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Implementation of Ridge Regression and SHAP for Analyzing Anxiety Levels Based on the Digital Behavior of Social Media Users

Yuri Yuliani [1], Kukuh Panggalih [2*], Kudiantoro Widianto [3], Erni [4], M. Iqbal Alifudin [5], Irwan Heliawan [6]

[1] *Bina Sarana Informatika University, Faculty of Engineering and Informatics, Information Systems Program, Jl. Kramat Raya, Senen District, Central Jakarta 10450, Indonesia*
[2,3,5] *Bina Sarana Informatika University, Faculty of Engineering and Informatics, Information Technology Program, Jl. Kramat Raya, Senen District, Central Jakarta 10450, Indonesia*
[4] *Bina Sarana Informatika University, Pontianak Campus, Faculty of Engineering and Informatics, Informatics Study Program, Jl. Abdul Rahman Saleh No. 18, Pontianak Tenggara District, West Kalimantan 78124, Indonesia*
[6] *Nusa Mandiri University, Faculty of Information Technology, Informatics Program, Jl. Jatiwaringin Raya No. 02, Makasar Subdistrict, East Jakarta 13620, Indonesia*

Keyword

Anxiety Digital Behavior; Anxiety Levels; Explainable Artificial Intelligent; Machine Learning; Ridge Regression; SHAP

****Corresponding Author:***
kukuh.kpg@bsi.ac.id

Abstract

Advances in technology have led to an increase in the frequency of smartphone, social media, and various digital app usage in daily life. These digital activities give rise to various digital behaviors—such as screen time, number of notifications, social media usage, and sleep patterns—which can be evaluated to understand users mental health. High digital device usage is suspected to be associated with increased anxiety levels among users. Therefore, this study aims to analyze the impact of digital behaviors on anxiety levels by utilizing explainable machine learning approaches and AI. This study uses the dataset, comprising 500 data points obtained from Kaggle. The research stages consist EDA, feature engineering, target leakage evaluation, comparison of several machine learning algorithms, cross-validation, and model interpretation using SHAP. Based on the EDA results, the variables social_media_time_min, notification_count, and digital_addiction_score showed a positive relationship with anxiety_level. During the model-building process, the variable digital_wellbeing_score was removed because it had a very high correlation with anxiety_level -0.84, which could lead to potential target leakage. The algorithm comparison revealed that the Ridge Regression model performed best compared to Random Forest, SVR, and XGBoost Regression, with an R^2 score of 0.221 and an RMSE of 1.627. Additionally, the results of 5-Fold Cross Validation showed an average R^2 Score of 0.158 with a standard deviation of 0.062, indicating that the model demonstrated fairly consistent performance. The SHAP interpretation reveals that notification_count and social_media_time_min are the variables that most strongly influence the prediction of anxiety_level. The results of this study indicate that digital behavior affects users anxiety levels, although the relationships among the variables remain quite complex. This study also emphasizes the importance of evaluating the target leakage and understanding the model in the development of machine learning-based mental health analysis to ensure that the prediction results are more objective and clear.

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1. Introduction

The way people go about their daily lives has been shaped by technological advancements. The use of smartphones, social media platforms, and digital applications has become an integral part of how we communicate, entertain ourselves, and work. The frequent use of digital devices generates a wide range of digital traces that can be analyzed using data science and machine learning methods.

Excessive use of digital devices can have a negative impact on users' mental health, such as causing anxiety, stress, and sleep disturbances. Previous research has shown that digital activities such as social media use, the duration of digital device use, sleep patterns, and the frequency of notifications are linked to users' mental well-being [1],[2].

In AI, machine learning has been widely applied to identify and predict mental health conditions based on user behavioral data. Previous research has shown that smartphone behavioral data can be used to estimate the risk of mental disorders by utilizing machine learning methods and digital phenotyping [3]. Additionally, previous research has also shown that machine learning algorithms such as Linear Regression, Random Forest, and XGBoost can be used to analyze mental health conditions based on users' digital and psychological behavioral indicators [4]. Similarly, research indicates that machine learning algorithms have the potential to advance digital data-based mental health analysis [5].

Beyond model accuracy, understanding prediction results is also a crucial aspect of current AI research. Most machine learning models are black-box in nature, making them difficult for users to understand. Consequently, recent research has begun incorporating Explainable Artificial Intelligence (XAI) to enhance model transparency. One popular XAI technique is SHAP (SHapley Additive exPlanations), which can help determine the importance of features so that the model's predictions are clearer and easier to understand [6].

Research in Indonesia on mental health using machine learning continues to make progress. The results show that a combination of XGBoost and SHAP techniques can be used to clearly analyze the relationship between mental health and students' academic performance [7]. In addition, other studies have revealed that behavioral features can be utilized to support the early detection of mental health conditions using explainable AI approaches [8].

In addition, research conducted by Ditto Ridhwan Wibowo, Fajar Rakhmat Umbara, and Ridwan Ilyas shows that the SHAP method can be applied to analyze the importance of features in mental health classification using machine learning, thereby making model interpretation clearer [9].

Although previous studies have used machine learning methods to analyze mental health, most of them have focused on classifying depression or other mental disorders. Furthermore, previous studies have focused on the performance of predictive models without providing a detailed, interpretable analysis of how each digital behavior variable influences anxiety levels, nor have they addressed model interpretation or the potential for predictive bias resulting from the dominance of certain features.

Therefore, this study will analyze the impact of digital behavior on anxiety levels using Exploratory Data Analysis (EDA), a comparison of several machine learning algorithms, cross-validation, and model interpretation using SHAP. The data used is sourced from the "Mental Health and Digital Behavior (2020–2024)" dataset obtained from Kaggle. This study is expected to provide insights into the influence of digital factors on users' anxiety levels and to create a predictive model that is interpretable and clear.

2. Research Method

This study employs a quantitative approach using machine learning regression methods. The data is then utilized as secondary data to examine the relationship between digital behavior and anxiety levels using machine learning and Explainable Artificial Intelligence (XAI). The data used is sourced from Kaggle, uploaded by Atharva Soundankar under the title "Mental Health and Digital Behavior (2020–2024)," consisting of 500 data points (Database link: https://www.kaggle.com/datasets/atharvasoundankar/mental-health-and-digital-behavior -20202024). The data covers various factors related to online habits and mental health conditions.

Tabel 1. Dataset Variabel

No	Variabel
1	daily_screen_time_min
2	num_app_switches
3	sleep_hours
4	notification_count
5	social_media_time_min
6	focus_score
7	mood_score
8	anxiety_level
9	digital_wellbeing_score

Although the dataset has a variable structure relevant to the research objectives, there is no clinical validation or official scientific publication from the dataset creators; therefore, this study prioritizes exploratory analysis over clinical representation of users' mental health conditions. Additionally, the relatively small dataset size may limit the model's ability to generalize to larger populations.

Riley et al. noted that sample size is a critical factor in the development of predictive models because it affects the model's performance and ability to process new data [10]. Furthermore, other studies have emphasized that research based on secondary digital data often faces challenges related to data quality, completeness of information, and potential biases that can affect the validity of research findings [11].

This study was conducted in the following stages:

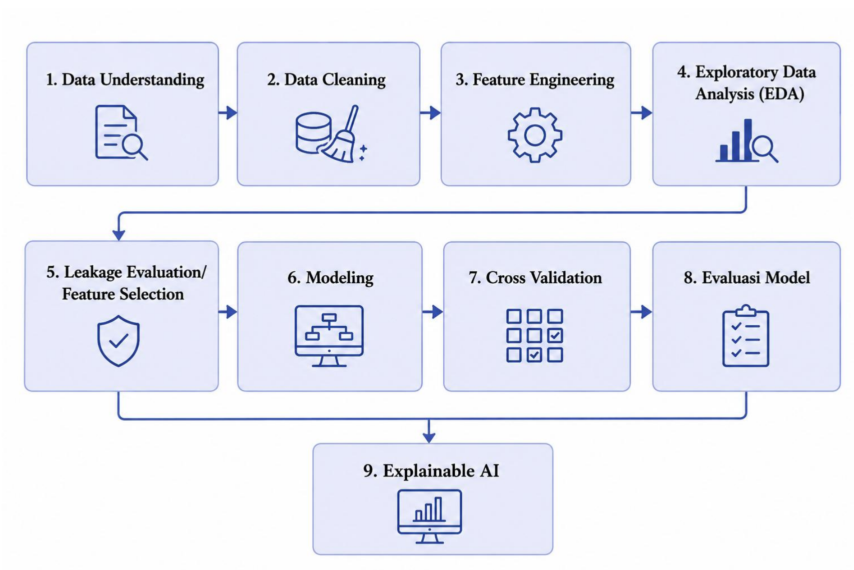


Figure 1. Research Phase

The Data Understanding stage aims to examine the characteristics and quality of the dataset before further analysis is conducted. At this stage, the dataset is inspected by evaluating the total number of records, identifying the data types of each variable, detecting missing values, and generating descriptive statistics to obtain an overall understanding of the data distribution and its underlying characteristics.

The Data Cleaning stage is performed to ensure that the dataset is suitable for machine learning analysis. This process includes removing missing values, eliminating duplicate records, and identifying as well as handling potential outliers that may negatively affect model performance. These preprocessing steps are intended to improve data quality and enhance the reliability of the predictive model.

During the Feature Engineering stage, a new feature named digital_addiction_score is constructed to represent the overall level of digital addiction. This metric is calculated as the average of three normalized variables, namely daily_screen_time_min, social_media_time_min, and notification_count, as expressed in Equation (1).

$$\text{digitasl\_addiction\_score} = \frac{daily\_screen\_time\_\min + social\_media\_time\_\min + notification\_count}{3} \quad (1)$$

Exploratory Data Analysis (EDA) is conducted to understand the distribution of the variables and identify potential patterns within the dataset. Several visualization techniques are employed, including histograms to examine data distributions, scatter plots to observe relationships between variables, correlation heatmaps to measure the strength of variable associations, and boxplots to identify potential outliers.

To prevent data leakage and improve model generalization, a Leakage Evaluation and Feature Selection process is carried out. This stage involves analyzing correlations among variables, identifying features that may introduce target leakage, and removing variables that could provide information unavailable during real-world prediction. As a result, only relevant and unbiased features are retained for model development.

The stability and generalization capability of the predictive model are evaluated using 5-fold cross-validation. In this procedure, the dataset is divided into five subsets, where four subsets are used for training and the remaining subset is used for validation. This process is repeated five times so that each subset serves as the validation set once, providing a more robust estimate of model performance.

The Modeling stage employs the XGBoost Regression algorithm because the target variable, anxiety_level, is represented as continuous numerical data. Before training, the dataset is divided into 80% training data and 20% testing data to enable model development and subsequent performance evaluation on unseen data.

The predictive performance of the proposed model is assessed using several regression evaluation metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2 Score). These metrics provide complementary information regarding prediction accuracy, error magnitude, and the model's ability to explain the variance of the target variable.

To improve model interpretability, this study incorporates an Explainable Artificial Intelligence (XAI) approach using SHapley Additive exPlanations (SHAP). SHAP is utilized to determine the importance of each feature and to explain how individual features contribute to the model's prediction outcomes, thereby enhancing the transparency and interpretability of the XGBoost Regression model.

3. Result and Discussion

3.1 Result

3.1.1 Exploratory Data Analysis (EDA)

Based on Exploratory Data Analysis (EDA) and the results of the correlation heatmap, the variable social_media_time_min has a positive correlation with anxiety_level, with a value of 0.31. Additionally, notification_count (with a value of 0.30) and digital_addiction_score (with a value of 0.28) also show positive correlations with anxiety_level.

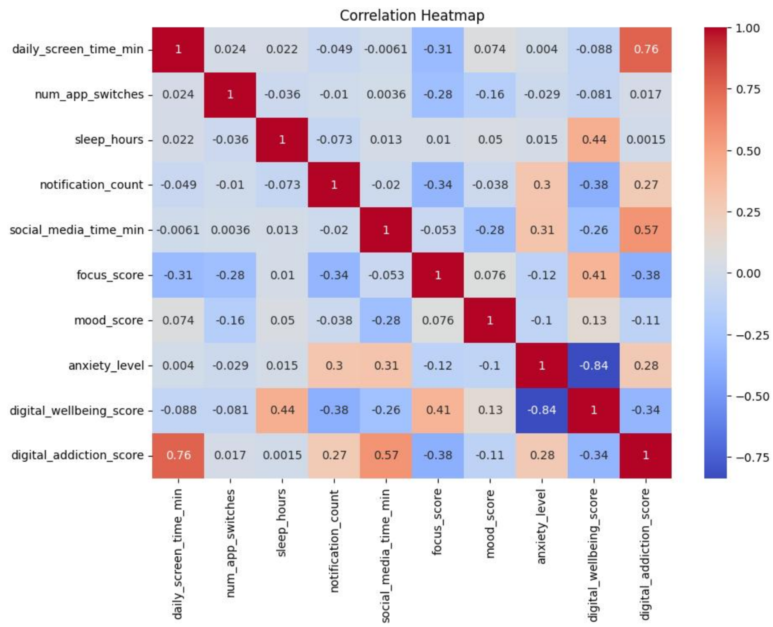


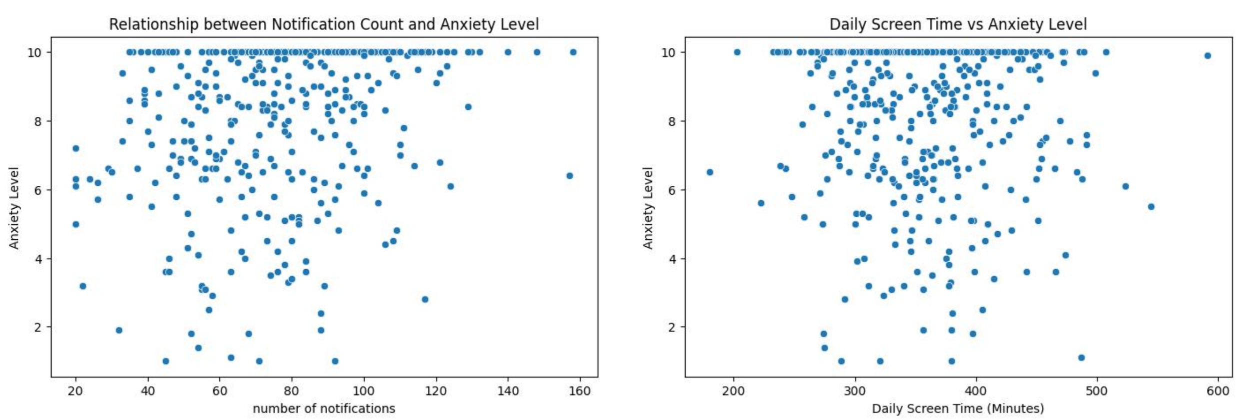
Figure 2. Correlation Heatmap Visualization

The results indicate that an increase in social media use, the number of notifications, and the level of digital dependence tends to be accompanied by an increase in users' anxiety levels.

Meanwhile, the variable num_app_switches shows a negative correlation with anxiety_level, with a value of -0.029. Furthermore, the variables mood_score (with a value of -0.1), focus_score (with a value of -0.12), and digital_wellbeing_score (with a value of -0.84) indicate that users tend to have lower anxiety levels.

Meanwhile, the sleep_hours variable showed a correlation coefficient of 0.015 with anxiety_level, and daily_screen_time_min showed a correlation coefficient of 0.004 with anxiety_level. These values indicate that the relationship between these two variables and anxiety_level is very weak.

Furthermore, based on the results of the scatterplot visualization, several digital behavior variables show a correlation with users' anxiety levels.



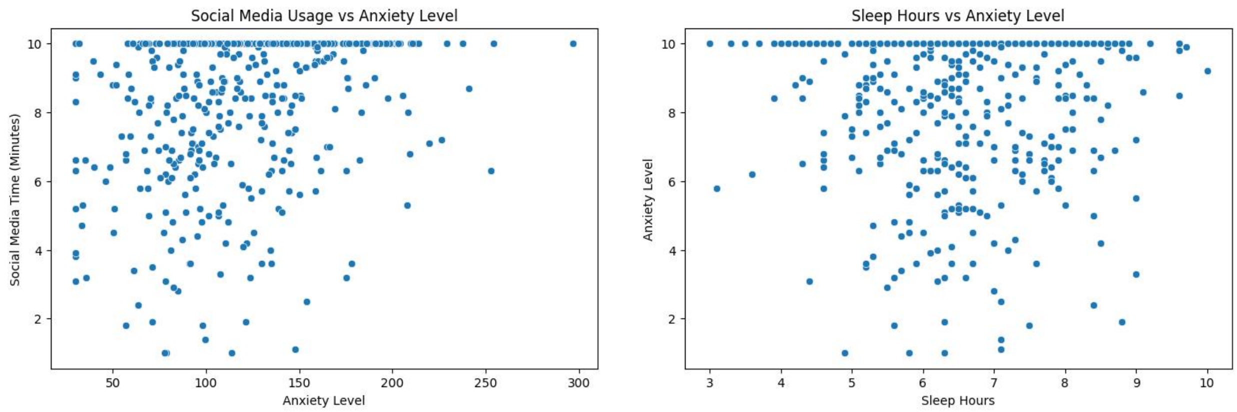


Figure 3. Scatterplot Visualization

The scatterplot visualizing the relationship between social_media_time_min and anxiety_level shows a positive correlation between social media usage and users' anxiety levels. Based on the correlation heatmap results, the `social_media_time_min` variable has a correlation coefficient of 0.31 with `anxiety_level`. The scatterplot between `social_media_time_min` and `anxiety_level` indicates a positive correlation between social media usage and users' anxiety levels. Most of the data is concentrated among users with social media usage of approximately 80–180 minutes per day and anxiety_levels in the range of 7–10. Additionally, some users with social media usage exceeding 200 minutes also tend to have high anxiety_levels. This suggests that increased social media usage tends to be accompanied by an increase in users' anxiety levels.

Furthermore, the scatterplot visualizing the relationship between notification_count and anxiety_level also indicates a positive correlation. Based on the correlation heatmap results, notification_count has a correlation coefficient of 0.30 with anxiety_level. The scatterplot shows that most users with approximately 50–120 notifications have an anxiety_level in the range of 7–10. This indicates that users with a high number of notifications tend to have higher anxiety levels compared to users with a low number of notifications.

Meanwhile, the scatterplot visualizing the relationship between daily_screen_time_min and anxiety_level shows a fairly wide distribution of data and does not reveal a strong pattern of association. Based on the correlation heatmap results, daily_screen_time_min has a correlation coefficient of only 0.004 with anxiety_level, indicating that the relationship between daily screen time and anxiety levels in this dataset is very weak.

Meanwhile, the scatterplot between sleep_hours and anxiety_level also shows a fairly random distribution of data. Based on the results of the correlation heatmap, sleep_hours has a correlation coefficient of 0.015 with anxiety_level, indicating that the relationship between sleep duration and anxiety levels in this dataset is very weak.

3.1.2 Removal of the Digital Wellbeing Score Variable

The correlation heatmap results show that the digital_wellbeing_score variable has a strong negative correlation with anxiety_level, with a value of -0.84. This value is significantly higher than that of other variables, which could potentially cause it to dominate the features in the machine learning model's predictions.

Therefore, the variable `digital_wellbeing_score` was excluded from the machine learning model development process to ensure that the predictions are more objective and reflect the relationships among digital behavior variables more realistically.

3.1.3 Comparison of Machine Learning Algorithms

A comparison was conducted of several machine learning algorithms, namely Ridge Regression, Random Forest Regression, Support Vector Regression (SVR), and XGBoost Regression. The models were evaluated using the MAE, MSE, RMSE, and R^2 Score metrics.

Table 2. Comparison of Machine Learning Algorithms

Model	MAE	MSE	RMSE	R^2 Scoure
Ridge Regression	1.264	2.647	1.627	0.220
Random Forest	1.273	2.797	1.672	0.176
SVR	1.190	3.005	1.733	0.115
XGBoost	1.514	3.972	1.993	-0.168

From a comparison of these algorithms, the Ridge Regression model performed best compared to the other algorithms.

The Mean Absolute Error (MAE) value of 1.264 indicates that the model's average prediction error relative to the actual anxiety_level values is relatively small. This suggests that the model's predictions are fairly close to the actual values.

The Mean Squared Error (MSE) value of 2.647 indicates that the model's average squared prediction error is relatively low. The lower the MSE value, the better the model's performance in making predictions.

The Root Mean Squared Error (RMSE) value of 1.627 indicates that the model's prediction error remains within a relatively low range. This suggests that the model is capable of generating anxiety_level predictions with a fairly stable error rate.

Meanwhile, the R^2 score of 0.220 indicates that the model can explain approximately 22% of the relationship between digital behavior variables and anxiety_level. This value indicates that the model has a relationship with anxiety_level.

3.1.4 Cross Validation

To ensure the model's stability, a 5-fold cross-validation process was performed on the Ridge Regression model, with evaluation based on the R^2 score.

The cross-validation results show that the model achieved an average R^2 score of 0.158 and a standard deviation of 0.062. These figures indicate that the Ridge Regression model can generalize the data relatively stably across each test fold. Although the R^2 Score is still considered low, these results indicate that the digital behavior variable is associated with the user's anxiety level, even though the relationship between these variables remains weak and complex.

Furthermore, the low standard deviation indicates that the model's performance tends to be consistent across each fold, meaning the model does not experience significant overfitting. These results also show that removing the `digital_wellbeing_score` variable successfully reduces the potential for target leakage in the machine learning model.

3.1.5 Model Interpretation Using SHAP

Based on the results of the SHAP summary plot, the variables `notification_count` and `social_media_time_min` show a positive relationship with `anxiety_level`.

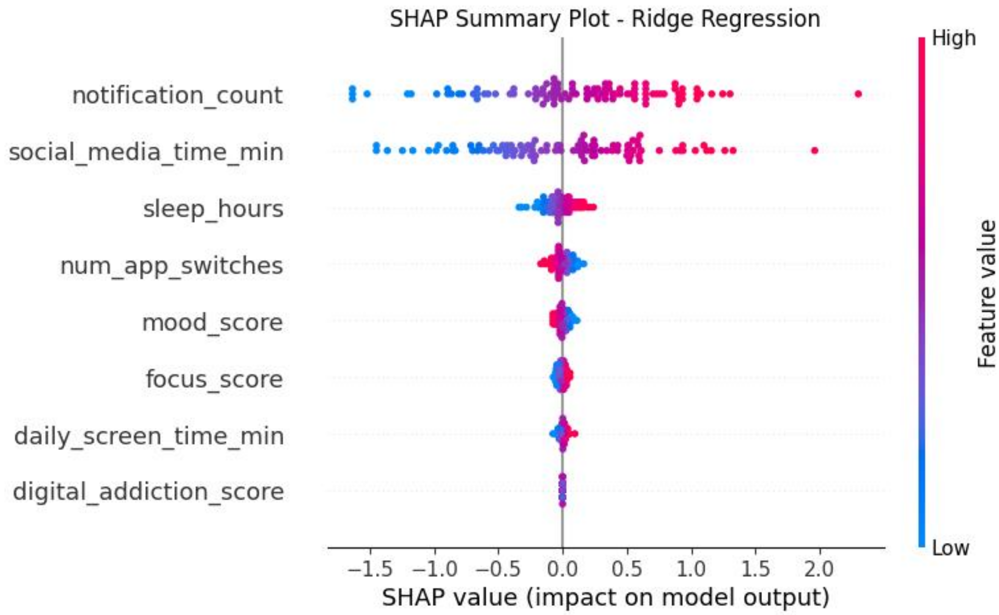


Figure 4. SHAP Summary Plot Results

The SHAP results indicate that the `notification_count` variable has the greatest influence on the predicted `anxiety_level`. The SHAP summary plot shows that SHAP values range from -1.6 to +2.3. This suggests that users with a high number of notifications tend to have higher `anxiety_level` scores. Conversely, users with low notification counts have lower anxiety_levels.

Furthermore, the variable `social_media_time_min` also showed a positive impact on the predicted anxiety levels. The distribution of SHAP values ranged from approximately -1.4 to +2.0. These findings indicate that users with high social media usage tend to have higher predicted anxiety levels compared to users with low social media usage.

Furthermore, the variables sleep_hours, num_app_switches, mood_score, and focus_score influence the model's prediction results, although their contributions are relatively smaller than those of notification_count and social_media_time_min. Meanwhile, the variable daily_screen_time_min also contributes to the model's prediction results, although its influence is the smallest compared to the other variables.

Meanwhile, the digital_addiction_score variable makes a very small contribution to the Ridge Regression model's predictions. This indicates that variables resulting from feature engineering do not always have a significant impact on the performance of machine learning models. It is likely that the information contained in this variable is already included in the original features, such as notification_count and social_media_time_min. Therefore, its contribution to the Ridge Regression model is smaller.

The results of the study indicate that several digital behavior variables are associated with users' anxiety levels. Based on the EDA results, the variables social_media_time_min and notification_count show a positive relationship with anxiety_level. These findings are supported by the SHAP results, which indicate that these two variables are the most important features in the Ridge Regression model.

The results of this study indicate that social_media_time_min has a positive correlation with anxiety levels. This aligns with previous research showing that high social media use is associated with increased symptoms of anxiety and depression among adolescents and young adults [1]. Furthermore, another study explains that the intensity of social media use is strongly linked to users' mental health, particularly regarding anxiety and psychological stress [12].

These findings align with the Fear of Missing Out (FoMO) theory, which explains that excessive social media use can increase anxiety due to the urge to constantly keep up with other users' social activities. Social media users often feel psychological pressure due to the need to always stay connected to their digital social environment. As explained in previous research, FoMO is a psychological condition in which a person feels anxious about missing out on experiences or activities that others are having, which drives more intense engagement on social media. This condition can increase psychological stress and anxiety, particularly among users who actively monitor social activities in the digital environment [13].

Furthermore, the findings of this study can also be understood through Social Comparison Theory, which posits that individuals tend to compare themselves to others through social interactions on digital media. High levels of social media use can increase anxiety resulting from social comparisons with others' lives, particularly when users are constantly exposed to information about others' achievements, lifestyles, or social activities on social media.

These findings are consistent with previous research showing that social comparison on social media is linked to psychological well-being and can influence users' emotional states [14]. Furthermore, another study found that social comparison is one of the factors contributing to increased anxiety among social media users [15]. Furthermore, another study indicates that upward social comparison on social media has a positive relationship with appearance anxiety, where individuals tend to experience higher anxiety when comparing themselves to the idealized representations displayed by other users [16].

The variable `notification_count`, which emerged as the most significant feature in the SHAP results, also indicates that the frequency of digital notifications has an impact on users' anxiety levels. This finding can be explained by Cognitive Load Theory, which posits that prolonged exposure to information can increase users' cognitive load. A high volume of notifications can lead to digital distraction, reduce focus, and increase psychological stress due to the overwhelming amount of digital information received. Previous research has shown that smartphone notifications have a negative impact on users' cognitive control and attention [17]. Another study explains that constantly appearing digital notifications have the potential to increase cognitive load, disrupt concentration, and affect users' psychological well-being [18].

The results of the machine learning algorithm comparison show that the Ridge Regression model performs best compared to the other algorithms. These findings suggest that the relationship between digital behavior variables and anxiety levels in this dataset is linear, making a linear regression model with regularization more appropriate than more complex models such as Random Forest, SVR, or XGBoost Regression However, the Ridge Regression model yielded an R^2 value of 0.220 on the test data and an average R^2 of 0.158 during cross-validation. These results are nearly identical to those of a previous study reporting R^2 values of 0.26 for anxiety, 0.22 for depression, and 0.33 for stress in the analysis of the relationship between Internet Addiction and the psychological conditions of students [19]. The similarity in R^2 values between the two studies suggests that predictive models involving digital behavior and psychological conditions generally yield moderate explanatory power because mental health is influenced by various complex factors that cannot be fully represented by digital behavior variables.

The Explainable Artificial Intelligence (XAI) approach uses SHAP (SHapley Additive exPlanations) to enhance the transparency of model prediction results. SHAP is one of the XAI methods that can explain the contribution of each variable to the model's prediction results in a consistent and easily interpretable manner [20]. This is also supported by previous research stating that the XAI approach plays a crucial role in enhancing transparency and trust in machine learning models, particularly in the healthcare domain and data-driven decision-making [21].

Based on the SHAP results, the variables `notification_count` and `social_media_time_min` were found to be the most influential factors on anxiety levels. This indicates that the frequency of notifications and social media usage have a greater impact than other digital behavior variables in the model. Thus, the use of SHAP helps explain the relationship between digital behavior and anxiety levels more transparently and supports the interpretation of the research findings.

4. Conclusions and Future Works

This study analyzed the relationship between digital behavior and anxiety levels using EDA, a comparison of machine learning algorithms, cross-validation, and model interpretation using SHAP. The EDA results indicate that the variables social_media_time_min (with a value of 0.31), notification_count (with a value of 0.30), and digital_addiction_score (with a value of 0.28) have a positive relationship with anxiety_level, exhibiting higher values compared to other variables.

Subsequently, during the model development stage, the variable `digital_wellbeing_score` was removed because it had a strong negative correlation of -0.84 with `anxiety_level`, which could lead to target leakage. In the algorithm comparison results, the model that produced the best performance was the Ridge Regression model with an R^2 score of 0.221 and an RMSE of 1.627. The 5-Fold Cross Validation results showed an average R^2 score of 0.158 with a standard deviation of 0.062, indicating that the model has relatively stable generalization capabilities and does not experience significant overfitting.

Although this study successfully demonstrated a relationship between digital behavior and anxiety levels, it still has several limitations. First, the research dataset relies solely on digital behavior variables and therefore cannot comprehensively reflect psychological, social, or environmental factors. Second, the size and characteristics of the dataset remain limited, so the model's generalizability to a broader population cannot yet be fully confirmed. Third, the relatively low R^2 score indicates that the variables in this study cannot fully explain the total variation in users' anxiety levels.

This study also has methodological limitations because the machine learning model applied is still based on simple regression, so it cannot yet capture the more complex nonlinear relationships between digital behavior variables and users' psychological conditions. Furthermore, the SHAP interpretation in this study focuses on feature contributions to the model and cannot yet directly explain the causal relationship between digital behavior and users' anxiety levels.

Future research is recommended to use a larger and more diverse dataset. Additionally, other variables related to mental health could be included. More complex machine learning and XAI approaches should be employed so that the model's predictions and interpretations can be more accurate and comprehensive.

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