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An Ai-Enabled Personalized Learning and Behavioral Analytics Framework for Integrating Educational Outcomes, Nutritional Awareness, And Psychological Well-Being

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E-mail: thimmarajuphd@gmail.com**ABSTRACT**

Multidimensional student information can be integrated for personalized educational support, using artificial intelligence (AI) and behavioural analytics. In this research, an AI-based personalized learning framework with behaviour and psychological well-being is created. A quantitative secondary data analytical design was used, with 1,000 records of students with demographic, learning, behavioural, lifestyle, psychological, and educational variables. Descriptive statistics, group comparisons, correlation analysis, unsupervised clustering, and machine-learning approaches were used to describe the student profiles and predict the educational performance. Previous GPA showed the highest positive correlation with examination score and study hours, and motivation had positive correlation with academic performance. Examination outcomes were negatively related to stress and examination anxiety. Significant differences in examination scores existed between the various study environments and between the various diets but not between the various learning styles. Based on AI, two learner profiles were identified that differed mainly in the dimensions of motivation, examination anxiety and academic achievement. Linear regression had the best score in predicting the examination scores with R² of 0.891, MAE of 3.20 and RMSE of 4.13 in the tested prediction models. The class imbalance in the dropout-risk classification poses a challenge for interpreting the overall classification accuracy. The results show that multidimensional profiling of learners and prediction of their educational outcomes may be achieved by combining academic, behavioural, lifestyle and psychological data with AI-based data analysis. It remains to be longitudinally and externally validated for use in educational decision-support systems.

Keywords: Artificial intelligence; Personalized learning; Behavioural analytics; Educational outcomes; Psychological well-being**Introduction**

The advent of artificial intelligence (AI) has significantly contributed to the transformation of education, as it has the potential to shift the focus from a one-size-fits-all approach to a more personalized and data-driven learning experience. As more student-level data are available, the ability to incorporate academic growth, student engagement, student behavior, and other factors that influence learning is enabled. The use of data-driven educational analytics can help in achieving a more comprehensive view of student development by converting data from diverse sources into actionable insights (Akramova et al., 2025). In this transition, AI can enable real-time analysis of learner attributes and help foster adaptive learning spaces that can adapt to the needs of individual students (Rane et al., 2023). Furthermore, AI tools can be combined with learning analytics to augment pedagogical decision-making by allowing teachers to detect trends and patterns in student performance, thereby creating targeted interventions (Sajja et al., 2025).

One of the most promising applications of AI in the world of education is personalized learning. In contrast to uniform teaching methods, personalized learning considers variations in learning styles, motivation, learning environments, access to academic support, and self-regulatory skills. AI technologies can help in creating personalized learning paths, interpreting the characteristics of learners and adapting their learning experiences accordingly (Bohdan, 2025). In the field of educational systems, AI is being increasingly applied to offer customized content, feedback, and learning trajectories to fulfil the specific needs of every learner (Hariyanto et al., 2025). The use of AI for personalization could therefore foster greater personalization in learning and teaching by adapting the teaching methods to the learner's skills, preferences, and learning

outcomes. From a psychological point of view, this personalisation is also significant as it is not only related to academic ability but also to individual cognitive, motivational and emotional characteristics, which affect the effectiveness of learning (Wang, 2025).

However, student performance grows in the context of the broader behaviors and lifestyles. Time spent studying, time spent in front of a screen, social-media time, sleep, physical activity, diet quality, social interaction, and extracurricular activities could all affect how well students can participate in educational activities. In lifestyle-related contexts, AI applications can potentially incorporate various behavioral metrics and provide personalized insights that can help encourage healthier behaviors (Saeed & Nashwan, 2025). Likewise, for college students, AI, learning behaviors, and psychological well-being are becoming increasingly intertwined in contexts using technology to foster learning (Vlastegui et al., 2023). Consideration of these dimensions in combination then could offer a more holistic picture of educational outcomes than the academic indicators alone.

The psychological well-being of the student is another important aspect of student development. Engagement and persistence, including academic functioning, can be impacted by mental health, stress, examination anxiety, motivation and emotional adjustment. Digital intelligence is linked to sustainable learning as well as digital mental well-being, highlighting the importance of addressing the psychological aspect in technology-rich education (Alruwaili et al., 2025). Meanwhile, the psychological impact of AI use could also have been different for the students, and systematic attention needs to be paid to the emotional and behavioral effects of AI (Kundu & Bej, 2024). The growing intersection of digital well-being and AI also emphasizes the need for students' mental and emotional balance in the face of technological advancements (Mandal & Hawamdeh, 2025).

Despite such progress, these areas of education, behaviors, lifestyles and psychology are often analysed individually. AI can provide a chance to bring these dimensions into one analytical model with the ability to recognize multidimensional learner profiles and factor that are related to education outcomes. Intelligent systems can be used to help engage cognitive processes, and they can also include psychological factors (Adilet, 2024); however, there are pedagogical, psychological, and ethical concerns that need to be carefully considered when implementing intelligent systems in education (Pahuja et al., 2024). Furthermore, tailoring AI-generated health information to individual learners exhibits the capacity of smart technologies to link learning with other health-related behaviors and awareness (Tbaishat & Elfadel, 2025). Therefore, the present study proposes a personalized learning and behavioral analytics framework powered by AI that integrates the educational outcome, lifestyle behaviors and psychological well-being.

Objectives:

- To characterize students' learning, behavioral, lifestyle, psychological, and educational profiles using multidimensional student data.
- To examine the relationships between learning characteristics, lifestyle behaviors, psychological well-being, and educational outcomes.
- To develop and evaluate AI-based models for predicting educational outcomes and identifying distinct learner profiles to support personalized educational strategies.

2. Materials and Methods

2.1 Study Design

A quantitative, secondary-data analytical design was used for the study of the relationships between personalized learning characteristics, behavioral and lifestyle factors, psychological well-being and educational outcomes. The study included a traditional statistical approach and an AI-based approach to analyse the data and create an integrated framework for learner profiling and predicting educational outcomes. The method used was an analytical one, where the data was gathered by observation, and no experimental manipulation or direct contact with the subjects was made.

2.2 Data Source and Study Sample

A structured student-level data set with multi-dimensional data on demographic characteristics, academic performance, learning characteristics, lifestyle behaviors, and psychological indicators was used as the data source (Kumar, 2025). A cleaned dataset of 1,000 students' records, with 31 variables, was used for the present analysis. Each record was for one student. The data was screened prior to analysis to maintain the completeness, consistency and appropriateness of the variables for statistical and AI analysis. Records available for the study had a full set of data on the variables needed for the proposed analytical framework.

2.3 Study Variables

The variables were grouped under conceptually related domains based on the objectives of the study. Student and contextual characteristics were age, gender, academic major, semester, parental education level, family income ranges, parental support levels, internet quality, and part-time work. The characteristics of personalized learning were reflected by learning style, study environment, access to tutoring, motivation score

and time-management score. Behavioral and lifestyle variables included amount of time spent studying per day, social media use, Netflix use, total screen time, sleep time, frequency of exercise, diet quality, social activity and extracurricular activity. The measures used for psychological well-being included mental-health rating, stress level, examination-anxiety score, and motivation level. Examination score, past grade point average (GPA), attendance percentage, and dropout risk were used as educational outcomes. The principle continuous measure of current academic achievement was examination score, and the categorical indicator of educational vulnerability was dropout risk.

2.4 Data Preprocessing

Prior to statistical analysis, the dataset was checked for missing observations, duplicate records, inconsistent categorical labels and implausible values. Variable types and ranges of numbers were checked, and categorical values were standardized to avoid inconsistencies. Student identifiers were kept only for student record identification and were not used for predictive modelling. Machine-readable representations were used for categorical predictors, and continuous ones were scaled as needed by algorithms used. Each predictor variable was then split from the target outcome based on the type of analysis being performed. Transformations were estimated based on the training data for predictive modelling and then applied to the test data to keep information leakage to a minimum.

2.5 Statistical Analysis

Descriptive statistics were first employed to describe the study population and characteristics of the major domains of the framework. Mean, standard deviation, median, minimum and maximum values were provided for continuous variables, and the frequencies and percentages were provided for categorical variables. The distribution of the learning characteristics, distribution of lifestyles, distribution of psychological indicators and distribution of educational outcomes were analysed to determine the overall profile of the students. Correlation analysis was used to check the relationships between continuous behavioral, lifestyle, psychological and educational variables. To gain a visual appreciation of the direction and magnitude of relationships between the major study variables a correlation matrix was produced. Comparisons were also done by groups to see if there were differences in educational outcomes based on other categorical variables such as learning style, learning environment, diet quality, and other learner characteristics. A two-sided P value of <0.05 was statistically significant. All the statistical analysis was done in Google Colab.

2.6 AI-Enabled Learner Profiling

To determine the various learner profiles from multiple student characteristics, an unsupervised machine learning technique was used. After proper preprocessing, the following variables were added to the profiling process: Personalized learning, Study behaviour, Lifestyle patterns and psychological well-being. The grouping of the students in this study was because they share similar multidimensional characteristics and not using educational outcome labels to form the groups. Within the clusters' cohesion and between the clusters' separation were assessed to determine the appropriate cluster solution. The learner profiles were then coded around key features of the learner's learning, behavioral, lifestyle, psychological and academic profile to identify whether they were relevant to the provision of personalised learning support.

2.7 Educational Outcome Prediction

The supervised machine learning models were built to assess the ability of the multidimensional student characteristics to predict educational outcomes. Examination score was considered as a continuous prediction target while dropout risk was considered as a categorical outcome. Characteristics of learning and indicators of behavior or lifestyle, psychological measures and appropriate demographic and contextual variables were all explored as potential predictors. Data was split into a training part and a testing part such that the training and the testing was done on different data observations. To ensure no results were based on the performance of a single modelling approach, multiple candidate algorithms were compared. For examination-score prediction, regression models were evaluated and for prediction of dropout-risk, classification models were evaluated. Only variables that were available in the data were used in model development and held out test data were not used in model fitting.

2.8 Model Performance Evaluation

The coefficient of determination (R^2), mean absolute error (MAE) and root mean squared error (RMSE) were used for assessing the predictive performance for the continuous educational outcome. Model performance was evaluated with accuracy, precision, recall and F1-score and the area under the receiver operating characteristic curve (ROC-AUC) was used to classify dropouts if applicable. These complementary measures were used to compare the models to find the best predictive model instead of using only the overall accuracy.

2.9 Model Interpretability and Identification of Key Predictors

Model interpretability analysis was conducted to identify the strongest students' characteristics predicting educational outcomes. The results of the best performing models were analyzed on the bases of the feature importance estimates and compared the relative contribution of the personalized-learning characteristics, behavioral and lifestyle factors, psychological indicators and contextual variables. This was analysed in conjunction with the traditional statistical analysis to detect potentially important factors for learner support. Predictive relationships were not considered to be causal.

2.10 Ethical Considerations

The study relied on secondary data only and there was no recruitment or intervention or interaction with human participants. The personally identifying information was not present in the analytical data set and the student identifiers were only provided to differentiate student records and were not used in predictive analysis. Data was used for research and analysis purposes only and confidentiality and integrity of data was respected. The investigation was a secondary analysis of the already collected data, and no further information was obtained from individual students. The results were analysed and reported at an aggregate level while maintaining the confidentiality and anonymity of the participants.

3. Results

3.1 Characteristics of the Study Population

A total of 1,000 student records were analysed in the study. The average age of the participants was 22.05 ± 3.76 years old; the participants were evenly distributed among males, females, and other genders. Biology was the most common academic discipline (18.1%) followed by Arts (17.5%) and Engineering (16.4%). Nearly half of the participants had tutoring services (50.8%). Descriptive features of the population of the study are described in Table 1.

Table 1. Demographic and contextual characteristics of the students (N = 1,000)

Characteristic	Category/Statistic	n (%) / Mean $\pm$ SD
Age (years)	Mean $\pm$ SD	22.05 $\pm$ 3.76
Gender	Male	340 (34.0%)
	Female	327 (32.7%)
	Other	333 (33.3%)
Major	Biology	181 (18.1%)
	Arts	175 (17.5%)
	Engineering	164 (16.4%)
	Computer Science	163 (16.3%)
	Business	160 (16.0%)
	Psychology	157 (15.7%)
	Access to tutoring	508 (50.8%)
	No	492 (49.2%)

3.2 Learning, Behavioral, Lifestyle, and Psychological Characteristics

The students reported an average study time of 4.16 ± 2.07 hours per day and an average sleep time of 7.06 ± 1.42 hours per day. An average screen time of 9.70 ± 2.87 hours was observed. The average rating of the mental state was 6.80 ± 1.89 , while the average stress level and examination anxiety were 5.00 ± 2.00 and 8.62 ± 1.75 , respectively. The motivation and time management scores were 5.37 ± 2.80 and 5.45 ± 2.62 . These behavioral and psychological characteristics are summarized in Table 2.

Table 2. Descriptive statistics of major behavioral, lifestyle, psychological, and educational variables

Variable	Mean $\pm$ SD	Median	Range
Study hours/day	4.16 $\pm$ 2.07	4.20	0.0–11.9
Social-media hours	2.55 $\pm$ 1.47	2.60	0.0–5.0
Netflix hours	2.03 $\pm$ 1.15	2.00	0.0–4.0
Sleep hours	7.06 $\pm$ 1.42	7.05	4.0–11.4
Screen time	9.70 $\pm$ 2.87	9.70	1.3–19.8
Mental-health rating	6.80 $\pm$ 1.89	6.90	1.0–10.0
Stress level	5.00 $\pm$ 2.00	5.00	1.0–10.0
Motivation level	5.37 $\pm$ 2.80	5.00	1–10
Examination anxiety	8.62 $\pm$ 1.75	10.00	5–10
Time-management score	5.45 $\pm$ 2.62	5.50	1–10
Attendance (%)	70.38 $\pm$ 17.66	70.20	40.0–99.9
Previous GPA	3.60 $\pm$ 0.48	3.80	1.9–4.0
Examination score	88.90 $\pm$ 11.94	94.00	48–100

The distribution of lifestyle characteristics showed that 50.7% of students had good diet quality, compared with 35.1% reporting fair and 14.2% reporting poor diet quality. Learning styles were relatively evenly represented, with Visual being the most frequent (26.3%). The distribution of these characteristics is shown in Figure 1.

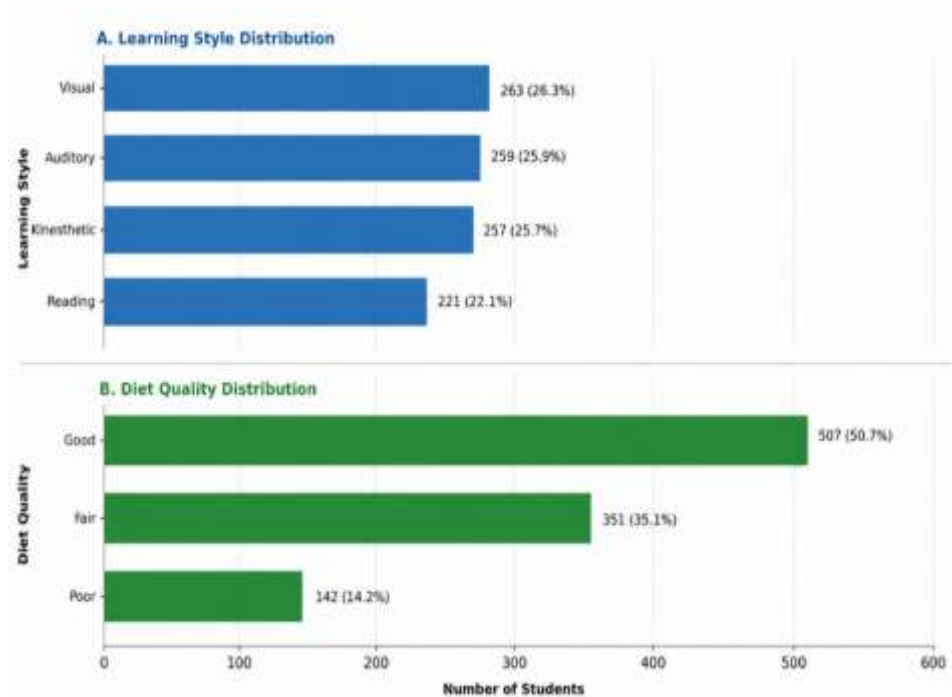


Figure 1. Distribution of learning styles and diet-quality categories among students

3.3 Educational Outcomes According to Learning and Lifestyle Characteristics

The mean scores for the examinations varied slightly among the four groups of learning styles, with the mean score for auditory learners being 88.63 and for kinesthetic learners 89.18, with no statistical significance between them ($F = 0.098$, $p = 0.961$). Examination scores were not also statistically significantly different for the diet quality categories ($F = 1.247$, $p = 0.288$). Study environment on the other hand had a statistically significant relationship with examination scores ($F = 14.623$, $p < 0.001$), with the highest mean score for students in quiet environments. The comparisons are presented in Table 3 and visualized in Figure 2.

Table 3. Examination scores according to selected learning and lifestyle characteristics

Characteristic	Category	Examination score, Mean $\pm$ SD	p-value
Learning style	Auditory	88.63 $\pm$ 12.20	0.961
	Kinesthetic	89.18 $\pm$ 11.80	
	Reading	88.98 $\pm$ 12.33	
	Visual	88.81 $\pm$ 11.56	
Diet quality	Fair	88.56 $\pm$ 12.12	0.288
	Good	89.43 $\pm$ 11.44	
	Poor	87.80 $\pm$ 13.18	
Study environment	Café	86.96 $\pm$ 12.73	<0.001
	Co-Learning Group	90.33 $\pm$ 10.69	
	Dorm	84.56 $\pm$ 13.73	
	Library	90.79 $\pm$ 11.04	
	Quiet Room	92.23 $\pm$ 9.21	

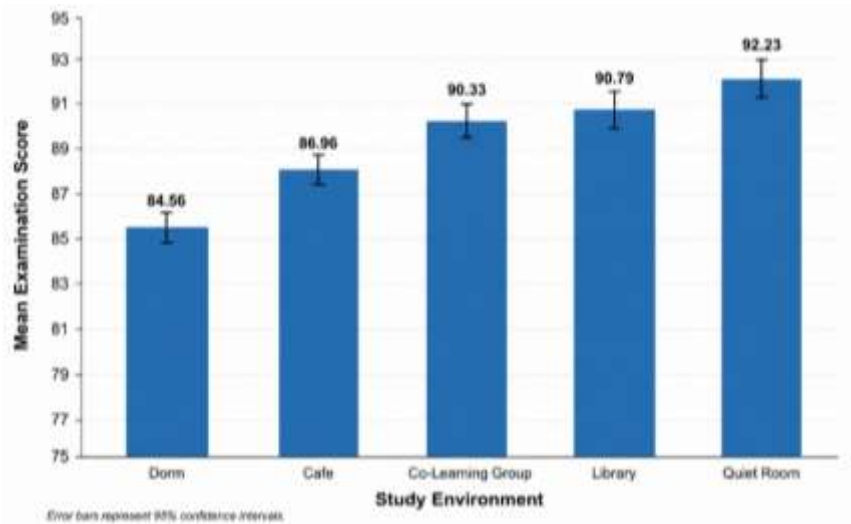


Figure 2. Mean examination scores across different study environments

3.4 Relationships Between Behavioral, Psychological, and Educational Indicators

The correlation analysis results showed that the strongest correlation variable with examination score was previous GPA ($r = 0.943$). Study hours ($r = 0.298$), screen time ($r = 0.240$), and motivation ($r = 0.222$) had positive correlations with examination score. On the other hand, examination anxiety ($r = -0.211$) and stress ($r = -0.160$) had negative correlations with examination score. Other variables had relatively weak correlations. The main correlations are presented in Table 4, and the general picture is illustrated in Figure 3.

Table 4. Correlations of selected variables with examination score

Variable	Pearson's r with examination score	Direction/Strength
Previous GPA	0.943	Very strong positive
Study hours/day	0.298	Weak positive
Screen time	0.240	Weak positive
Motivation level	0.222	Weak positive
Sleep hours	0.096	Very weak positive
Mental-health rating	0.035	Very weak positive
Social-media hours	0.003	Negligible
Time-management score	-0.078	Very weak negative
Stress level	-0.160	Weak negative
Examination anxiety	-0.211	Weak negative

Correlations of selected variables with examination score

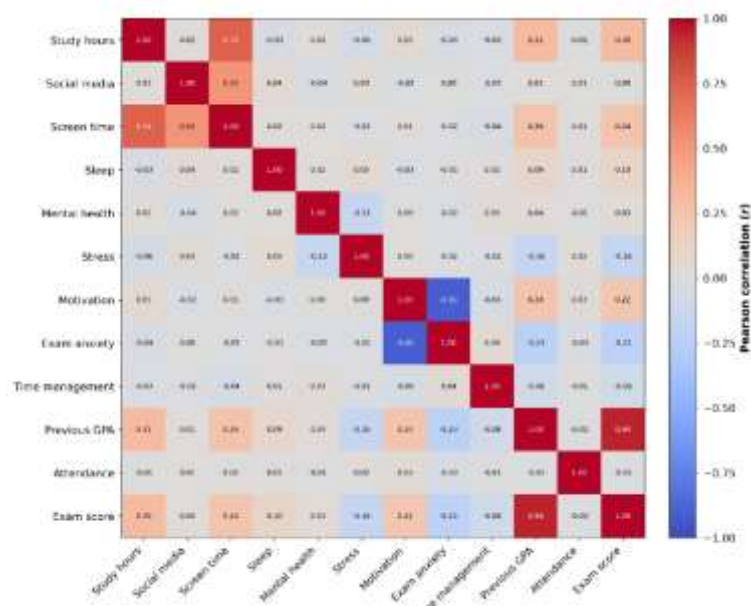


Figure 3. Correlation heatmap of behavioral, lifestyle, psychological, and educational indicators

3.5 AI-Based Learner Profiling

The unsupervised clustering analysis was tested with the solutions that comprised of two to five clusters. It was found that a two-cluster solution had the highest silhouette coefficient (0.120); however, its low value suggested that there was not much natural separation in multidimensional student data. Cluster 1 had 631 students and was marked by low levels of motivation and high levels of examination anxiety; Cluster 2 had 369 students and exhibited high levels of motivation and low levels of examination anxiety. Cluster 2 also had higher average examination marks and GPA. The learner profiles are summarized in Table 5, and their multidimensional separation is represented in Figure 4.

Table 5. Characteristics of the two AI-derived learner profiles

Characteristic	Cluster 1 (n = 631)	Cluster 2 (n = 369)
Study hours/day	4.12	4.23
Mental-health rating	6.76	6.86
Stress level	4.96	5.08
Motivation level	3.57	8.44
Examination anxiety	9.83	6.56
Time-management score	5.49	5.38
Examination score	87.26	91.69
Previous GPA	3.53	3.71
Attendance (%)	69.69	71.55

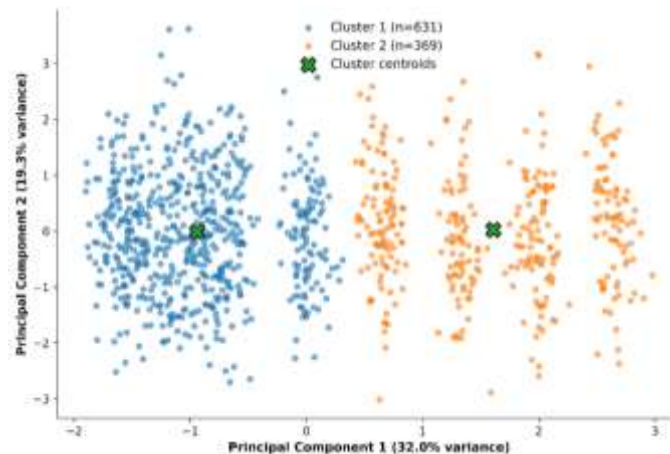


Figure 4. Visualization of AI-derived student learner profiles based on multidimensional behavioral and psychological characteristics

3.6 Prediction of Educational Outcomes

Three machine learning techniques were evaluated in terms of their ability to predict examination scores. Linear regression had the highest performance on the test set, having explained about 89.1% of the variation in examination scores ($R^2=0.891$), with MAE=3.20 and RMSE=4.13. Performance of gradient boosting was comparable, while random forest regression was not far behind. Model comparison is given in Table 6 and Figure 5.

Table 6. Performance of AI/ML models for predicting examination scores

Model	R^2	MAE	RMSE
Linear Regression	0.891	3.20	4.13
Gradient Boosting	0.888	3.29	4.19
Random Forest	0.883	3.35	4.28

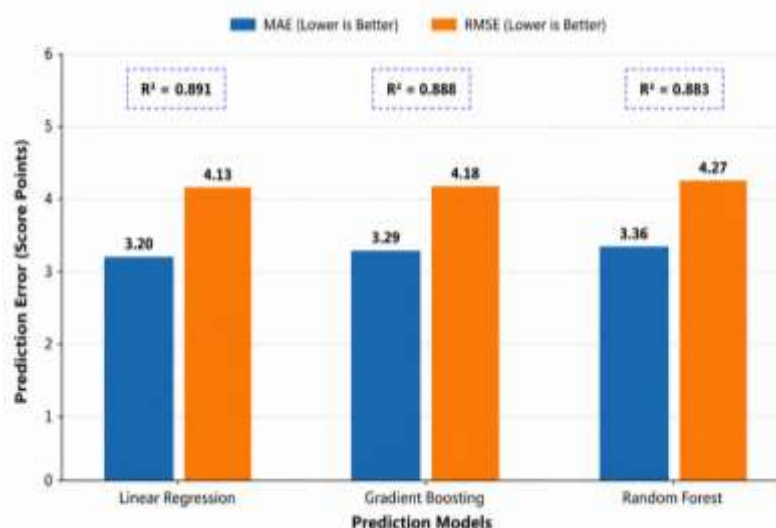


Figure 5. Comparative predictive performance of machine-learning models for examination-score prediction

3.7 Overall Findings of the Integrated Framework

Overall, it can be noted that educational performance showed the strongest link to prior academic success, while study behavior, motivation, stress, and exam anxiety provided extra information. Profiling through AI separated students mainly based on their motivational and anxiety profiles, even if the clusters were not very well-separated. The model performed excellently in predicting continuous scores on examinations but was limited by the use of standard classification techniques due to data imbalance.

4. Discussion

The current study revealed the benefits of combining characteristics of personalized learning, behavioral and lifestyle trends, psychological health, and educational outcomes in an AI-supported analytical approach. Study hours, motivation, screen time, stress and examination anxiety were found to be the strongest correlates of examination performance, with previous GPA also providing information about students' performance. These results further highlight the importance of multidimensional AI systems that take both performance and well-being of the individual into account, rather than operating separately (Agarwal et al., 2025). Emotional Intelligence (EI) has also been suggested for creating AI systems that are more emotionally intelligent, human-centred, and can aid in learning as well as well-being (Cinar & Bilodeau, 2024).

There were not significant differences between the categories of learning style and there was significant relationship between study environment and examination scores. The performance of students who studied in quiet rooms was comparatively better than the performance of students who studied in dormitory rooms. This indicates that personalization cannot be limited to instruction aligned with a nominal type of learning style, but it also has to include contextual and behavioral aspects. This wider personalization can be achieved through AI-driven adaptive education, which dynamically adapts to learner characteristics and patterns (Kristianingsih & Maharani, 2025). Personalized learning pathways using behavioral design can also boost motivation and competency development by tailoring learning experiences to each student's needs (Liu et al., 2025). Likewise, personalization can be linked to opportunities for enhancing learner self-efficacy and showing potential for educational value of individual AI support (Peddi & Manoharan, 2025).

Student performance was interpreted using an extra dimension of lifestyle characteristics. The score on the examination itself did not differ significantly by the diet quality scores, but the combined scores of study behavior, screen exposure, sleep, exercise, and social activity do provide helpful contextual information to be used for learner profiling. This can benefit the application of behavioral-health analytics in college settings, where digital solutions can integrate various behavioral and psychological data points to enable personalized interventions (Garcia Colato et al., 2025). Importantly, the not strong independent association for an individual lifestyle variable will not rule out an association when it is included in a multidimensional learner profile.

The psychological indicators were especially relevant to the integrated design. Motivation showed a positive correlation with the performance in the exam, while examination anxiety and stress showed a negative correlation. These patterns suggest that we need to think about emotion in educational analytics, along with academic indicators. The use of AI for emotional support and mental health care has been growing and investigated among various populations (da Silva, 2025). AI systems can recognize emotions in educational settings, which might help in providing personalized social-emotional support (Javed et al., 2025), and AI-driven emotion detection in classrooms has been correlated with student engagement and learning results (Ilyas et al., 2025). Thus, AI-powered mental health assistance in schools can supplement academic

interventions, generating a list of students who might need extra support (Lee, 2025).

The AI-informed learner profiling also revealed two groups of students with a key distinction based on their motivation, examination anxiety and performance in school. These profiles show how behavioral data analytics can go beyond averages of a population and highlight combinations of characteristics that are relevant for personalized intervention, despite the modest level of cluster separation. This seamless integration aligns with the shift towards psycho-wellness models integrating artificial intelligence (AI) with applications that promote well-being (Subahani et al., 2025). AI technologies for SEL also highlight the capabilities of AI in capturing and addressing affective aspects of learning (Sethi & Jain, 2024). Affective Computing can also enhance the online learning space by integrating emotional intelligence with personalized support (Shifa et al., 2025).

For the estimation of examination scores, predictive modelling of the two varied approaches yielded strong results, with linear regression accounting for about 89% of the variance in the test set, and slightly outperforming gradient boosting and random forest models. On the contrary, dropout-risk classification was limited by significant class imbalance issues: high overall accuracy does not necessarily mean good identification of the vulnerable students. The results thus suggest that the application of AI should not be the sole factor in deciding on educational intervention but should be used as a decision support tool. This aligns with the fact that AI's role in SEL can lead to better engagement and emotional health if it is personalized based on cognitive and emotional needs (Zong & Yang, 2025). In general, the approach could be used for early detection and personalized education service, but further validation, long-term research, more balanced classes and prospective assessment are needed to make it possible in practice.

5. Conclusion

This study showed that an AI based personalized learning and behavioral analytics framework can be used to integrate learning outcomes with students' learning characteristics, lifestyle behaviors and psychological well-being. Previous achievement was found to be strongly related to academic performance and study behavior, motivation, stress, examination anxiety and environment were found to add another layer of understanding regarding differences in student outcomes. Study environment was found to be a significant differentiating factor while there was comparatively limited difference in examination performance for learning style and diet quality. The AI-driven learner profiling revealed the presence of different groups of learners mainly varying on the dimensions of motivation, examination anxiety and academic performance, highlighting the potential of multidimensional profiling in supporting personalization in education. Results from the predictive modelling also indicated that examination performance can be estimated with a high level of accuracy; linear regression had the best overall performance of the models tested. But the very imbalanced nature of the dropout-risk outcome made reliable identification of at-risk students even more important than correct classification. Overall, these results suggest that AI-driven educational analytics can offer a more holistic view of student performance by considering the interplay between academic, behavioral, lifestyle, and psychological factors. However, the results should be interpreted as correlating relationships and not as causal. In the future, the suggested framework should be validated with real-world student populations, independent and longitudinal data, and personalized interventions should be assessed prior to deployment in educational decision-support systems.

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