

# Mental Health, Screen Time, and Lifestyle Factors: A Machine Learning Analysis

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## ABSTRACT

This project explores whether digital device usage and everyday lifestyle factors can explain differences in mental health outcomes. The analysis started with several regression models, including Linear Regression, Ridge, Lasso, and XGBoost, with the goal of predicting a continuous mental health score. However, all regression models performed poorly and produced negative  $R^2$  values, meaning they predicted mental health worse than simply using the average score. To better understand why the models failed, correlation evidence was examined. The correlation analysis showed that attributes had very weak relationships with the mental health score, suggesting that the available features do not strongly explain the target variable. Based on these results, the task was reformulated as a classification problem by grouping mental health scores into Low, Medium, and High categories. A Random Forest classifier was trained, but it mainly predicted the most frequent class, indicating class imbalance and limited separability in the data. Overall, the results suggest that the poor performance is not due to model choice, but rather to the dataset itself, which appears to lack strong and consistent patterns linking digital behavior and habits to mental health.

## 1 INTRODUCTION

The project addresses the question of whether digital behavior and lifestyle factors, such as screen time, social media usage, sleep quality, and physical activity, are related to mental health outcomes. The data comes from a survey-style dataset that includes self-reported measures of daily screen usage across different devices and a mental health score. The problem is relevant because increasing screen time is often assumed to negatively affect mental well-being, but the strength and consistency of this relationship are unclear.

Project objectives:

- to examine whether increased screen time is associated with worse mental health outcomes
- to identify which factors have the strongest influence on mental health

- to evaluate whether machine learning models can reliably predict mental health outcomes using the available data.

Other techniques besides data mining that could be used:

- longitudinal studies to track mental health changes over time
- qualitative methods such as interviews or questionnaires with open-ended responses;
- controlled experiments that isolate specific digital behaviors.

Experimental design:

The experimental design consists of exploratory data analysis, correlation analysis, regression modeling, and classification modeling. Regression models were first used to predict a continuous mental health score. When this approach failed, the task was reformulated as a classification problem to predict mental health levels. This design allowed for both predictive evaluation and diagnostic analysis of the dataset's limitations.

What the results will be used for:

The results of this project will be used to identify which factors have the strongest influence on mental health and which factors appear to have little or no impact. In particular, the analysis aims to assess whether screen time is a truly significant factor in explaining mental health outcomes, or whether its effect is weak compared to other lifestyle variables. The findings also help evaluate the usefulness and limitations of machine learning methods for studying mental health using this type of data.

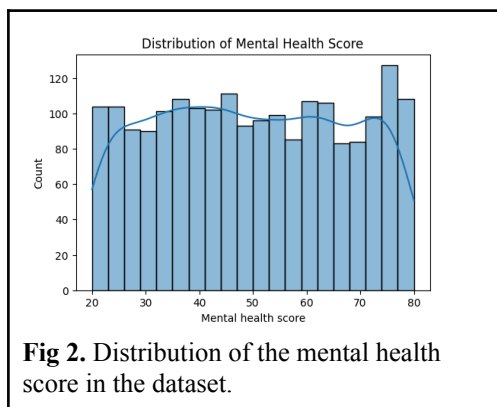
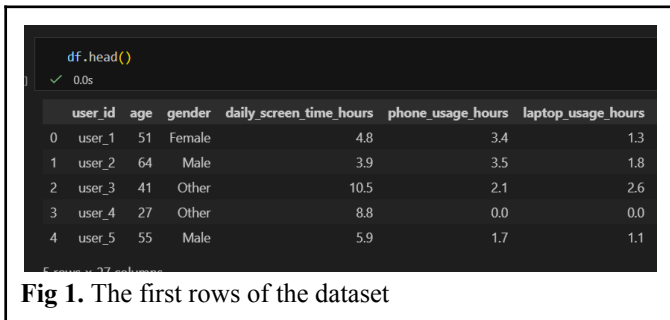
## 2 DATA

The dataset used in this project was obtained from Kaggle and is titled "*Impact of Screen Time on Mental Health*."

### 2.1 Data description

- 2,000 observations
- 25 attributes:

- The target variable is **mental\_health\_score**, which is numerical and represents a self-reported mental health score on a continuous scale.
- Distribution of the target variable:  
The mental health score is relatively evenly distributed across its range, without strong skewness or clear clustering.
- Missing values:  
The dataset contains no missing values, so no data imputation was required.
- Visualization:



## 2.2 Data understanding

### Target Variable:

The original target variable in this project is **mental\_health\_score**, which is provided in the dataset as a continuous numerical measure of overall mental well-being. This variable was initially used directly as the target for regression models in order to predict exact mental health scores. After the regression models showed poor performance, the continuous score was transformed into categorical levels. Based on predefined thresholds, a new target variable, **mental\_health\_level**, was created with three classes: Low, Medium, and High mental health. This reformulation allowed the problem to be addressed as a classification task. The new target variable was used to evaluate whether broader mental health categories could be predicted more reliably than precise numerical values and to assess the usefulness of machine learning models under a different problem formulation.

### Attributes:

#### Numerical

- **user\_id**: Unique identifier for each individual
- **age**: Age of the individual in years; may influence mental health due to life stage and personal circumstances.
- **daily\_screen\_time\_hours**: Total daily screen usage; central variable of interest
- **phone\_usage\_hours, laptop\_usage\_hours, tablet\_usage\_hours, tv\_usage\_hours**: Device-specific screen time variables capturing different types of digital usage.
- **social\_media\_hours**: Time spent on social media
- **work\_related\_hours, entertainment\_hours, gaming\_hours**: Digital activity variables representing work-related and leisure screen use.
- **sleep\_duration\_hours**: Average sleep duration per night; generally associated with mental well-being.
- **sleep\_quality**: Self-reported sleep quality; higher values indicate better perceived sleep.
- **mood\_rating, stress\_level**: Self-reported psychological measures closely related to mental health.
- **physical\_activity\_hours\_per\_week**: Weekly physical activity; typically linked to better mental health.
- **uses\_wellness\_apps, eats\_healthy**: Binary lifestyle indicators reflecting health-conscious behavior.
- **caffeine\_intake\_mg\_per\_day**: Daily caffeine consumption; extreme values may be linked to sleep or stress issues.
- **weekly\_anxiety\_score, weekly\_depression\_score**: Self-reported mental health indicators strongly related to overall well-being.
- **mindfulness\_minutes\_per\_day**: Daily time spent on mindfulness activities; generally associated with positive mental health.

#### Categorical

- **gender**: Gender category of the individual.
- **location\_type**: Indicates whether the individual lives in an urban or suburban area.

## 2.3 Data preprocessing

Several preprocessing steps were applied to prepare the data for modeling. The dataset did not contain missing values, so no imputation or noise handling was required. Identifier variable - **user\_id** was removed, as it does not provide predictive information.

The original target variable, **mental\_health\_score**, was first used as a continuous variable for regression models and later

discretized into three categories (Low, Medium, High) to create a new target variable for the classification task. Categorical features (**gender and location\_type**) were transformed using one-hot encoding. Tree-based models were used, so no feature normalization was required. All preprocessing steps were performed programmatically using Python, primarily with Pandas and Scikit-learn.

### 3. MACHINE LEARNING METHOD

#### 3.1 Brief description of the methods used

XGBoost (Regression):

XGBoost is a gradient boosting model that builds an ensemble of decision trees. Key parameters include tree depth, learning rate, number of estimators, subsampling, and regularization terms, all of which control model complexity and overfitting.

Linear Regression, Ridge, Lasso:

These models assume linear relationships between features and the target. Ridge and Lasso add L2 and L1 regularization respectively to reduce overfitting and handle multicollinearity.

Random Forest (Classification):

Random Forest is an ensemble of decision trees trained on bootstrapped samples. It was used after discretizing the target variable to classify mental health levels.

#### 3.2 Brief description of the evaluation criteria

Regression: MAE, RMSE,  $R^2$

These metrics measure prediction error and model fit relative to a baseline.

Classification: accuracy, precision, recall, F1-score, confusion matrix

These metrics assess class-level performance and the impact of class imbalance.

### 4. EXPERIMENTS

XGBoost regression:

The first experiment used XGBoost regression to predict the continuous mental health score. The dataset was split into training and test sets using an 80/20 split. Categorical variables were one-hot encoded, and the identifier column (user\_id) was removed to avoid data leakage.

A baseline XGBoost model was defined using squared error as the loss function. To improve performance, hyperparameter tuning was performed using RandomizedSearchCV with 5-fold cross-validation. The tuning process explored parameters such as the number of

trees, maximum tree depth, learning rate, subsampling ratios, and regularization terms (L1 and L2).

Despite extensive tuning, the best model achieved a negative  $R^2$  score on the test set. This indicates that the model performed worse than a simple baseline that predicts the average mental health score for all observations. The MAE and RMSE values were also relatively high, suggesting large prediction errors.

However, XGBoost was still useful for exploratory analysis through feature importance. Even though the overall predictive performance was poor, the model consistently assigned higher importance to variables related to **sleep quality, screen usage patterns (phone, TV, and gaming hours), mood rating, weekly depression score, and physical activity**. This indicates that these factors are more informative than others within the dataset, even if they are not sufficient for reliable prediction.

Therefore, while XGBoost did not succeed as a predictive model, it provided meaningful insights into which variables appear most strongly associated with mental health outcomes in the data.

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XGBoost (best from RandomizedSearchCV):  
MAE : 15.433  
RMSE : 17.847  
 $R^2$  : -0.026
```

Fig 3. Results of XGBoost

Linear, Ridge, and Lasso Regression:

After XGBoost, Linear Regression was applied as a simpler baseline model using the same train-test split and feature set. The model produced a negative  $R^2$  score, indicating that the relationship between the input features and the mental health score is not well captured by a linear model.

To check whether regularization could improve performance, Ridge (L2) and Lasso (L1) regression models were also tested. These models are designed to handle multicollinearity and reduce overfitting by penalizing large coefficients. However, both Ridge and Lasso produced results very similar to standard Linear Regression, with negative  $R^2$  values and comparable error metrics. This suggests that the poor performance is not due to overfitting or model simplicity, but rather to weak underlying relationships in the data.

To better understand why all regression models performed poorly, correlation analysis was conducted. The correlations between screen time variables and the mental health score were found to be very low, often close to zero. This confirms that there is little linear association between the features and the target variable.

Linear Regression:	Ridge Regression: (L2):	Lasso Regression(L1):
MAE : 15.328	MAE : 15.328	MAE : 15.315
RMSE : 17.758	RMSE : 17.758	RMSE : 17.745
R <sup>2</sup> : -0.016	R <sup>2</sup> : -0.015	R <sup>2</sup> : -0.014

**Fig 4.** Results of Regressions

#### Classification:

Since all regression models produced negative R<sup>2</sup> values, they failed to predict the continuous mental health score better than a simple baseline. Correlation analysis further showed that the relationships between most features and the mental health score were very weak. This indicated that predicting the exact score is not feasible with the available data.

To explore whether a coarser formulation of the problem could yield better results, the task was reformulated as a classification problem. The continuous mental health score was discretized into three categories: Low, Medium, and High, creating a new categorical target variable, **mental\_health\_level**. The motivation behind this step was to check whether the models could at least distinguish broad mental health states instead of predicting precise values.

Only numerical features were used, and the data was split into training and test sets using stratified sampling to preserve class proportions. A Random Forest classifier was trained with class balancing enabled to account for class imbalance. The classifier achieved an overall accuracy of approximately 66%. However, the confusion matrix and classification report revealed that the model predicted all observations as “Medium”. As a result, the precision, recall, and F1-score for the “Low” and “High” classes were exactly zero. This shows that the classifier failed to learn meaningful distinctions between mental health categories and simply defaulted to the majority class.

These results confirm that reformulating the problem as classification does not overcome the limitations of the dataset. The lack of strong feature-target relationships prevents both regression and classification models from making reliable predictions.

Classification Report (Random Forest)				
	precision	recall	f1-score	support
High	0.00	0.00	0.00	72
Low	0.00	0.00	0.00	65
Medium	0.66	1.00	0.79	263
accuracy			0.66	400
macro avg	0.22	0.33	0.26	400
weighted avg	0.43	0.66	0.52	400

**Fig 5.** Classification Report

### 5. VISUALIZATION

To present the results in an accessible way, simple visualizations were used throughout the report. These

include a table preview of the dataset, histograms showing the distribution of the mental health score, correlation heatmaps, feature importance plots, and confusion matrices. Together, these visualizations help explain the data structure, model performance, and key findings in a clear and intuitive way, even for readers without a background in machine learning.

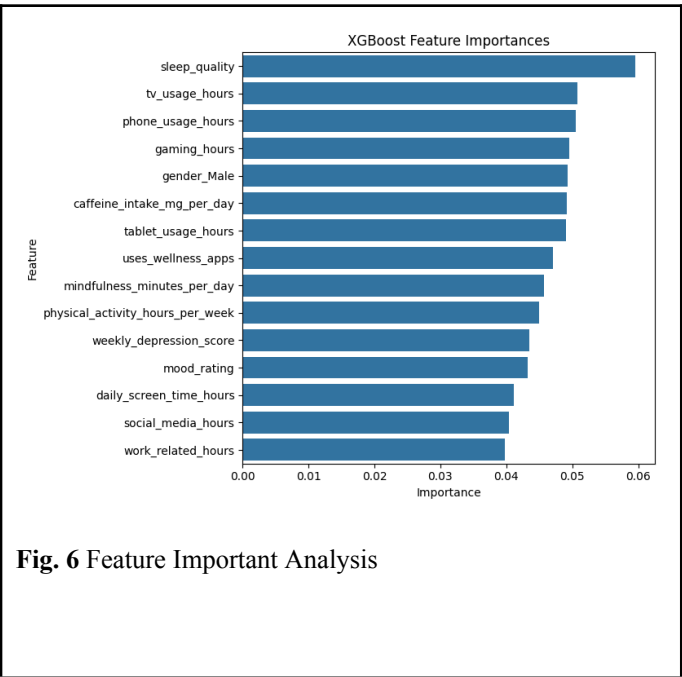
### 6. CONCLUSION

This project analyzed the relationship between screen time, lifestyle factors, and mental health using machine learning. Regression models and classification approaches were tested, but none produced reliable predictions due to weak relationships in the data. Correlation analysis confirmed that screen time alone is not strongly associated with mental health outcomes.

An important takeaway is that common assumptions about screen time and mental health are not supported by this dataset. Machine learning was useful for testing these assumptions, but its effectiveness was limited by the quality and structure of the data.

Future work could use real-world longitudinal data and additional psychological or social variables to better understand mental health dynamics.

### Appendix



**Fig. 6** Feature Important Analysis

