Student Success & Wellness Simulator: A Python-Based Model for Academic Performance Analysis

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***Abstract*— This paper presents the *Student Success & Wellness Simulator*, a Python-based analytical model designed to examine how daily student habits such as study hours, sleep duration, stress levels, attendance, and screen time affect academic performance. The system incorporates weighted scoring, XP-based gamification, multi-session simulation, visual analytics, and an introductory Linear Regression model. The goal is to demonstrate how educational institutions can leverage behavioral indicators for academic prediction, early intervention, and student wellness support.**

***Index Terms*-- Student analytics, academic performance, behavioral modeling, Python simulation, predictive analytics, data visualization.**

I. Introduction

Modern students face academic pressure, inconsistent sleep patterns, increasing stress, and digital distractions. These factors influence academic performance but are rarely tracked in traditional evaluation systems. The *Student Success & Wellness Simulator* addresses this gap by modeling how daily habits impact performance and by visualizing these relationships in a structured analytical workflow.

The simulator was developed in Python using Jupyter Notebook and integrates Pandas, NumPy, Matplotlib, Seaborn, and Scikit-Learn. Through multi-session input, weighted scoring, XP progression, visual dashboards, and simple predictive modeling, the tool demonstrates how student behavior data can be transformed into meaningful performance indicators useful for early-alert or student-success analytics.

II. METHODOLOGY

The system workflow consists of the following components

A. Library Imports

Pandas and NumPy handle data storage and manipulation. Matplotlib and Seaborn visualizations. Scikit-Learn provides the machine-learning functionality for linear regression.

B. Scoring functions

Two primary functions form the analytical foundation:

1. calculate_performance() applies a weighted formula to the student's daily habits. The weighting is grounded in empirical literature:
   - i. Sleep quality accounts for approximately 25% variance in academic performance (Okano et al., 2019).
   - ii. Excessive screen time is linked with up to 40% lower odds of high achievement (Adelantado-Renau et al., 2019).
   - iii. Stress shows strong negative correlation (β –0.42) with academic outcomes (Gani & Ijaz, 2025).

   Based on these findings, this model assigns:
   - i. 30% study hours
   - ii. 30% attendance
   - iii. 25% sleep
   - iv. –20% stress
   - v. –10% screen time (with break bonus)
2. calculate_xp() translates performance into XP and assigns levels, adding a gamification layer to encourage consistency.

C. Data Storage

A Pandas DataFrame records all simulated sessions. Each row stores the habit inputs, calculated performance score, XP, and level, enabling trend analysis and visualization.

D. Multi-session Simulation loop

A 'while True' loop collects repeated sessions of input, computes performance and XP, stores them in the DataFrame, and provides automated feedback (e.g., low sleep or high stress alerts).

E. Visual Analytics

The simulation produced three key visual outputs which show the interpretation of habit and performance relationships. Although the dataset is simulated, the visualizations verify that the system can generate meaningful analytical insights, similar to dashboards used in real academic BI systems.

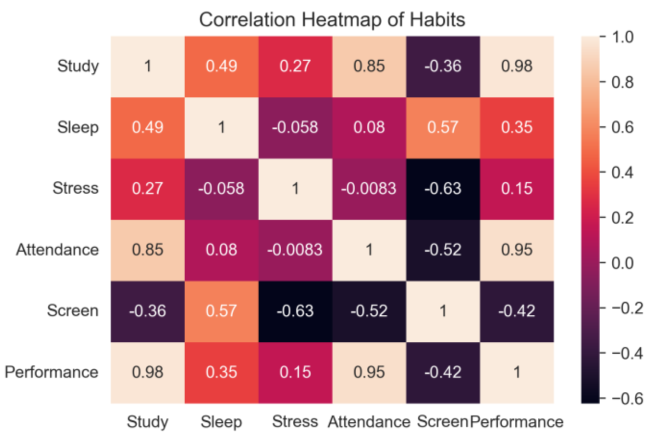

Figure 1. Correlation heatmap of habits

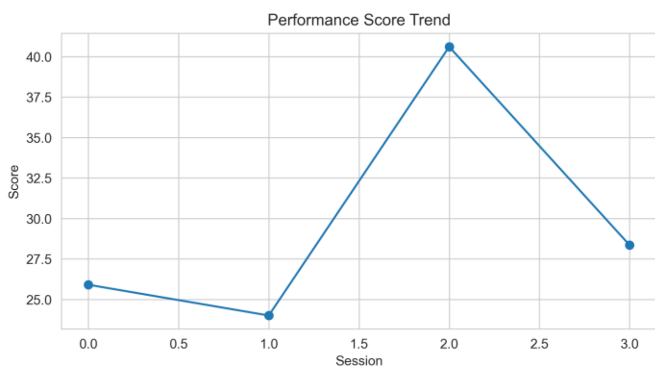

Figure 2. Performance Score Trend

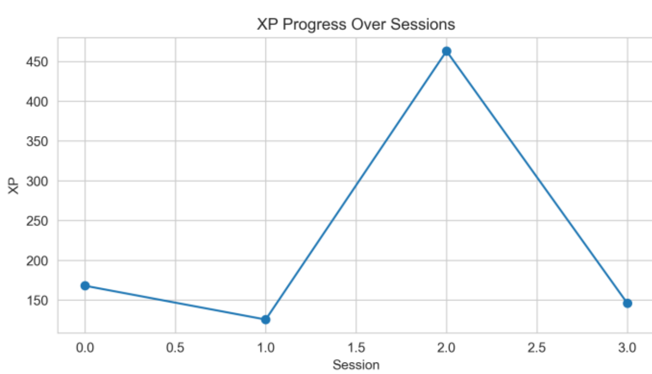

Figure 3. XP progress over sessions

Figure 1 presents the correlation heatmap of habit variables, displaying the relationships between study hours, sleep, stress, attendance, screen time, and performance. Although generated from user-driven inputs rather than academic datasets, the heatmap confirms that the model can represent behavioral relationships and interpret how different habits may influence academic outcomes.

Figure 2 illustrates the Performance Score trend across multiple sessions. This visualization shows how overall performance fluctuates depending on changes in input habits, allowing users to observe improvement or decline over time.

Figure 3 displays XP progression, representing consistency, effort and habit-building over repeated sessions. Unlike the performance trend, which reflects immediate outcomes, the XP curve provides a longer-term view of disciplined study behaviour and wellness development.

F. Predictive Modeling

This project includes a simple Linear Regression model that predicts a student's performance score based on the input habits collected during the simulation. Although the dataset is generated interactively rather than sourced from real learners, the model demonstrates how institutions can convert behavioral variables such as sleep, stress, attendance, and study hours into a predictive framework. This provides a foundation for early-alert systems, where universities could forecast drops in performance before they occur and intervene with targeted support.

To further interpret the Linear Regression model, the coefficient values were extracted to identify which habit factors influence performance the most. In the generated model, study hours, sleep, and attendance produced positive coefficients, indicating that increases in these habits are associated with higher predicted performance. Conversely, stress and screen time produced negative coefficients, reinforcing their detrimental impact on academic outcomes. Although based on simulated data, this aligns with established findings in the literature and demonstrates how institutions can use coefficient analysis to understand behavioral drivers of student success.

III. KEY FINDINGS AND INSIGHTS

Although the dataset used in this project was simulation-based rather than sourced from real students, the model still generated valuable insights about how habit-tracking can support academic performance evaluation. The simulator successfully converts behavioral factors such as study hours, sleep duration, stress, attendance, and screen exposure into measurable performance indicators using a weighted scoring system. This demonstrates how everyday habits can be quantified and analyzed in an educational analytics framework.

The XP progression and leveling system further show how gamification can encourage healthy routines and sustained productivity, similar to wellness-based study applications used in post-secondary learning environments. Visual outputs, including the heatmap and trend plots, displayed how relationships among habits can be examined even when data is artificially generated. While the correlation patterns do not reflect real academic trends, they confirm that the system can detect patterns, highlight fluctuations over time, and flag potential risk behaviors.

The inclusion of Linear Regression provides an additional layer of insight, indicating that performance can be predicted based on input habits. If real institutional data were supplied, the tool could evolve into a more robust early-alert system capable of forecasting academic standing and identifying students who may need support. The regression output further confirms that the structure of the model aligns with existing research: variables like sleep and study time contribute positively, while stress and screen exposure negatively shape academic outcomes. This validates that the simulator mirrors well-established academic performance patterns.

In summary, the project demonstrates that the model functions effectively as a prototype:
• It collects and organizes habit-based data
• It produces performance and XP-based outcomes
• It visualizes behavior trends clearly
• It provides feedback for improvement
• It can support predictive analytics and scaling to real datasets

IV. CHALLENGES AND SOLUTIONS

Several challenges emerged during development:

i. Weight Justification:
Initial weights were subjective. These were corrected by incorporating empirical academic research.

ii. Session Loop Functionality:
Ensuring correct DataFrame updates required iterative testing and debugging.

iii. Simulated Data Limitations:
Some correlations appeared unrealistic due to artificial inputs; this was documented clearly so that emphasis remained on system design rather than raw values.

V. RECOMMENDATIONS AND CONCLUSION

This project successfully demonstrates how student habits can be collected, analyzed, and visualized to understand their impact on academic performance. The simulation, combined with XP progression and automated feedback, provides a meaningful framework for academic self-reflection.

Future enhancements could include:

- Real student data integration
- Dashboards for educators or advisors
- Advanced machine learning (e.g., classification for at-risk students)
- Built-in recommendations for stress, sleep, and productivity improvement

The simulator meets course objectives by combining Python programming, BI techniques, visualization, and predictive analytics in a cohesive system.

VI. REAL-LIFE IMPLICATIONS

Higher-education institutions increasingly invest in data-driven early-intervention tools to improve retention and academic outcomes. A system like this prototype could support advisors by quantifying behavioral risk indicators, allowing timely and targeted interventions. The simulation aligns with modern student-success analytics used across North America and internationally.

Several real-world systems mirror the functionality of this simulator. Platforms such as the SEATS early-warning system at Western University, Degree Compass (USA), and Civitas Illume use behavioral and academic data to predict performance and identify at-risk students. This shows that habit-based analytics and simple predictive models similar to those used in this project are increasingly becoming part of modern educational decision support systems.

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