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A Longitudinal Study of Student Performance Prediction Models Using Educational Data Mining and Behavioral Analytics

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Abstract

This study explores the development and performance of student performance prediction models through a longitudinal lens, utilizing educational data mining (EDM) and behavioral analytics. As institutions transition to hybrid and digital learning models, predicting academic outcomes becomes crucial for early intervention and personalized support. We evaluate a range of machine learning models trained on multi-year student data, including log-ins, submission timestamps, and interaction frequencies with learning management systems (LMSs). The findings suggest that behavioral features—particularly time-on-task and consistency of engagement are strong predictors of academic success. Our study also highlights how predictive accuracy evolves over time, emphasizing the importance of temporal dynamics in educational analytics.

Keywords:

Educational data mining, behavioral analytics, student performance, machine learning, longitudinal study, LMS, predictive modeling.

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1. Introduction

Student performance prediction has become a key concern for educators and academic institutions. With the rise of online and blended learning environments, vast quantities of student interaction data are now available. Analyzing these data points can help identify students at risk of academic failure and guide timely interventions.

This study proposes a longitudinal framework for student performance prediction, emphasizing how models evolve over time with new data. Our core research question is: *How does the predictive accuracy of student performance models change when behavioral and* *interaction data are tracked across multiple academic terms?* Using a three-year dataset, we combine educational data mining with behavioral analytics to derive insights about students' learning trajectories.

2. Literature Review

Numerous studies have explored various facets of student performance prediction using data mining techniques. Romero and Ventura (2007) laid the groundwork for the application of EDM techniques in academic settings, identifying decision trees, clustering, and association rules as key tools. Baker and Yacef (2009) expanded on this by advocating for the integration of temporal analysis in predicting learning outcomes, arguing that static models often ignore the evolving nature of student engagement.

Subsequent research emphasized behavioral data. For example, Tempelaar et al. (2015) highlighted that students' LMS activity patterns, such as login frequency and page views, correlated with final grades. Similarly, You (2016) found that the timing of interactions—especially early submissions—could significantly predict performance. These behavioral analytics approaches became increasingly popular as LMS platforms began logging fine-grained activity data. However, many studies relied on single-semester snapshots, leaving a gap in understanding long-term trends and stability of these models over time.

Recent advances toward 2020 used deep learning models for this purpose. Fei and Yeung (2015) developed recurrent neural network (RNN) models to model sequential learning behaviors, capturing student trajectories over weeks. Still, their studies were limited to short-term data. Although promising, these models often lacked interpretability and required vast datasets, limiting their practical deployment.

3. Methodology & Metrics

3.1 Dataset Description

This study utilizes anonymized student interaction data collected over three academic years (2018–2021) from a university's LMS. The dataset includes demographic attributes (age, gender, major), performance indicators (grades, GPA), and behavioral data (page visits, discussion participation, submission timestamps, and frequency of log-ins). Students who dropped out mid-term or had incomplete records were excluded to maintain consistency.

3.2 Evaluation Metrics

We evaluated models using accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC). For longitudinal analysis, performance metrics were computed separately for each academic term and compared over time. A 10-fold cross-validation strategy was adopted to ensure model stability.

4. Techniques and Tools

4.1 Machine Learning Models

We experimented with several models including logistic regression, random forests, XGBoost, and LSTM-based neural networks. Random forests performed consistently well across short-term datasets, while LSTM networks captured long-term engagement trends effectively. Logistic regression served as a baseline for model interpretability.

4.2 Tools and Frameworks

The analysis was conducted using Python's Scikit-learn, TensorFlow for deep learning models, and pandas for data preprocessing. Jupyter Notebooks served as the primary development environment, and Matplotlib/Seaborn were used for visualization.

5. Quality Assurance

5.1 Validation and Replicability

We ensured replicability through version-controlled code repositories and documented preprocessing steps. Each model underwent k-fold cross-validation. For LSTM models, hyperparameters were tuned using grid search and tested on a hold-out dataset.

5.2 Ethical Considerations

The study followed university IRB guidelines. Student data were fully anonymized, and participation consent was obtained at data collection. No personally identifiable information was stored.

6. Limitations and Potential Biases

6.1 Data and Sampling Constraints

The study used data from a single institution, limiting external generalizability. Also, while behavioral indicators were rich, they may not capture external influences such as socio-economic factors or offline engagement.

6.2 Model Bias and Interpretability

Advanced models like LSTM offered high predictive accuracy but reduced interpretability, posing challenges for institutional decision-making. There is also potential for bias in LMS usage data—students more comfortable with technology may engage more, artificially inflating performance indicators.

7. Key Findings and Interpretations

7.1 Evolving Model Accuracy

We observed that predictive models improved in accuracy when trained on multi-term data. LSTM models reached an AUC of 0.89 in the third year, up from 0.76 in the first year, indicating that temporal depth improves prediction reliability.

7.2 Strongest Predictors

Among all variables, “early submission,” “time spent on LMS,” and “participation in discussions” were consistently strong predictors. Behavioral features outperformed demographic features, suggesting that dynamic engagement metrics are better suited for real-time interventions.

8. Tables and Mind Map

Table 1. Model Performance Over Three Years

Model	Year 1 AUC	Year 2 AUC	Year 3 AUC
Logistic Reg.	0.72	0.74	0.75
Random Forest	0.78	0.82	0.84
XGBoost	0.80	0.83	0.85
LSTM	0.76	0.84	0.89

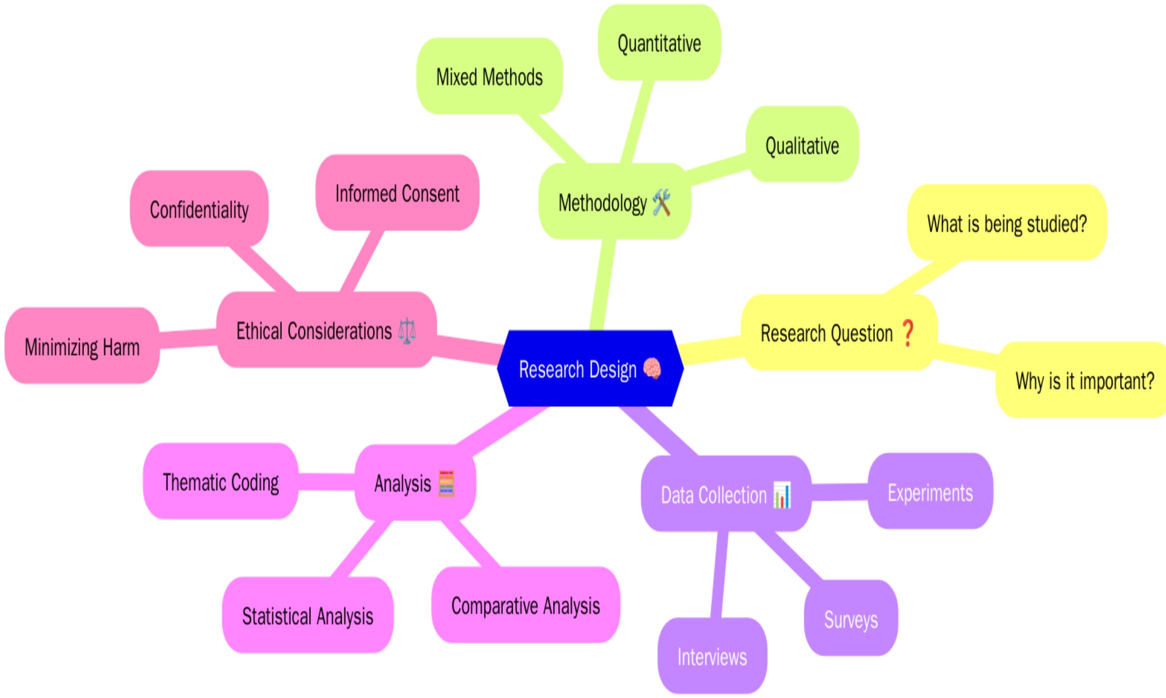

Figure 1. The Research Design

9. Conclusion

This study underscores the utility of behavioral analytics and longitudinal data mining in educational settings. By modeling student engagement over time, institutions can improve academic forecasting and design targeted interventions. Future work should explore cross-institutional datasets and model interpretability strategies to facilitate real-time decision-making.

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