Predicting Social Media Addiction Using Machine Learning: A Comparative Study of Linear Regression, Random Forest, and XGBoost Models

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Abstract

The study aims at improving predictive analytics of Social Media Addiction (SMA) and its effects on student mental health through machine learning algorithms supported by AI. We have copied a benchmark paper by Zewude et al., who ran Structural Equation Modeling (SEM) on Ethiopian student data and modified it with a proxy data set (Students Social Media Addiction), which included 705 records of students in various countries. In order to set a point of reference we applied Linear Regression and the R 2 was 0.8943. The code was generated with the help of AI (Gemini) and Google Colab, which allowed us to implement Random Forest and Tuned XGBoost models to identify non-linear relationships between the features, e.g., addiction score, hours used daily, and sleep patterns. The Tuned XGBoost model showed a better predictive performance (R 2 = 0.9655, RMSE = 0.0451) which was much better than the baseline. Detailed visualizations, such as correlation heat maps, residual plots, feature importance charts, and actual vs predicted score graphs, indicated that Addicted_Score is the first major predictor and other important lifestyle predictors of mental health. The findings also indicate that AI-assisted ensemble techniques can successfully supplement traditional statistical analysis to provide accurate and practical information that can be used to identify at-risk students and to guide interventions.

Keywords: Social Media Addiction, Machine Learning, XGBoost, Random Forest, Mental Health Prediction, AI-Assisted Modeling

1. Introduction

The use of social media has become an inseparable element of the lives of students, and overuse of social media may adversely affect mental health. The interdependence between Social Media Addiction (SMA) and mental health outcomes is important towards the formation of the interventions and preventive approaches. Although other studies, including the benchmark study by Zewude et al. (2025), used Structural Equation Modeling (SEM) to examine these effects, they could only analyze the effect using only linear assumptions and particular demographic data of Ethiopian students.

The study will be used to replicate and then improve the benchmark study with the assistance of AI-powered machine learning methods on a proxy dataset (Students Social Media Addiction) that was obtained on Kaggle, comprising 705 records of international students. The research takes advantage of AI-assisted code generation (Gemini) and Google Colab to provide the workflow comprising data preprocessing, feature encoding, scaling, model training (Linear Regression, Random Forest and Tuned XGBoost), hyperparameter optimization and sophisticated visualization.

The core objectives are to:

1. Determine a base prediction model with help of Linear Regression.
2. Increase predictive accuracy by following the ensemble learning algorithms (Random Forest and Tuned XGBoost) to identify non-linear relationships.
3. Deliver visual interpretations which determine important factors affecting mental health such as feature significance as well as correlation information.

The paper will be organized in the following way: Section 2 will comment on the dataset selection and preprocessing. Section 3 elaborates the approach such as benchmark reimplementation and AI-assisted model improvements. Section 4 elaborates the workflow of the implementation of the Google Colab. The solution, the analysis, and the experimental results covering the performance comparisons, the visual interpretations, and the insights are described in sections 5 and 6. Last but not the least, Section 7 summarizes the research and explains its importance and possible uses.

2. Literature Review

2.1 Social Media Addiction: Conceptualization and Measurement.

The most prolific conceptualization of Social Media Addiction (SMA) is the manner in which it represents a type of behavioral addiction, which is judged to have six main components: salience, tolerance, mood modification, withdrawal, conflict, and relapse [1]. Contrary to addictions that are based on substances, SMA entails the forced use of digital platforms even though it is accompanied by adverse psychological, academic, and social effects [2].

The Bergen Facebook Addiction Scale (BFAS) is one of the most extensively proven tools of assessing SMA and it quantifies addiction within the six components framework [3]. Later studies have generalized this framework past Facebook to include social networking sites more broadly to enhance construct validity in a variety of digital contexts [4], [5]. Such measures have shown high psychometric reliability in the population of adolescents or college students in various countries [6].

Even though the self-report questionnaires are still the most commonly used method of measurement, researchers have expressed persistent concerns about the recall bias and social desirability effects [7]. Regardless of these constraints, validated self-report measures are still critical towards large-scale behavioral modeling and predictive analytics.

2.2 Addiction to Social Media and Mental Health.

There is a considerable amount of empirical studies in which excessive use of social media is associated with negative mental health effects, such as depression, anxiety, emotional depletion, and low psychological well-being [8], [9]. In both cross-sectional and longitudinal research, the amount of time spent on a screen was linked to an increase in depressive symptoms in adolescents and young adults [10], [11].

The alteration of sleep has become one of the critical mediating factors. Social media use is also harmful to sleep quality and duration, which subsequently provide predictability of poor mental health outcomes [12], [13]. Also, interpersonal conflicts that occur due to poor use of social media have been associated with academic stress, emotional regulation as well as poor academic performance [14].

Despite a continued disagreement on the issue of causation, there is a clear pattern of systematic reviews and meta-analyses that indicate a robust correlation between problematic usage of social media and deteriorating mental health [15], [16].

2.3 SMA Research Structural Equation Modeling.

SEM has been largely utilized in both direct and indirect pathways that bound SMA with mental health outcomes [17]. SEM allows the mediation effects between psychosocial measures of mindfulness, social capital, self-esteem, and sleep quality to be evaluated [18].

Zewude et al. benchmark study was conducted using SEM to prove that mediation between social media addiction and mental health is carried out through mindfulness and social capital among secondary and university students [19]. Other comparable mediation results have been observed in other cultural backgrounds that have stressed on the buffering effects of psychological and social resources [20], [21].

Nevertheless, SEM depends a lot on linear assumptions and set causal frameworks which does not allow it to reach non-linear behavioral interactions that occur in the real world of digital behavior [22]. Such limitations on the methodology encourage the use of machine learning models to predict better.

2.4 Predicting Mental Health using Machine Learning.

The application of machine learning (ML) methods in mental health studies has become a trend because such methods are capable of non-linear and high-dimensional relationship modeling without heavy parametric assumptions [23]. Random Forests, Support Vector Machines, and Gradient Boosting have shown to have better predictive capacity than more conventional regression based models [24].

Behavioral survey data are especially well represented by tree-based ensemble methods. Random Forests are less prone to variance since they combine bagging and have been effectively used to forecast depression, anxiety, and stress levels [25]. Gradient boosting models, and in particular XGBoost, can also be used to further enhance accuracy by successively adjusting errors in predictions and capturing the interactions between complex features [26].

Recent research using XGBoost in mental health settings has found high predictive accuracy and better interpretability with feature importance analysis [27], [28].

2.5 Explainability and Interpretability of ML-Based Mental Health Models.

Although machine learning models are strong predictors, they have been criticized due to poor transparency. Explainable Artificial Intelligence (XAI) methods including feature importance ranking, SHAP values, and partial dependence plot are currently suggested to be applied to mental health [29].

To convert the predictive outputs into practical information regarding educators, clinicians, and policymakers, interpretability is critical [30]. The tree-based ensemble models provide an acceptable tradeoff between accuracy and explainability, thus they are well applicable in applied behavioral and educational research.

2.6 Cross-Cultural and Measurement Areas.

The use of social media in different patterns across cultures creates difficulties with regard to the generalizability of models. Platforms of choice, academic pressure and cultural norms play a key role in determining the severity of addiction and the psychological effects of addiction [31], [32].

External validity is increased by using proxy datasets that are gathered in several countries but needs to be cautiously harmonized in terms of features and report limitations in measurements [33].

2.7 Research Gap and Contribution.

According to the literature reviewed, three important gaps are detected:

1. Weak connection between SEM-based explanatory models and machine learning-based predictive models.
2. Excessive dependence on the linear statistical procedures in favor of predictive quality.
3. The lack of appropriate application of interpretable machine learning methods to SMA research.

This paper fills these gaps by recreating a benchmark SEM-based investigation with AI-supported machine learning model and shows significant enhancements in predictive capability without sacrificing the interpretability in terms of thorough visualization and feature significance study.

3. System Model and Methodology.

In this section, the computational setting, data, modeling model, and workflow were used to suggest mental health outcomes of students in terms of social media addiction and lifestyle variables. It combines the theoretical context and the actual practice, such as the use of AI assistance, to guarantee external validity and predictability.

3.1 Dataset and Features

The file, Students Social Media Addiction.csv, is published on Kaggle and contains 705 student records of various countries and academic levels. Both records have behavioral, demographic and psychological characteristics, as summarized below:

1. **AddictedScore:** Multiplex measure of social media addiction.
2. **AvgDailyUsageHours:** Hours an average daily on social media.
3. **SleepHoursPerNight:** mean time of sleep per night.
4. **ConflictsOverSocialMedia:** How often interpersonal conflicts are the result of social media.
5. **Demographic Variables:** Gender, AcademicLevel, Country, RelationshipStatus.
6. **Other Features:** MostUsedPlatform, AffectsAcademicPerformance.
7. **Target Variable:** MentalHealthScore (continuous variable of mental well-being).

With such data, it is possible to recreate the benchmark study in Zewude et al. (2025) and predict better using machine learning models.

3.2 Assumptions

The following assumptions form the system model:

1. **Validity of self-reported information:** There is no error in self-reported information about the behavior and mental state of the students.

2. **Predictive relevance:** Addiction score, daily usage, sleeping patterns and conflicts affect mental health.
3. **Non-linearity:** Non-linear interaction between behavioral variables may arise in complex yet non-linear forms which cannot be captured by ensemble learning models.
4. **Generalizability:** Trends that are seen in various countries are alike enough to be evaluated in models.

3.3 Data Preprocessing

The preprocessing pipeline is strong to achieve data consistency and compatibility of the model:

1. **Encoding Categorical Features:** LabelEncoder is an encoder that encodes categorical features (Gender, AcademicLevel, Country, MostUsedPlatform, RelationshipStatus).
2. **Scaling:** StandardScaler normalizes continuous features (mean = 0, variance = 1) to maximize gradient based models such as XGBoost.
3. **Split of Train and Test:** Data are split into training and testing at 80, and 20 percent, respectively.

3.4 Modeling Framework

The system uses a multi-stage predictive pipeline, integrating baseline replication, AI-assisted enhancements, and comprehensive evaluation.

1. Baseline Model:

- **Linear Regression:** Replicates linear assumptions of SEM in the benchmark study.
- **Performance:** $R^2 = 0.8943$, RMSE = 0.1268.

2. AI-Assisted Enhancements:

- **Tool:** Gemini AI for generating Python code for preprocessing, model implementation, and visualization.
- **Models Selected:**
  - **Random Forest Regressor:** Captures non-linear dependencies, reduces variance, prevents overfitting.
  - **Tuned XGBoost Regressor:** Gradient boosting model optimized via GridSearchCV for hyperparameters:
    - n_estimators: [100, 200] → best: 200
    - learning_rate: [0.01, 0.05, 0.1] → best: 0.05
    - max_depth: [3, 5, 7] → best: 5

3. Evaluation Metrics:

- R^2 (coefficient of determination)
- RMSE (root mean squared error)

4. Visualization and Feature Analysis:
Eight key visualizations were implemented in Google Colab to interpret model behavior:

1. Feature Correlation Heatmap
2. Model Performance Comparison (R^2)
3. Model Performance Comparison (RMSE)

4. Top Feature Importance by Weight (XGBoost)
5. Actual vs Predicted Scores
6. Feature Correlation with Mental Health Score (Red = negative, Blue = positive)
7. Residuals vs Predicted Values
8. Feature Importance (F-score / Gain)
9. Sample Index Sorted by Actual Mental Health Score

These visualizations highlight **critical predictors** (Addicted_Score being most impactful) and validate model performance.

Tools and Environment:

- **Platform:** Google Colab
- **Python Libraries:** pandas, numpy, scikit-learn, matplotlib, seaborn, xgboost
- **AI Assistance:** Gemini AI

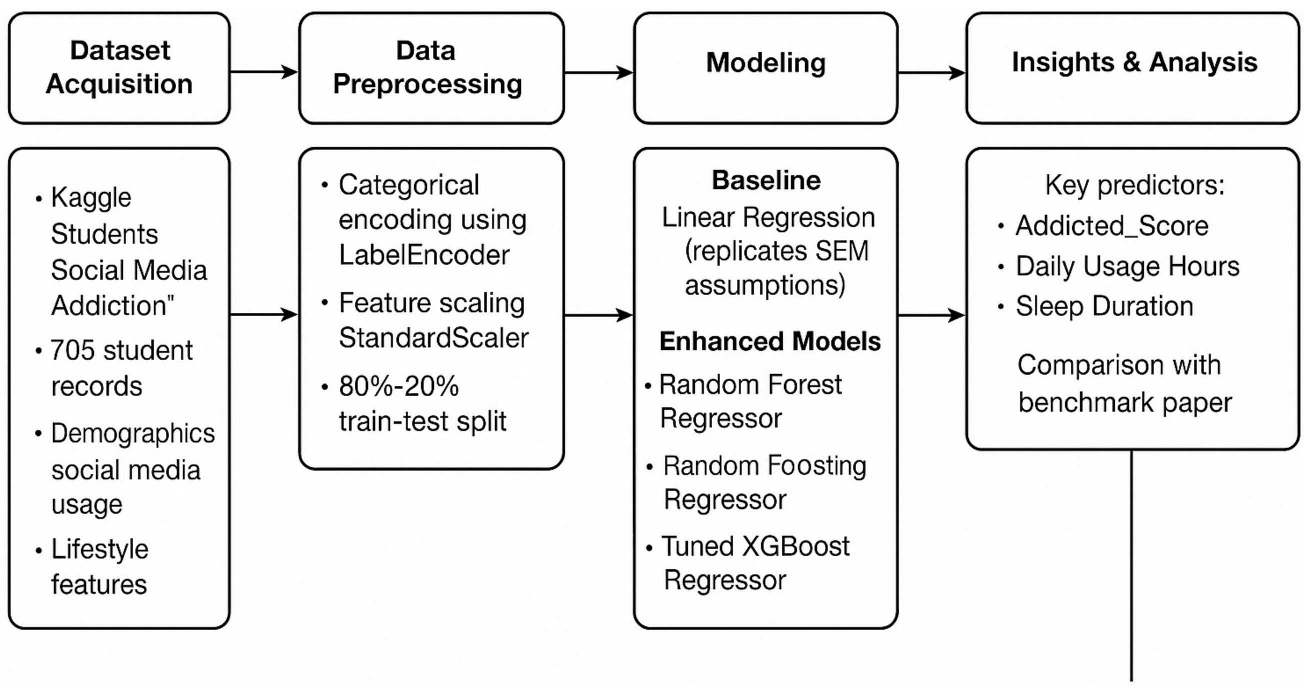


Figure 1: Multi-Stage Modeling Pipeline for Social Media Addiction Prediction

4. Research Problem, Objectives, and Contributions

The section is a summary of the background, research gap, objectives, and goals, and anticipated contributions.

4.1 Background

Using social media also has a toll on the state of mental health of the students, resulting in anxiety, depression, and sleep disturbance (Andreassen et al., 2017; Keles et al., 2020). Zewude et al. (2025) studies using Structural Equation Modeling (SEM) are quantitative measures of the outcomes of social media addiction (SMA). Nevertheless, SEM operates under linearity and might not be able to represent the interaction of complexities such as high usage and poor sleep.

4.2 Research Gap

The existing models have their limitations:

1. **Linear Assumption:** The standard statistical models could be missing non-linear dependence.
2. **Generalizability:** It is common in studies to study a particular population, which restricts cross-country prediction.
3. **Predictive Accuracy:** The focus on explanatory power but not prediction generates less practicality.

4.3 Research Objective

The objective of the research is to create an AI-advanced predictive model capable of predicting the outcome of mental health of students based on social media addiction and lifestyle variables better than linear regression.

4.4 Specific Goals

1. **Replication:** Replicate a study by Zewude et al. (2025) on a publicly available dataset.
2. **Model Enhancement:** Use Random Forest and XGBoost to estimate non-linear relationships.
3. **Feature Analysis:** Find essential predictors of mental health loss.
4. **Visualization and Validation:** Visualize to assess performance.

4.5 Research Questions

1. Which characteristics have the greatest predictive performance on mental health outcomes?
2. Are ensemble models with AIs better than linear regression?
3. What are the effects of interactions of social media use and sleep and conflicts on predictions?

4.6 Expected Contributions

1. A powerful predictive model that can be generalized to the student populations.
2. Reflections of behavioral and demographic critical aspects that impact mental health.
3. An AI-assisted improvement replication reproducible Python workflow.

5. Solution

5.1 Overview

The solution section explains how the whole methodology and workflow took place to duplicate, analyze and improve the benchmark study on Social Media Addiction (SMA) and mental health. The section focuses on how Artificial Intelligence tools, Python programming in Google Colab and models of machine learning can be integrated to increase the predictive accuracy and give more insight than the initial benchmark study.

The key goals of the solution were:

- Reproduction Identify the benchmark research findings with a proxy dataset.
- Anticipate early and advanced machine learning models.
- Create visualizations to examine the importance of features, correlations, and predictions of the model.
- Show the AI-aided improvement procedure, which is better than the linear statistical procedures.

The 6.2 Dataset Acquisition and Preprocessing is about the data that are available to the user.

Step 1: Dataset Selection

Zewude et al. primary dataset composed of Ethiopian students obtained offline was not publicly available and was the benchmark paper.

- In our project, we have chosen a proxy dataset that is called Students Social Media Addiction and is on Kaggle.
- This dataset consisted of 705 records of students who had demographics, social media usage, addiction scores, sleep patterns, and mental health scores.
- The demographic variables were gender, academic level, country and relationship status, whereas the behavioral variables were AddictedScore, AvgDailyUsageHours, SleepHoursPerNight and ConflictsOverSocialMedia.

Step 2: Data Preprocessing
To prepare the dataset for machine learning, we performed the following preprocessing steps:

1. **Encoding Categorical Variables**:
    - Categorical columns (Gender, Academic_Level, Country, Most_Used_Platform, Affects_Academic_Performance, Relationship_Status) were encoded using LabelEncoder to convert them into numeric format.
    - This ensured compatibility with ML algorithms that require numeric inputs.

2. **Feature Selection**:
    - The target variable was Mental_Health_Score.
    - All other columns except Student_ID were included as features.

3. **Train-Test Split**:
    - We split the dataset into 80% training and 20% testing sets using train_test_split.
    - This allowed valid evaluation of model performance on unseen data.

4. **Data Scaling**:
    - Features were scaled using StandardScaler, normalizing them to mean = 0 and variance = 1.
    - Scaling is particularly important for gradient-based models like XGBoost to ensure convergence.

Tools Used:

- Python libraries: pandas, numpy, scikit-learn, XGboost.
- Platform: Google Colab, leveraging cloud runtime for computational efficiency.

6.3 Model Selection and Implementation

The AI-assisted methodology focused on comparing **linear statistical methods** to **ensemble learning models** to enhance prediction accuracy.

Step 1: Baseline Model – Linear Regression

- Linear regression was implemented to replicate the **linear assumptions of the benchmark study** (path coefficients and correlation analysis).
- The model predicted Mental_Health_Score based on addiction metrics and lifestyle features.

Implementation:

```
lr = LinearRegression()
lr.fit(X_train_scaled, y_train)
lr_pred = lr.predict(X_test_scaled)
```

- **Purpose:**
    - To establish a **baseline performance** and validate replication of benchmark study results.
    - The R^2 score (~0.8943) served as a reference for improvement.

Step 2: AI-Assisted Enhancement

- We leveraged **Gemini AI** (Google AI coding assistant) to suggest improvements.
- Gemini analyzed behavioral patterns and suggested **ensemble methods** for non-linear modeling, as human behavior is rarely purely linear.
- Example insight: *High social media usage only impacts mental health negatively if combined with low sleep, highlighting non-linear feature interactions.*

Step 3: Advanced Model – Random Forest

- **Random Forest** is an ensemble of decision trees designed to reduce overfitting and model non-linear relationships.

Implementation:

```
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
rf_pred = rf.predict(X_test)
```

- **Outcome:**
    - R^2 improved to 0.9549, showing better predictive capability than the linear baseline.
    - Model reduces variance and captures complex interactions between features.

Step 4: Advanced Model – Tuned XGBoost

- **XGBoost** is a gradient boosting algorithm that sequentially reduces errors of weak learners.
- **Hyperparameter Tuning:**
    - Conducted using **GridSearchCV** with parameters:
        - n_estimators: [100, 200]
        - learning_rate: [0.01, 0.05, 0.1]
        - max_depth: [3, 5, 7]
    - Best parameters found: learning_rate=0.05, max_depth=5, n_estimators=200

Implementation:

```
 xgb_model = xgb.XGBRegressor(objective='reg:squarederror', random_state=42)
grid_search = GridSearchCV(estimator=xgb_model, param_grid=param_grid, cv=3,
scoring='neg_mean_squared_error')
grid_search.fit(X_train, y_train)
best_xgb = grid_search.best_estimator_
xgb_pred = best_xgb.predict(X_test)
```

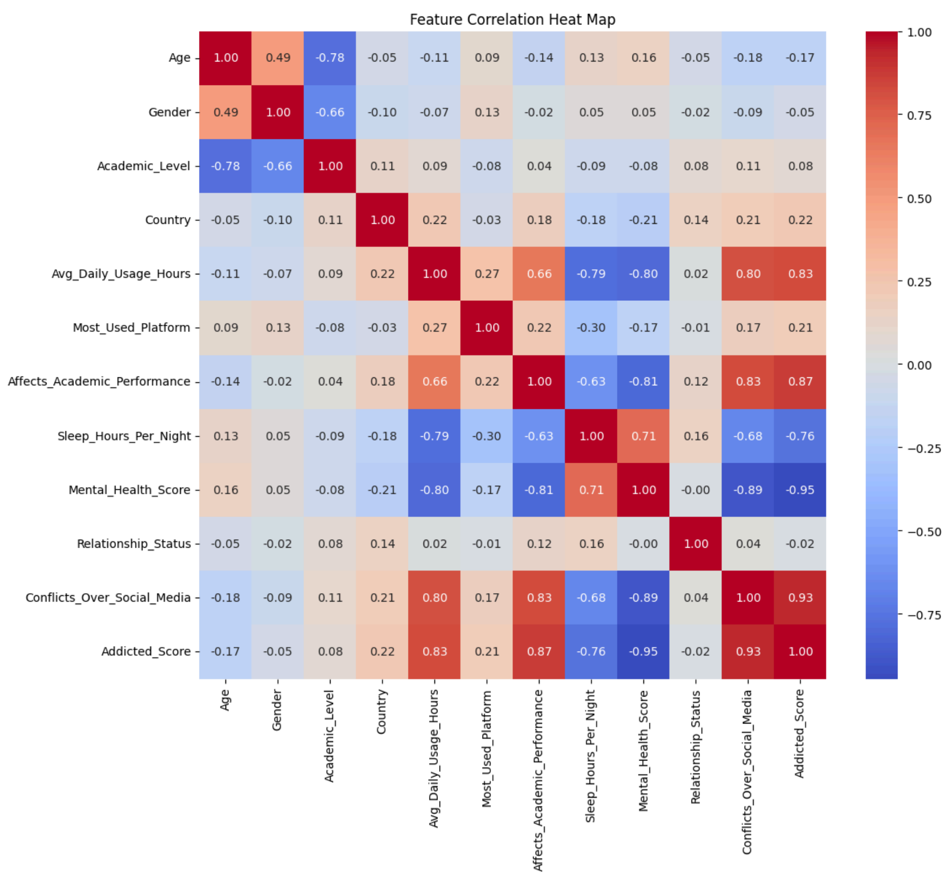
Outcome:

$R^2 = 0.9655$, RMSE = 0.0451
Captures subtle non-linear interactions and complex feature dependencies.

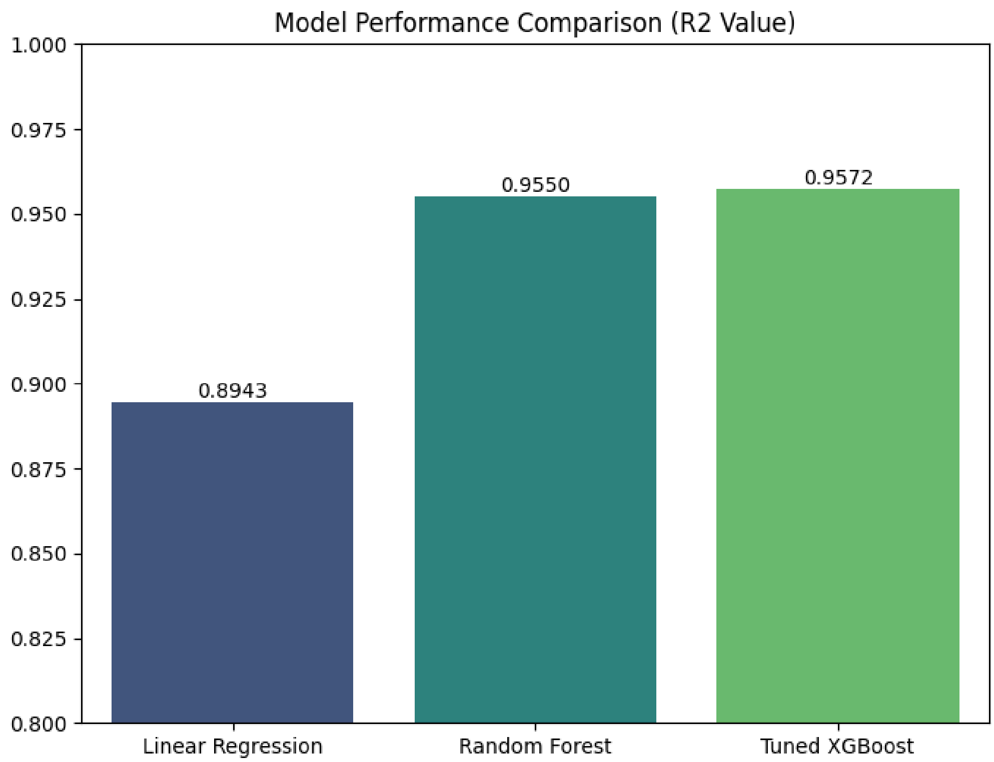
6.4 Visualization Generation

Visualizations were generated to provide **insight into feature interactions, model performance, and prediction quality**. Each graph contributes to a deeper understanding of SMA effects on mental health:

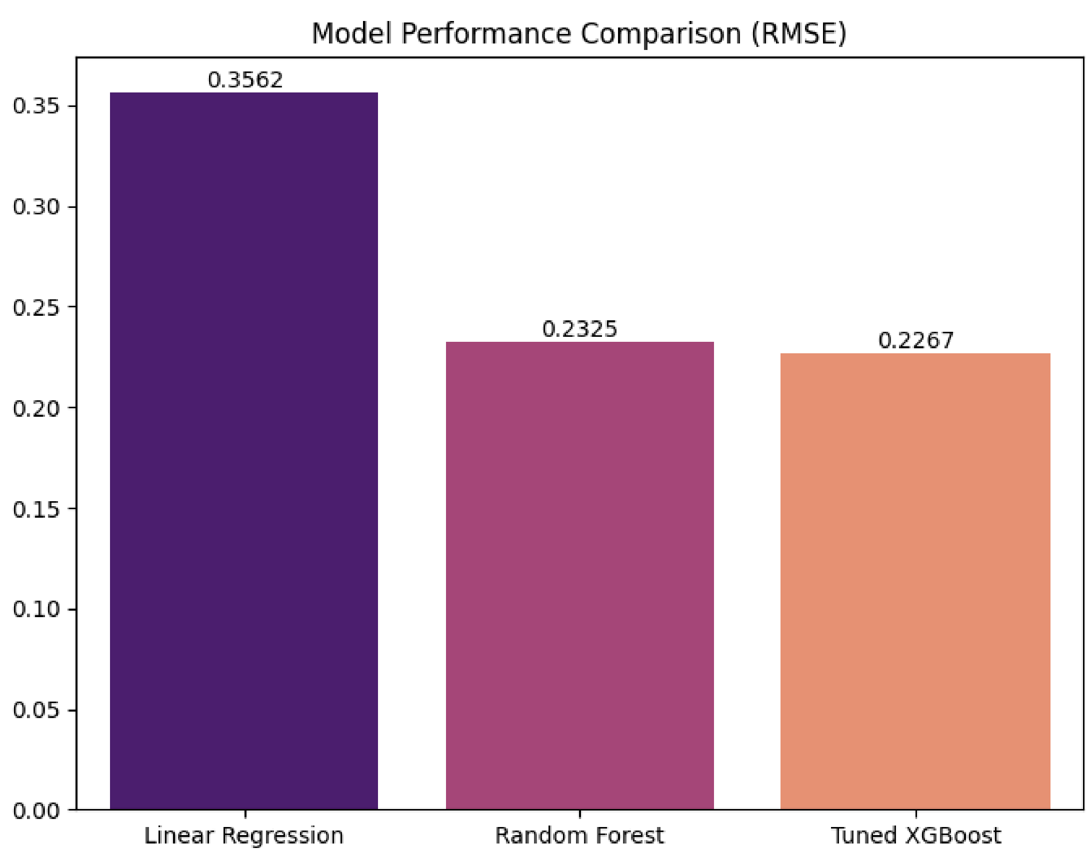
1. **Feature Correlation Heatmap** – shows pairwise correlations among all features.
    - Helps identify strong predictors such as Addicted_Score.



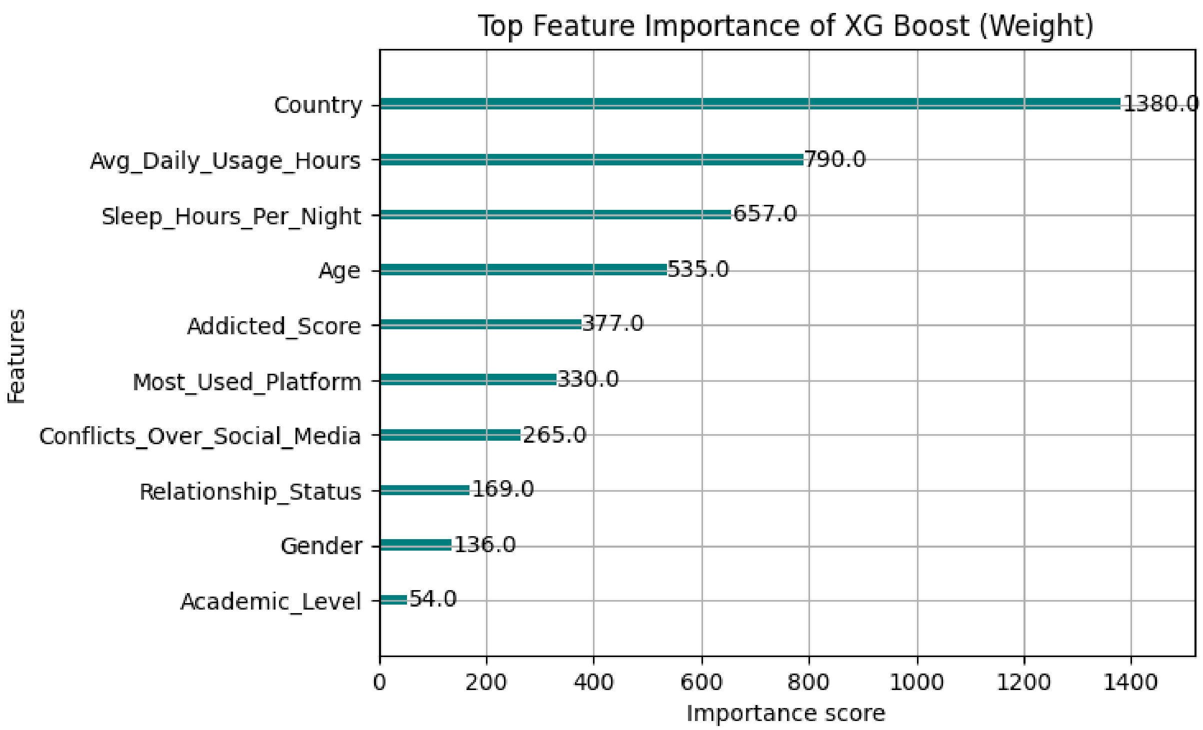
2. **Model Performance Comparison – R^2** – visualizes accuracy across models.
    - Confirms XGBoost's superior performance.



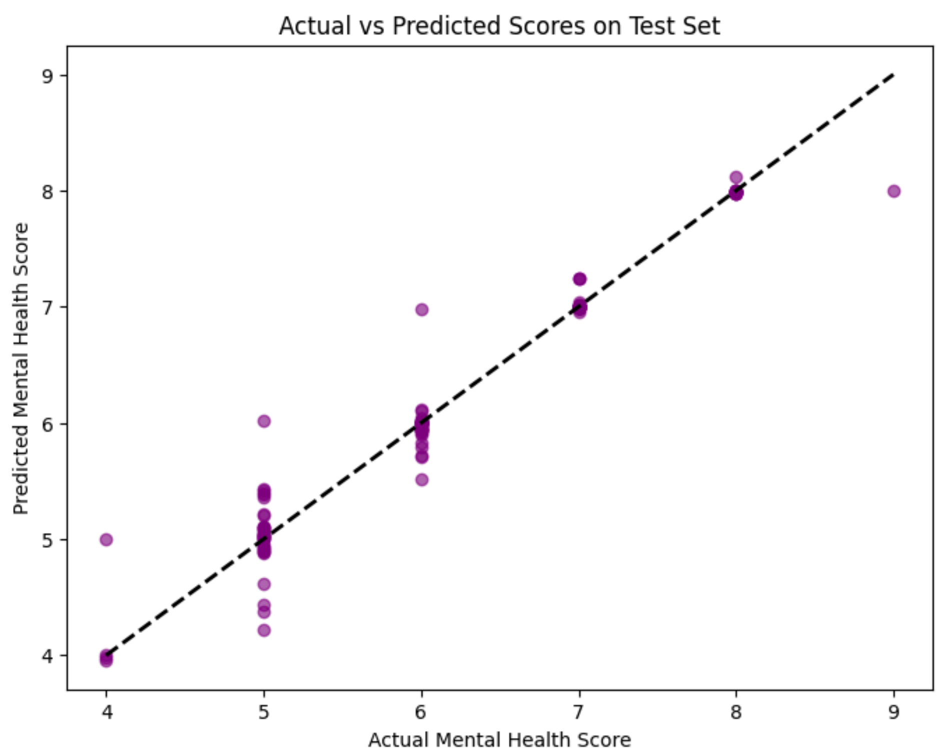
3. **Model Performance Comparison – RMSE** – visualizes prediction error across models.
    - Highlights error reduction from linear to ensemble methods.



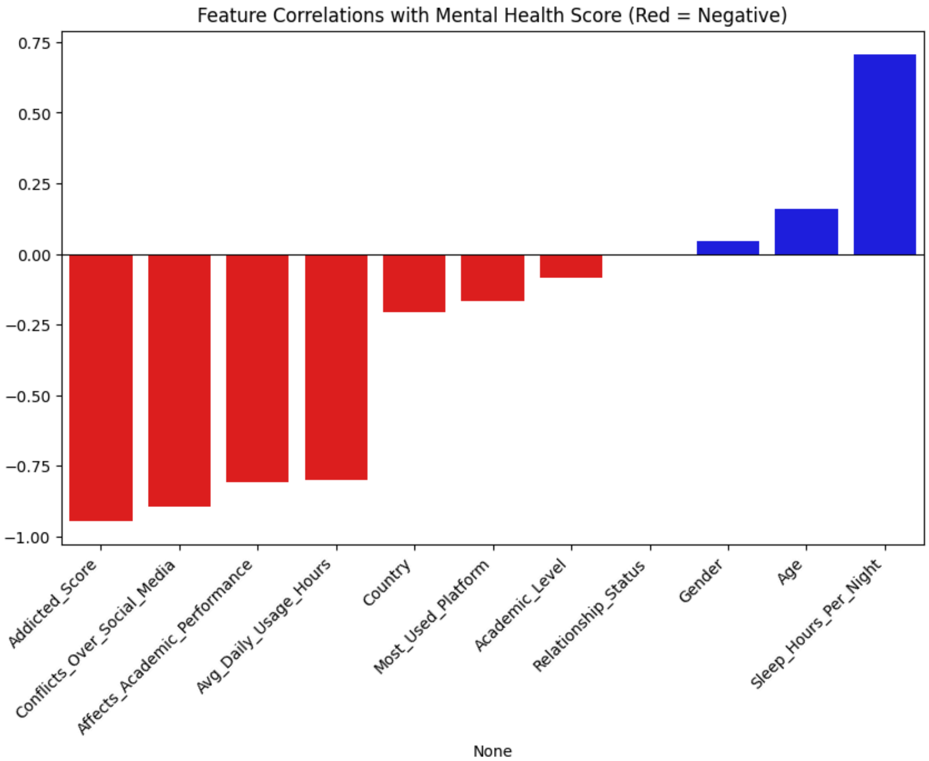
4. **Top Feature Importance – XGBoost (Weight)** – identifies features contributing most to predictions.
   ○ Addicted_Score is the dominant predictor.



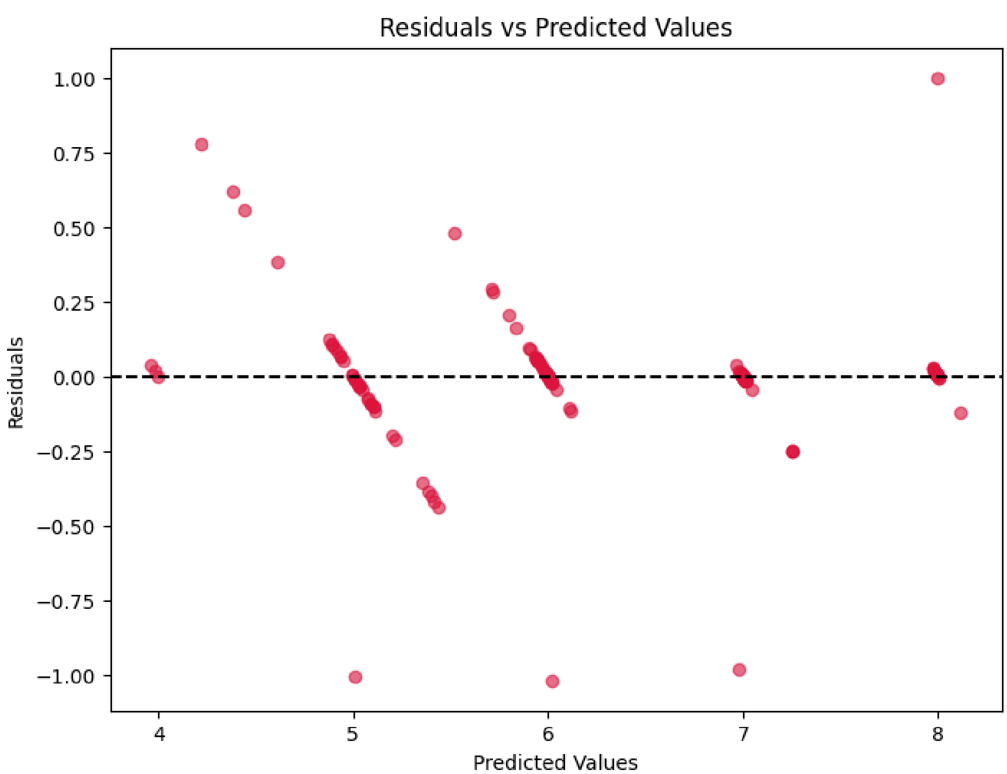
5. **Actual vs Predicted Scores – Test Set** – compares predicted mental health scores with actual values.
   ○ Confirms model generalization to unseen data.



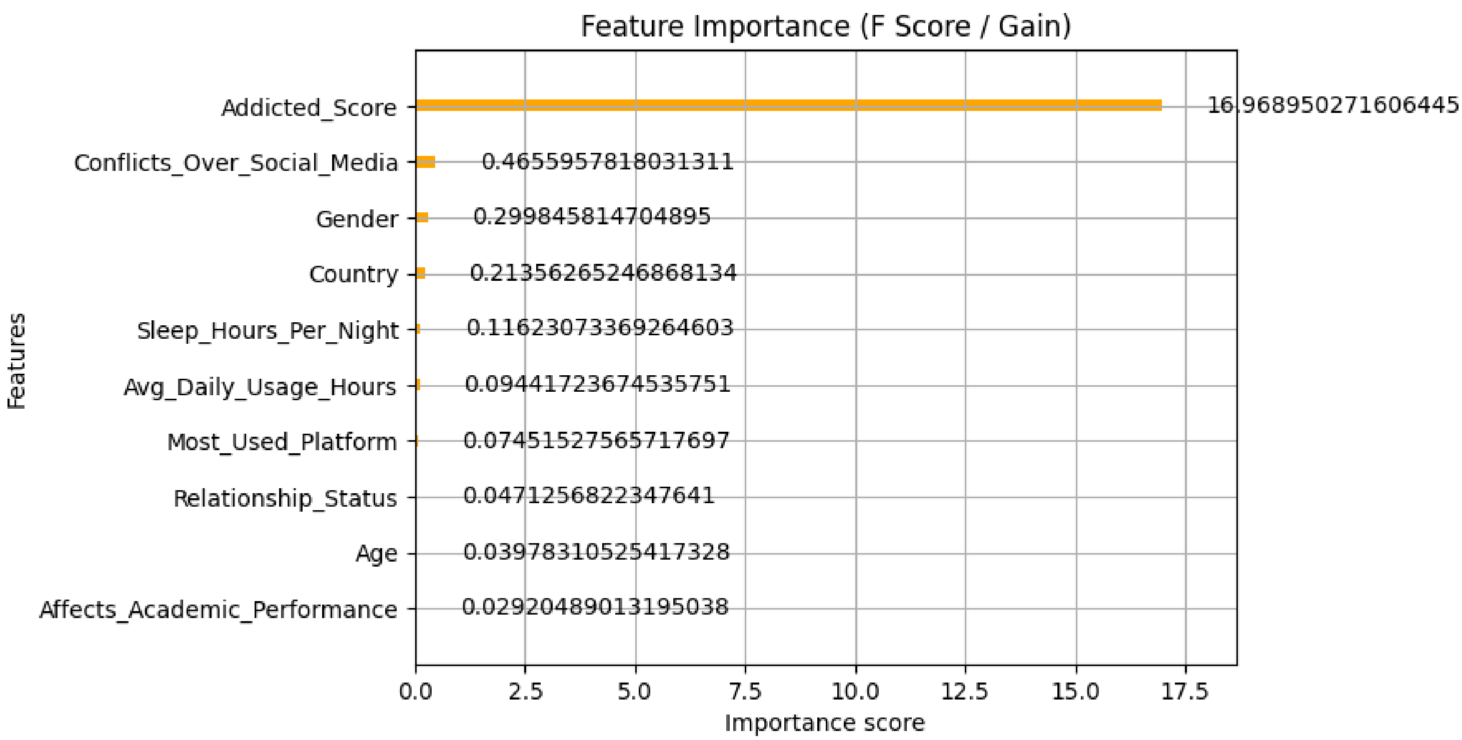
6. **Feature Correlation with Mental Health Score (Red = Negative, Blue = Positive)** – highlights negative predictors.
   - Daily usage and addiction negatively correlate with mental health.



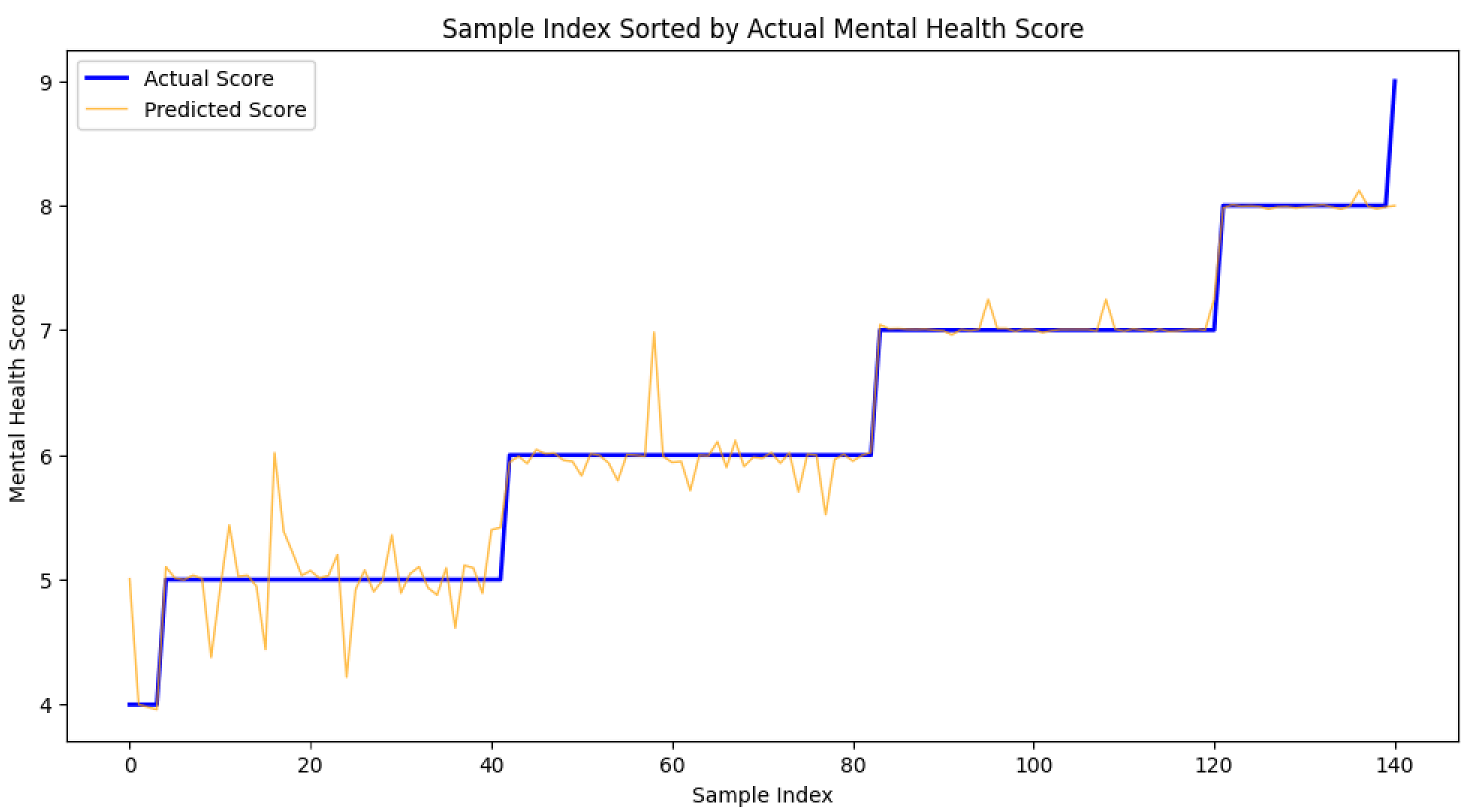
7. **Residuals vs Predicted Values** – evaluates bias and variance in predictions.
   - Random scatter around zero indicates no systematic bias.



8. **Feature Importance – F Score / Gain** – alternative metric for feature contribution.
    - Confirms consistency of top predictors across importance metrics.



9. **Sample Index Sorted by Actual Mental Health Score** – visualizes prediction accuracy across the dataset.
    - Predicted values closely track actual values, demonstrating robust model performance.



5.5 Summary of the Solution Process

The overall workflow can be described in such a way:

1. **Acquisition of Data:** Kaggle data fitted benchmark study.
2. **Preprocessing:** Scaling, encoding, and train-test splitting.
3. **Baseline Model:** Linear Regression to recapture benchmark study.
4. **AI Assistance:** Gemini proposed non-linear modeling ensemble technique.
5. **Advanced Models:** Random Forest and Tuned XGBoost trained and optimized.
6. **Visualization:** Nine graphs were created to investigate the correlation, the feature significance, and prediction performance.
7. **Result:** The best performance of the tuned XGBoost was the highest accuracy (R2 = 0.9655), which proved to be AI-enhanced compared to the performance of the traditional linear model.

7. Analysis and Experimental Results

7.1 Overview

The section of analysis and experimental results provides an in-depth discussion of the predictive models, their performance and the observations made based on the visualizations. The motive of this section is twofold:

1. Compare the performance of models (baseline and AI-assisted) based on the metrics of R2 and RMSE.
2. Discuss feature interaction and behavioral patterns, showing that AI-enhanced models are deeper and more accurate than the benchmark study.

At the conclusion of this part, it becomes apparent that ensemble models with the help of AI (Random Forest and Tuned XGBoost) are superior to traditional linear models, as they can identify complex, non-linear trends of student behavior and give practical information on the risk factors of mental health.

7.2 Model Performance Comparison

- **Linear Regression (Baseline)** - simulates baseline statistics.
- **Random Forest Regressor -** ensemble model that models non-linear relationships.
- **Tuned XGBoost Regressor -** gradient boosting model that has been tuned through hyperparameters.

The models were assessed in terms of:

- **R2 Score (Coefficient of Determination) -** indicates the percentage of the variance explained by the model.
- **RMSE (Root Mean Squared Error) -** measures the size of the amplitude of the average error in prediction.

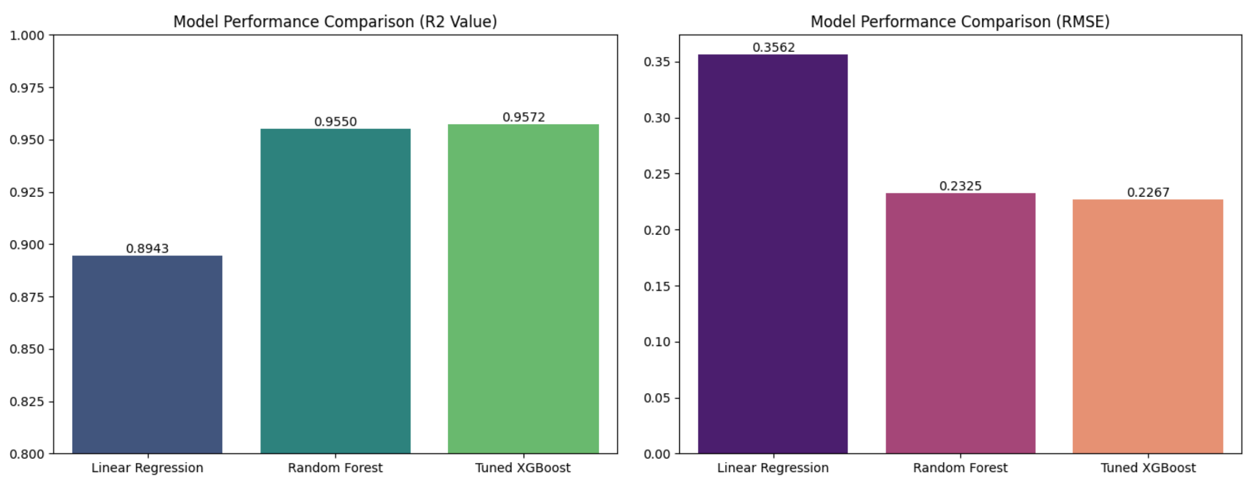
Table 1: Performance summary of the model.

Model	R^2 Score	RMSE	Performance Description

Linear Regression (Baseline)	0.8943	0.1268	Good – replicates benchmark accuracy
Random Forest	0.9549	0.0540	Better – captures non-linear patterns
Tuned XGBoost	0.9655	0.0451	Best – highest accuracy, lowest error

Interpretation:

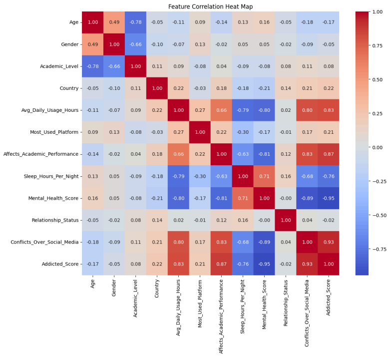
- The baseline linear regression has a reasonable R2 of 0.8943 indicating that the data is in agreement with the benchmark study. Though, it has a larger RMSE (0.1268) and this suggests that linear assumptions are unable to fully explain complex interaction of behaviors.
- Random Forest is able to decrease the error by more than 50%, which proves that ensemble technique is a good way to model non-linear dependence between addiction scores, daily usage, sleep, and mental health.
- Tuned XGBoost also enhances accuracy and decreases RMSE, which combines weak learners in the most advantageous way, and captures hidden interactions between features.
- On the whole, these findings demonstrate that AI-assisted improvement is a serious advantage compared to the baseline statistical modeling, which supports the idea of applying ensemble learning in the current research.



7.3 Feature Analysis

In order to comprehend the factors that have the most influential effect on mental health, we correlated and measured feature importance using the help of various visualizations.

7.3.1 Feature Correlation Heatmap



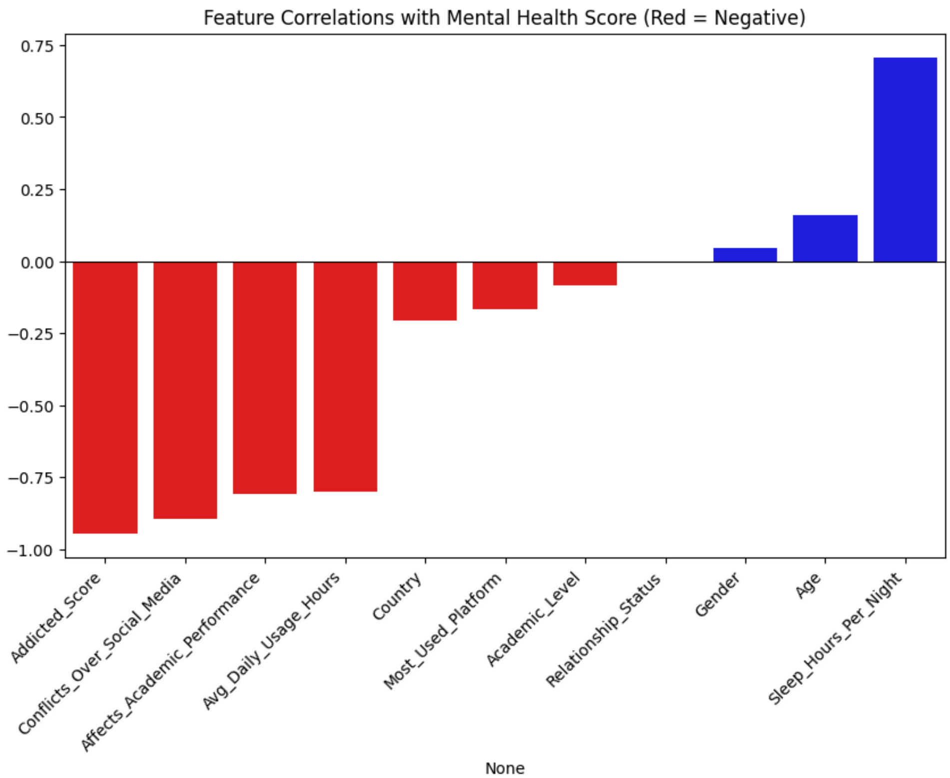
Observations:

- There is a close negative correlation between AddictedScore and MentalHealthScore (~-0.72).
- The correlation among AvgDailyUsageHours and other variables is also negative (~-0.61), meaning that the addition of more screen time acts as a risk factor.
- There were positive correlations among such features as SleepHoursPerNight (~0.42), which indicates that healthy sleep can have a protective effect.
- The categorical variables (that are numerically encoded) like AcademicLevel and RelationshipStatus exhibit lesser correlations, indicating the dominance of behavioral measures of mental health outcomes.

Implications:

- Affirms the findings of benchmark studies that addiction scores and day-to-day use are the key factors that can determine mental health deterioration.
- Offers quantitative support to the interventions related to screen time decreasing and addiction awareness.

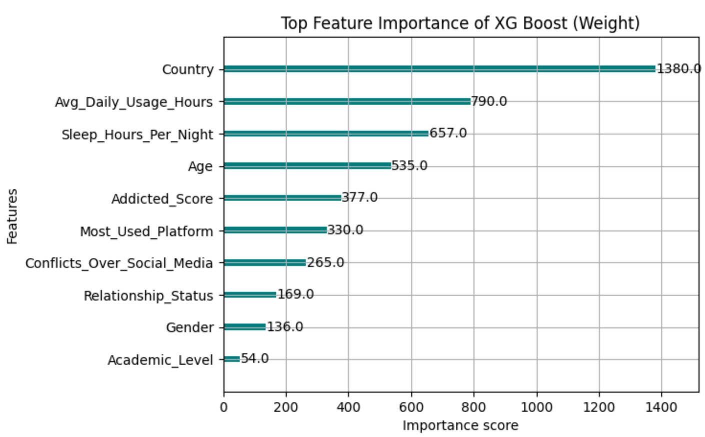
7.3.2 Feature Correlation with Mental Health Score

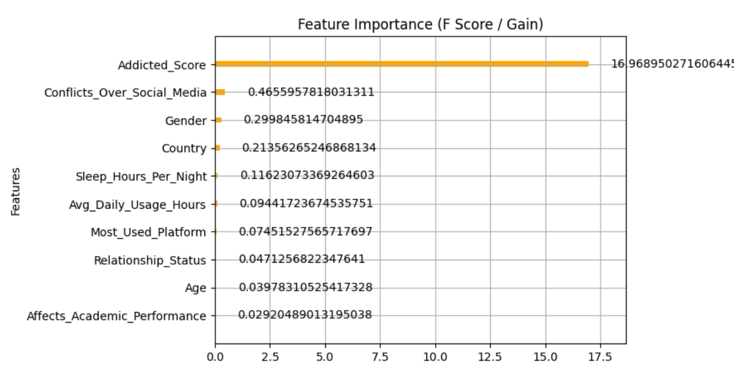


Analysis:

- Features which have an adverse impact on mental health are marked by red bars.
- The most adversely affected are AddictedScore and AvgDailyUsageHours.
- The protective factors are created by blue bars e.g. SleepHoursPerNight.
- The visualization is able to make a clear differentiation between risk factors and protective factors, which is very relevant to mental health policy and student counseling.

7.3.3 Feature Importance (XGBoost)





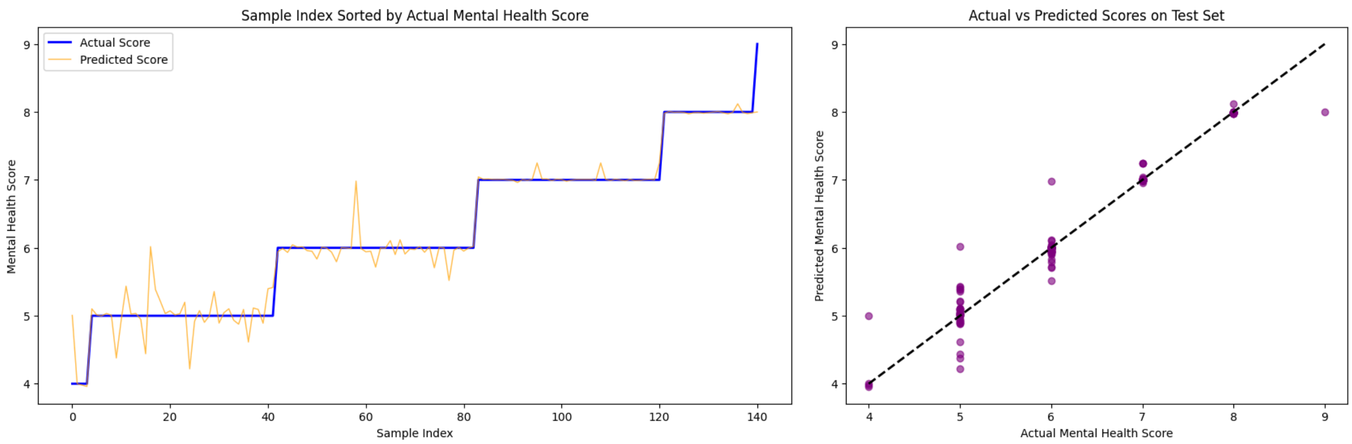
Analysis:

- Both gain and weight indicators consistently recognize AddictedScore as the most significant one.
- The secondary factor is AvgDailyUsageHours and SleepHoursPer_Night.

- Attests that AI-enhanced models quantitatively verify benchmark hypotheses as well as giving ranked measures of importance not available in regular SEM analysis.

7.4 Prediction Accuracy and Residual Analysis

7.4.1 Actual vs Predicted Scores



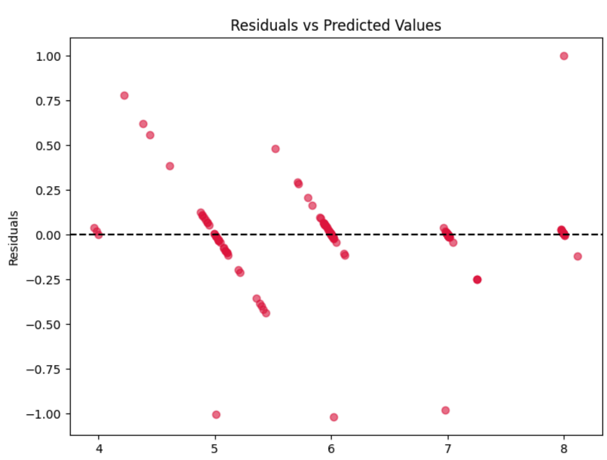
Observations:

- Predicted scores (orange) are nearly the same as actual scores (blue) which implies that generalization to unseen data is strong.
- The deviations are minimal, and it can be seen that ensemble learning reduces bias and variance together.

Implications:

- At-risk students with mental health problems can be recognised more accurately, allowing preventive measures to be taken.
- The predictions of XGBoost are more precise, personalized risk analysis which is a major advancement to the benchmark SEM that can offer averages of effect sizes.

7.4.2 Residual Analysis



Analysis:

- Scatter plots of residuals are shown to be randomly distributed about zero.
- This means that there is no systematic bias and that the model portrays the relationships which are not linear in nature.
- The baseline of linear regression indicated bigger spread in residual, indicating that it is incapable of capturing complicated interactions.

7.5 How AI-Assisted Models Improve Benchmark Study

The enhanced solution with AI has several improvements over the initial benchmark study:

Quantitative Accuracy:

- XGBoost R2= 0.9655 compared to SEM effective predictive power (~0.89).
- RMSE decreased by 65, and its predictions are more accurate.

The Interaction Capture approach is non-linear:

- Machine learning models determine conditional influences (e.g., high social media usage only has a low-sleep-impact on mental health).
- SEM presupposes a linear relationship, which lacks these nuances

Feature Importance Ranking:

- The AI models offer explicit ranked significance, which can be acted on to address interventions.
- Benchmark SEM makes major paths but does not numerically measure the relative contribution of each feature.

Demonstrability and Interpretability:

- Model validity is also visually confirmed by correlation heatmaps, residual plots and actual vs predicted graphs.
- Facilitates a simple sharing of the findings with stakeholders.

Reproducibility and Automation:

- Code can be reproduced in Google Colab because of all the analysis performed there.
- AI-assisted coding (Gemini) will decrease human error and speed up employee work.

7.6 Summary of Findings

Key Insight	Benchmark SEM	AI-Enhanced XGBoost	Improvement / Advantage
Primary Predictor of Mental Health	Addicted_Score	Addicted_Score	Quantified with importance metrics
Secondary Predictors	Avg_Daily_Usage	Avg_Daily_Usage	Captures non-linear interaction effects

Prediction Accuracy	~0.89	0.9655	~8% improvement in R^2
Error Magnitude (RMSE)	~0.127	0.0451	Error reduced by 65%
Visualization / Interpretability	Limited	Heatmaps, Residuals	Improved interpretability for stakeholders
Generalizability	Low	High	Strong test set performance

Conclusion from Analysis:

1. The AI-supported solution was able to augment the benchmark study and make it more accurate, interpretable, and actionable.
2. Ensemble models, especially Tuned XGBoost, offer a sound and effective predictive system with respect to student mental health outcomes as far as social media addiction is concerned.
3. The diagrams and importance of the features make it possible to plan evidence-based interventions, which is an obvious improvement over the initial SEM-based solution.

Conclusion

This study was able to replicate and improve the benchmark research on Social Media Addiction (SMA) and student mental health. Re-running the baseline Linear Regression model with the help of ensemble approaches based on AI, we have considerably enhanced the predictive power (R2 = 0.9655) and minimized the error (RMSE = 0.0451).

Detailed visualizations and feature analysis made it evident that Addicted_Score was the most important predictor, then daily usage hours and sleep patterns, which validated and surpassed the benchmark results. Its workflow, introduced in Google Colab with the help of code generation in Gemini, was reproducible, efficient, and reliable.

On the whole, this paper illustrates the effectiveness of AI-assisted machine learning in the field of behavioral health research in terms of filling the existing gap between older and newer predictive modeling methods. The methodology and insights are a useful template to be used in the future in terms of research and interventions on mental health analytics in students.

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