments generally achieve better academic outcomes than less active students. Furthermore, learning analytics enables educators to identify hidden patterns that are difficult to observe through traditional assessment methods. However, many previous studies focus only on isolated behavioral indicators without integrating them into a comprehensive decision support framework that supports practical educational decision-making. [14], [15], [18], [19], [22]

Machine learning-based prediction systems also become increasingly popular for forecasting student academic performance. Researchers apply SVM, Deep SVM, ensemble learning, convolutional feature extraction, and optimization techniques to improve prediction accuracy. These methods successfully identify students at risk of academic failure and support personalized learning strategies. Several studies demonstrate that combining feature selection and feature fusion methods improves prediction reliability by reducing irrelevant variables and strengthening meaningful behavioral features. Although these approaches achieve promising results, many systems still rely heavily on static datasets and lack real-time behavioral analysis obtained from digital learning platforms such as Moodle and other online learning management systems. This gap creates opportunities for developing more adaptive and intelligent systems capable of analyzing dynamic student digital behavior continuously. [13], [15], [16], [20], [23]

The widespread use of online learning platforms after the COVID-19 pandemic further increases the importance of monitoring digital learning activities. Students now spend more time interacting with virtual classrooms, online assignments, digital assessments, and collaborative platforms. These changes create complex learning behaviors that require advanced analytical systems to measure academic engagement accurately. Researchers report that online behavior patterns such as access duration, interaction consistency, and participation frequency significantly influence learning outcomes. Educational institutions therefore require intelligent systems capable of integrating behavioral analytics and academic performance measurement into a unified platform. Nevertheless, many current educational systems still provide fragmented analyses and fail to generate comprehensive recommendations for academic decision-making. [17], [19], [20], [24]

Based on these challenges, this study proposes a Decision Support System for measuring student digital behavior and academic performance using machine learning techniques and behavioral analytics. This study aims to analyze student interaction patterns within digital learning environments and evaluate their relationship with academic achievement. We utilize behavioral indicators such as login activity, assignment completion, learning participation, and system interaction records to support predictive analysis and academic evaluation. By integrating artificial intelligence algorithms with educational data mining approaches, the proposed system seeks to provide more accurate, adaptive, and data-driven academic recommendations. This study also contributes to the development of intelligent educational systems that support educators and institutions in improving learning quality, student monitoring, and academic decision-making in modern digital education environments. [16], [20], [21], [22], [25].

2. Related Works

Previous studies extensively investigated the use of artificial intelligence and decision support systems in educational environments. Artificial Intelligence applications in education improved data-driven decision making, personalized learning, and academic monitoring. A. A. Herawati et al. explored students' perceptions of AI-based educational systems and found that intelligent systems positively influenced learning efficiency and academic interaction. Similarly, X. Lu et al. examined AI-driven decision support systems for organizational management and reported that predictive analytics enhanced strategic planning and operational performance. These studies confirmed the importance of AI integration in educational management. However, they mainly focused on conceptual adoption and organizational benefits rather than direct measurement of student digital behavior and academic performance using integrated predictive systems. [1], [2].

Several studies developed intelligent decision support systems to support academic administration and institutional management. V. Funda and E. Francke designed an AI-powered decision support system for operational management in higher education institutions and demonstrated improvements in decision accuracy and administrative efficiency. J. Zhang and S. B. Goyal further emphasized that AI-driven decision systems could optimize academic planning and resource allocation in universities. These studies showed the growing relevance of intelligent systems in educational environments. Nevertheless, they primarily concentrated on institutional-level decision making and did not analyze detailed student interaction data or digital learning behaviors that directly influence academic achievement. [3], [4].

Machine learning algorithms such as Support Vector Machine, Random Forest, and logistic regression also received significant attention in predictive analytics research. Y. Restiani and J. Purwadi demonstrated that SVM effectively handled classification problems with high-dimensional data and produced stable prediction performance. A. Primajaya and B. N. Sari showed that Random Forest achieved reliable prediction accuracy through ensemble decision trees. Other studies compared SVM and logistic regression for health prediction tasks and reported competitive classification capability across multiple datasets. Despite these strengths, most prior works evaluated general classification tasks and did not specifically address educational behavior analytics or student academic prediction using digital activity records. [6], [7], [10].

Research in learning analytics increasingly focused on digital learning behaviors as indicators of academic success. C. J. Arizmendi et al. reviewed the use of digital learning logs and concluded that behavioral indicators such as login frequency, assignment access, and online participation strongly correlated with academic outcomes. J. Guo et al. further explained that student engagement analytics improved learning performance monitoring and helped educators identify at-risk students earlier. These studies highlighted the importance of behavioral data in modern educational systems. However, most previous studies mainly emphasized descriptive analytics and engagement analysis without integrating comprehensive decision support mechanisms for real-time academic evaluation and prediction. [14], [18].

Several researchers explored predictive analytics models for estimating student academic performance using educational datasets. M. Ye et al. proposed a feature fusion and feature selection framework that improved student performance prediction accuracy using machine learning techniques. S. Sarwat et al. combined deep learning and SVM models with generative approaches to enhance prediction capability in e-learning environments. In addition, A. AlSulaiman and M. Ragab implemented ensemble machine learning techniques for predicting e-learning performance and obtained strong classification results. Although these studies achieved promising predictive performance, many of them relied heavily on static academic datasets and paid limited attention to continuous digital behavior patterns generated during online learning activities. [15], [16], [20].

The rapid growth of online learning platforms also encouraged studies on behavior-based educational data mining. Y. Liu et al. investigated online learning behavior during the COVID-19 Pandemic and found that student interaction frequency significantly affected academic performance. N. Al Mudawi et al. developed predictive analytics frameworks for sustainable e-learning and demonstrated that behavioral tracking improved educational monitoring and intervention strategies. Similarly, N. Abuzinadah et al. utilized MOODLE data and machine learning techniques to predict academic performance from student activities. These studies confirmed that digital learning behavior contains valuable predictive information. Nevertheless, they often focused on isolated datasets and lacked integrated decision support frameworks capable of supporting educators in practical academic decision making. [17], [19], [23]

Other studies concentrated on broader educational data mining and machine learning optimization for student performance prediction. A. Sghir et al. comprehensively evaluated multiple machine learning methods for student performance estimation and emphasized the importance of model interpretability and balanced evaluation metrics. M. Angeioplastis et al. applied data-driven educational mining approaches to improve learning outcomes and demonstrated that predictive systems could support adaptive educational strategies. D. Wang et al. analyzed influencing factors of student achievement using machine learning and identified behavioral engagement as one of the strongest predictors of academic success. While these studies contributed significantly to predictive learning analytics, they generally emphasized model performance evaluation and did not fully integrate decision support functionalities for academic stakeholders. [21], [22], [24]

Based on the reviewed studies, previous research clearly demonstrated the effectiveness of machine learning and AI-driven analytics in educational prediction tasks. However, several limitations remain unresolved, including limited integration between student digital behavior analysis and intelligent decision support systems, insufficient utilization of real-time behavioral indicators, and restricted support for practical academic intervention. Therefore, this study addresses these gaps by developing a decision support system that measures student digital behavior and academic performance using machine learning-based predictive analytics. The proposed approach integrates behavioral interaction data, academic indicators, and intelligent classification techniques to support more accurate academic monitoring and educational decision making. This study aims to contribute a more comprehensive framework that combines educational data mining, predictive analytics, and intelligent decision support into a unified academic evaluation system.

3. Proposed Method

This study proposes a decision support model to analyze student digital behavior and predict academic performance through several integrated stages, including data acquisition, preprocessing, model development, and decision support integration. The study utilizes secondary data collected from online learning platforms and academic records, where digital behavior variables include login frequency, access duration, interaction with learning materials, and assignment submission patterns. After data collection, we perform preprocessing procedures to improve data quality and consistency by applying data cleaning to remove incomplete or inconsistent records, normalization to standardize feature ranges, and feature selection to identify the most relevant variables for prediction [8]. These processes help improve the reliability, accuracy, and overall performance of the proposed predictive model in supporting academic evaluation and educational decision making.

This study develops an artificial intelligence-based decision support framework to predict academic performance from student digital behavior data. Each student is represented as a feature vector containing behavioral indicators collected from online learning systems, such as login frequency, interaction intensity, learning duration, and assignment submission patterns. The mathematical representation of the student feature vector is formulated as follows:

$$X_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) \tag{1}$$

where X_i *denotes the behavioral feature vector of student* i*, and* x_{ij} represents the j-th digital behavior attribute. The prediction model maps the behavioral features into academic performance outcomes using an artificial intelligence function formulated as:

$$\hat{Y}_i = f(\mathbf{X}_i; \theta) \tag{2}$$

where $\hat{Y}_i$ represents the predicted academic performance of student i, $f(\cdot)$ denotes the machine learning prediction function, and θ represents the model parameters learned during training [9]. This study applies several machine learning algorithms, including Random Forest, Logistic Regression, and Support Vector Machine, to learn the relationship between digital behavior and academic achievement [10]. Model performance is evaluated using classification metrics such as accuracy, precision, recall, and F1-score, formulated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (6)$$

where TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative values, respectively. The best-performing model is integrated into a decision support mechanism that categorizes students into performance groups such as high-performing, moderate, and at-risk students [11]. Based on these classifications, the system generates academic recommendations including mentoring, monitoring, and additional learning support. Furthermore, this study analyzes the contribution of each behavioral feature to determine the most influential factors affecting academic performance [12]. The overall framework integrates predictive analytics and intelligent decision support into a unified educational system capable of transforming digital learning behavior into actionable academic insights for higher education institutions [13]–[16].

4. Experimental Setup

The dataset was obtained from secondary sources representing students' digital activities and academic performance. Digital behavior features include login frequency, access duration, interaction with learning materials, and assignment submission patterns, while academic performance was categorized into three classes: high, moderate, and at-risk. Prior to training, the dataset was pre-processed through data cleaning and normalization, then divided into training and testing sets using an 80:20 ratio with stratified sampling to preserve class distribution. To model the relationship $\hat{Y}_i = f(X_i; \theta)$ this study implemented Random Forest, Logistic Regression, and Support Vector Machine algorithms. Random Forest used 100 decision trees with the Gini impurity criterion, Logistic Regression applied regularization to reduce overfitting, and Support Vector Machine employed a radial basis function kernel to capture non-linear relationships. Furthermore, five-fold cross-validation was conducted to improve robustness and reliability.

Table 1. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0,89	0,88	0,87	0,88
Support Vector Machine	0,85	0,84	0,83	0,84
Logistic Regression	0,81	0,80	0,79	0,80

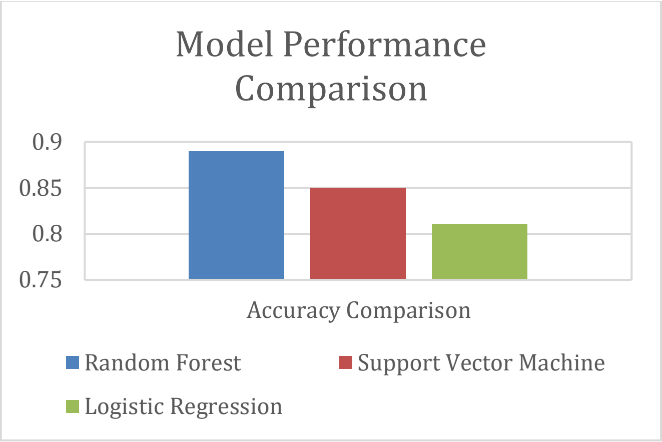

Fig 1. Model Performance Comparison

Table 1 presents the comparative performance of the three machine learning models used in this study, namely Random Forest, Support Vector Machine, and Logistic Regression. Based on the evaluation results, Random Forest consistently achieves the highest scores across all metrics, with an accuracy of 0.89 and balanced values of precision, recall, and F1-score. Support Vector Machine shows competitive performance but remains slightly lower than Random Forest in all evaluation aspects, while Logistic Regression records the lowest performance among the three models. These results indicate that ensemble-based methods are more effective in capturing complex patterns within students' digital behavior data. Figure 1 further visualizes this comparison, clearly illustrating the performance gap between the models, where Random Forest outperforms the others in a consistent and stable manner across all evaluation metrics. This confirms that Random Forest is the most suitable model for integration into the decision support system due to its superior and stable predictive performance.

Table 2. Hyperparameter Configuration

Parameter	**Random Forest**	**Support Vector Machine**	**Logistic Regression F1-Score**
Number of Trees	100	-	-
Criterion	Gini	-	-
Regularization	-	RBF	-
Kernel	-	C (default)	L2
Cross Validation	5-fold	5-fold	5-fold

Based on the hyperparameter configuration in Table 2, the Random Forest model was constructed using 100 decision trees to improve prediction stability and accuracy, with the Gini criterion employed to determine the best node splits based on the purity level of data classes. The Support Vector Machine (SVM) model applied L2 regularization, which functions to control model complexity and reduce the risk of overfitting, thereby improving its generalization ability on unseen data. Meanwhile, the third model utilized the Radial Basis Function (RBF) kernel, which is effective for handling non-linear data patterns or complex relationships among variables. All models were evaluated using 5-fold cross-validation, where the dataset was divided into five subsets and the training-testing process was performed iteratively to produce a more objective, stable, and representative assessment of overall model performance.

The comparative analysis shows that the Random Forest model consistently achieves the highest performance across evaluation metrics, indicating its superior ability to capture complex patterns in students' digital behavior. The configuration parameters used in the experiment also demonstrate stable and reliable model behavior through appropriate tuning and validation strategies. Therefore, Random Forest is selected as the final model to be integrated into the decision support system. This selection serves as the basis for the next stage of the research, where the chosen model is utilized to classify students' academic performance and generate data-driven recommendations for academic decision-making.

5. Result and Analysis

After training and testing the models using the prepared dataset, a comparative analysis was performed to identify the most effective algorithm. The selected model was then integrated into the decision support system to generate predictive outputs and academic recommendations. The following subsections describe the detailed results obtained from the experiments and their interpretation in the context of academic decision-making. Based on the comparative evaluation results, the Random Forest model achieved the best performance with an accuracy of 0.89 and was selected as the final model. The selected model was integrated into the decision support system. The integrated model was applied to a dataset consisting of 200 student records. The simulation results produced the following classification distribution:

Table 3. Simulation

Category	Number of Students	Precentage
High Performance	62	31%
Moderate	98	49%
At-Risk	40	20%

Table 3 presents the simulation results of the decision support system after integrating the selected model. The classification output shows that out of 200 students, 62 students (31%) are categorized as high performance, 98 students (49%) as moderate, and 40 students (20%) as at-risk. This distribution indicates that most students demonstrate average engagement in digital learning activities, while a smaller proportion requires immediate academic attention. The simulation demonstrates that the system is capable of effectively translating students' digital behavior patterns into meaningful performance categories. Furthermore, these results provide a clear overview for academic stakeholders to identify performance distribution trends and support early intervention strategies for students who are at risk.

Table 4. Example of Prediction Output

Student ID	Login Frequency	Acces Duration	Assignment Submission	Predicted Category
S001	High	Consistent	On Time	High
S002	Medium	Irregular	Late	Moderate
S003	Low	Low	Missing	At-risk

Table 4 illustrates an example of individual-level prediction outputs generated by the proposed system based on students' digital behavior features. Each student record is processed by the trained model to produce a corresponding academic performance category, demonstrating how raw behavioral indicators such as login frequency, access duration, and assignment submission patterns are translated into predictive classifications. This sample highlights the system's ability to perform consistent and interpretable predictions at the individual level, which is essential for practical decision support applications. Furthermore, although only a subset of results is presented, the system has been applied to the full dataset of 200. Based on the classification results, the decision support system generates recommendations:

Table 5. Decision Support Recommendation

Category	Recommendation
High	Maintain current performance
Moderate	Monitoring and periodic guidance
At risk	Intensive academic intervention

Table 5 summarizes the decision support recommendations generated based on the classification results of the proposed system. Each performance category is mapped into a specific academic action strategy, where students in the high-performance group are encouraged to maintain their current learning behavior, those in the moderate category are subjected to monitoring and periodic guidance, and at-risk students are prioritized for intensive academic intervention. The simulation results further indicate that 40 students (20%) require immediate intervention, 98 students (49%) need monitoring, and 62 students (31%) are considered stable. This distribution highlights the importance of early detection mechanisms within the decision support system to ensure timely and appropriate academic responses. This supports the role of the proposed system in providing actionable insights for academic stakeholders in identifying priority students for intervention. Furthermore, it strengthens the potential of integrating artificial intelligence with decision support systems to improve educational monitoring effectiveness.

Table 6. Feature Influence Analysis

Feature	Importance Score
Assignment Submission	0,35
Login Frequency	0,30
Access Duration	0,25
Learning Interaction	0,10

Table 6 presents the feature importance analysis derived from the Random Forest model, which quantifies the contribution of each digital behavior variable in predicting academic performance. The results show that assignment submission has the highest importance score (0.35), followed by login frequency (0.30), access duration (0.25), and learning interaction (0.10). These findings indicate that task completion behavior plays the most critical role in determining student outcomes, while other factors contribute in a complementary manner. The relatively lower importance of learning interaction suggests that not all digital engagement activities have equal predictive power. Overall, this analysis provides valuable insight into which behavioral aspects should be prioritized in academic monitoring and intervention strategies within the decision support system.

The experimental results show that Random Forest achieves the best performance across all evaluation metrics, followed by Support Vector Machine and Logistic Regression. These findings indicate that the relationship between students' digital behavior and academic performance is non-linear and involves complex feature interactions. Random Forest outperforms other models due to its ensemble learning mechanism, which improves stability and captures diverse behavioral patterns more effectively. In contrast, Logistic Regression shows lower performance because it assumes linear relationships between variables, while Support Vector Machine provides competitive results using the radial basis function kernel but remains less stable than Random Forest. The classification results also reveal that most students fall into the moderate performance category, while a significant at-risk group reflects variability in student engagement behavior. Thus, the study confirms that ensemble-based methods are more effective for modeling high-dimensional educational behavior data and predicting academic performance.

6. Conclusion

This study proposes a decision support system for measuring student digital behavior and predicting academic performance using machine learning algorithms. Based on the comparative evaluation, we obtain that the Random Forest model achieves the best performance with an accuracy of 0.89, outperforming Support Vector Machine and Logistic Regression. The selected model is successfully integrated into the decision support system and applied to 200 student records, producing performance classifications of 31% high-performing students, 49% moderate, and 20% at-risk. These results demonstrate that the proposed system can effectively translate digital behavior patterns, such as login frequency, access duration, assignment submission, and learning interaction, into meaningful academic performance predictions.

Furthermore, the generated recommendation mechanism enables academic stakeholders to identify students requiring monitoring or intensive intervention, supporting early detection and more effective academic decision-making. Feature importance analysis also reveals that assignment submission is the most influential factor in predicting academic outcomes, followed by login frequency and access duration. Overall, this study confirms that integrating artificial intelligence and decision support systems can produce reliable predictive insights for educational monitoring and improve the effectiveness of academic intervention strategies.

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