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Identifying Predictive Factors of Mood Swings and Mental Health

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Abstract

Mood swing is one of the common symptom related to mental health. It can be influenced by biological, psychological, and environmental factors. However, the process of identifying health is challenging and varies between individuals. Therefore, machine learning was employed to analyze the contributing factors to different level of mood swing. Gender, days indoors, growing stress, habit changes, coping struggles, work interest, and social weakness are among the important features found. It was reported that K-Nearest Neighbor performed the best across all metrics (accuracy=95.77%, precision=95.89%, recall=95.77%), suggesting that a distance-based approach is well-suited for this dataset followed by Support Vector Machine, Decision Trees and Random Forest. Consequently, early detection and targeted interventions would significantly improve the quality of life for affected individuals.

1. Introduction

Mental health is an important component in determining an individual's overall well-being. It can affect a person's feelings, way of thinking, and behavior in everyday life. According to the World Health Organization (WHO), 970 million people worldwide live with mental disorders with anxiety and depression being the most common. In Malaysia, mental health concerns are on the rise, with depression in the country doubling between 2019 and 2023 (World Health Organization, 2024).

Mood swings refer to rapid emotional fluctuations, often occurring without specific reason (Abbas et al., 2018). This is a common phenomenon, but it can have a significant impact on mental health. While occasional mood swings are normal, frequent or extreme mood swings may indicate a mental health problem. These mood swings can interfere with daily functioning, interpersonal relationships and subsequently affect the overall quality of life. External factors such as stress, sleep patterns, and environmental changes can influence mood. Mood swings often disrupt daily routines and can result in feelings of distress, low concentration, and emotional instability.

Maintaining a stable mood is very important. A stable mood is essential to emotional resilience, cognitive function, and overall quality of life. It enables individuals to effectively navigate daily challenges, build and maintain healthy relationships, and achieve personal and professional goals. On the other hand, unstable moods

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can interfere with decision-making processes and affect social interactions. This will further worsen mental health conditions, creating a vicious cycle that may be difficult to break without intervention.
Frequent, unexplained mood swings may be early warning signs of mental health conditions: Adolescents with mood instability are at higher risk of developing mood disorders, particularly if the instability escalates over time (Constantinides et al., 2018). Additionally, studies find associations between mood instability, higher stress levels, and patterns of rumination that worsen mental health outcomes (Kessing et al., 2024).

Although awareness of mental health care is increasing, there are significant gaps in understanding the complex relationship between mood swings and mental health. Furthermore, the process of identifying mental health is challenging as it may vary from individual to individual. Nevertheless, mood swings are one of the main factors that contribute to the identification of mental health. Accordingly, this study was conducted to identify factors that influence mood changes in individuals and develop a predictive model. By analyzing patterns and correlations, this study will be beneficial for early detection of mental health. This will facilitate early intervention for individuals at risk of experiencing mental health problems.

This paper is structured as follows; Section 2 presents the literature review of the current use of machine learning in mental health or mood swing, and Section 3 presents the methodology used in this research. Next, Section 4 reported the result of exploratory data analysis by describing the data used in the present study. Section 5 will present the model development and evaluation of the predictive models. Finally, Section 6 highlights the conclusion and future recommendations.

2. Literature Review

Mood swings are often intense shifts in emotional state. These fluctuations are common in certain mental health conditions, but can also occur in response to environmental stressors, hormonal changes, or other physiological factors among normal people (Siniver & Yaniv, 2019; Wang et al., 2024). While occasional mood swings are normal, persistent, or severe fluctuations it may indicate underlying conditions (Lobban et al., 2013). Marvel et al. (Marvel & Paradiso, 2004) estimates that mood instability affects 15–20% of the global population (Siniver & Yaniv, 2019). In Malaysia, statistic shows that 31.9% of menopausal women have mood swings (Gan et al., 2024) and 40% of individuals report significant disruption in daily life quality (Bowen et al., 2004).

The relationship between mood swings and gender has been studied, revealing potential moderating effects. Gender differences may influence how individuals experience and express mood swings, with factors such as hormonal changes, emotional intelligence, and coping mechanisms playing a role. Based on the study conducted by Abbas et al. (Abbas et al., 2018), university students experiencing homesickness and emotional challenges may show varying patterns of mood swings based on their gender, highlighting the importance of demographic factors in understanding these emotional fluctuations.

Mood swings and gender are closely related, with women experiencing a higher prevalence of anxiety disorders compared to men. Research suggests that hormonal fluctuations, such as changes in progesterone, estrogen, and oxytocin levels, may contribute to these differences. These hormonal variations can influence emotional regulation and heighten sensitivity to internal sensations. According to Murphy et al., this heightened interoceptive attention, combined with lower accuracy in interpreting internal states, is termed atypical interoception. This biological predisposition may explain why women are more susceptible to mood swings and anxiety-related conditions (Farhane-Medina et al., 2022).

One of the significant factors contributing to mood swings is work-related stress. The demands of a job, workplace pressure, and occupational responsibilities can create a high-stress environment. If this stress is not managed properly, it may lead to emotional instability and mental health issues. Work-related stress, job insecurity, or occupational demands significantly contribute to mental health issues (van der Molen et al., 2020). Employees who experience prolonged stress may develop mood swings which impact their overall well-being. On the other hand, being self-employed introduces unique psychological challenges that further worsen the mood swings such as financial instability or lack of work-life balance (Schonfeld & Mazzola, 2015). Without effective interventions for mental health, both employees and self-employed individuals may struggle with the psychological burden which may affect their mental health.

Besides, an individual's family history plays a crucial role in determining an individual's susceptibility to mental health issues, including mood swings. Genetic predispositions and familial stressors can heighten the likelihood of experiencing mood swings (Lippard & Nemeroff, 2020). Beyond genetics, the family environment itself can contribute to emotional instability. Growing up in a household where family members struggle with mental health issues may expose individuals to heightened stress as well.

According to the WHO, the COVID-19 pandemic led to a 25% surge in the global prevalence of anxiety and depression (World Health Organization, 2022). Prolonged indoor confinement during quarantine, can lead to social isolation, reduced physical activity, and increased stress. These limitations are associated with mood swings and deteriorating mental health. Based on the study done by Campos et al. (Campos et al., 2021), students reported experiencing severe mood swings, potentially stemming from social isolation and the broader challenges of the

pandemic. The lack of social interaction and restricted physical activity increase emotional instability, contributing to heightened feelings of distress and mood fluctuations. Additionally, significant changes in eating or sleeping patterns can disrupt biological rhythms, leading to fatigue, irritability, and mood swings. Lifestyle and dietary habits significantly influence depression, a common mental health issue. Isolation and disrupted routines especially during COVID-19 worsen the mental health challenges (Lee et al., 2022).

Therefore, to enable early intervention, machine learning is essential. Research on machine learning in mental health has shown a significant upward trend since 2018 (see Fig. 1). This increase reflects the growing recognition of artificial intelligence (AI) as a valuable tool for diagnosing, predicting, and managing mental health conditions.

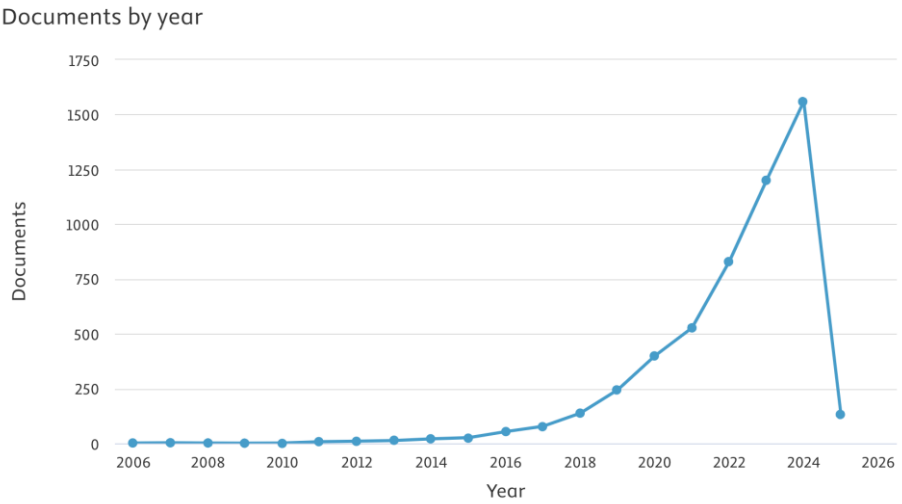


Fig. 1 *Trends of research on machine learning in mental health (Scopus, 2025)*

By leveraging predictive algorithms and data-driven insights, machine learning can help identify individuals at risk of mood swings and mental health disorders before symptoms escalate. Advanced models can analyze patterns in behavior, social interactions, and physiological indicators to detect early warning signs, allowing for timely and personalized interventions. The integration of machine learning in mental health care can enhance diagnostic accuracy, optimize treatment plans, and improve overall mental well-being. Table 1 provides an overview of existing studies on predicting mood swings or mental health using machine learning.

The research on the use of machine learning in mental health offers an in-depth look at various studies which are each carried out by different researchers with their specific objectives and approaches. Vaishnavi et al. (2022), Mohamed et al., (2023) and Mutalib et al., (2021) conducted a study focusing on using machine learning algorithms to predict mental health illnesses. Vaishnavi et al., (2022) aimed to identify the patterns that could serve as early warning signs, allowing for timely interventions and improved patient outcomes. Similarly, Mohamed et al., (2023) classify anxiety stages at an early phase using a pre-clinical mental health dataset for targeted interventions before symptoms become debilitating. On the other hand, Mutalib et al. (2021) focused on the students in higher education institutions. The authors classify the students into different categories of mental health problems, including stress, depression, and anxiety.

Tate et al. (2020) aimed to predict which children would develop mental health symptoms as they reached adolescence. Their research aimed to provide early identification of vulnerable cohorts, enabling preventive measures to mitigate long-term mental health issues. Furthermore, Kuhathasan et al., (2023) explored the predictors of perceived symptom change with acute cannabis use for mental health conditions. Using machine learning methods, the study aimed to identify patterns in symptom relief or exacerbation to inform safer and more effective treatment strategies. In the meantime, Garriga et al. (2023) aimed to enhance the prediction of mental health crises by integrating structured electronic health records (EHRs) with clinical notes.

Cheng and Haw (2023) analyzed external factors influencing mental health, such as environmental stressors, socioeconomic conditions, and lifestyle habits. As the factors for each individual may differ, thus it is important to understand how these variables are interconnected and contribute to mental health. Meanwhile, Hornstein et al. (2021) developed a machine learning model to predict treatment responses for mental health symptoms. Their objective was to personalise mental health care by tailoring interventions based on individual characteristics, increasing the likelihood of successful treatment outcomes.

Table 1 *Overview of existing studies for the prediction of mood swings or mental health using machine learning*

Title	Author	Objectives
Predicting Mental Health Illness using Machine Learning Algorithms	(Vaishnavi et al., 2022)	To utilize machine learning algorithms to predict mental health illness.
Predicting mental health problems in adolescence using machine learning techniques	(Tate et al., 2020)	To predict the cohort of children toward developing mental health symptoms reaching the adolescent stage
Machine learning from real data: A mental health registry case study	(Gentili et al., 2024)	To develop machine learning models for healthcare applications by addressing the challenge of imbalanced datasets.
A hybrid mental health prediction model using Support Vector Machine, Multilayer Perceptron, and Random Forest algorithms	(Mohamed et al., 2023)	To classify anxiety stages early using a pre-clinical mental health dataset
Combining clinical notes with structured electronic health records enhances the prediction of mental health crises	(Garriga et al., 2023)	To enhance the prediction of mental health crises by combining structured electronic health records (EHRs) with clinical notes.
Predictors of perceived symptom change with acute cannabis use for mental health conditions in a naturalistic sample: A machine learning approach	(Kuhathasan et al., 2023)	To investigate predictors of perceived symptom change with the usage of acute cannabis for mental health conditions (depression, anxiety, insomnia) using machine learning methods.
Predicting therapy outcome in a digital mental health intervention for depression and anxiety: A machine learning approach	(Hornstein et al., 2021)	To develop a machine learning model to predict treatment response for mental health symptoms
Mental Health Problems Prediction Using Machine Learning Techniques	(Cheng & Haw, 2023)	To analyze external factors influencing mental health
Mental Health Prediction Models Using Machine Learning in Higher Education Institution	(Mutalib et al., 2021)	To develop prediction models and classify students in higher education institutions into different categories of mental health problems (stress, depression, and anxiety)

The research on harnessing data mining techniques for advancements in mental health offers an in-depth look at various studies which is each carried out by different researchers with their own specific objectives and approaches.

3. Methodology

The methodology is explained in the following.

3.1 Data Acquisition

Mental Health Dataset (Jikadara, 2024) was used in this study. The dataset contains 300, 000 rows and 17 columns. The dataset includes key demographic information such as gender, occupation status, family history, and mental health history. Additionally, it incorporates variables directly related to mental health, including levels of growing stress, changes in habits, duration spent indoors, mood swings, coping struggles, and social weaknesses. These factors provide valuable insights into the relationship between personal circumstances and mental health outcomes.

3.2 Data Cleansing

Data cleansing is essential to ensure the quality of the data to be used in the analysis. This process involves rectifying or eliminating incorrect, improperly formatted, duplicated, or incomplete information within a dataset. This ensures that the conclusions and analyses drawn from the data remain consistent and precise. Based on the Mental Health Dataset, several data quality issues existed such as missing values, duplicate records, and incorrect data types.

Missing values need to be addressed as they can lead to biased or incorrect analysis results. The handling of missing values can be approached by deleting rows with missing values, especially if they constitute a small

portion of the dataset. Next, duplicate records were removed from the dataset as the presence of duplicate entries can distort statistical analysis and lead to invalid conclusions. Finally, the correct data types need to be ensured as it is crucial for accurate analysis. Verifying and correcting data types ensures that each attribute is appropriately formatted for analysis. For example, categorical variables in the dataset need to be encoded into numerical values using techniques such as one-hot encoding or label encoding to facilitate analysis by machine learning algorithms.

4. Exploratory Data Analysis

The characteristics of the total samples included 82% female, 23% housewives, 29% self-employed, 60% have no family history of mental illness, half seek mental health treatment (50%), 34% have experienced growing stress, and 37% have changes in habit (Jikadara, 2024). Fig. 2 illustrates the distribution of samples by variable category across different levels of mood swing as the outcome.

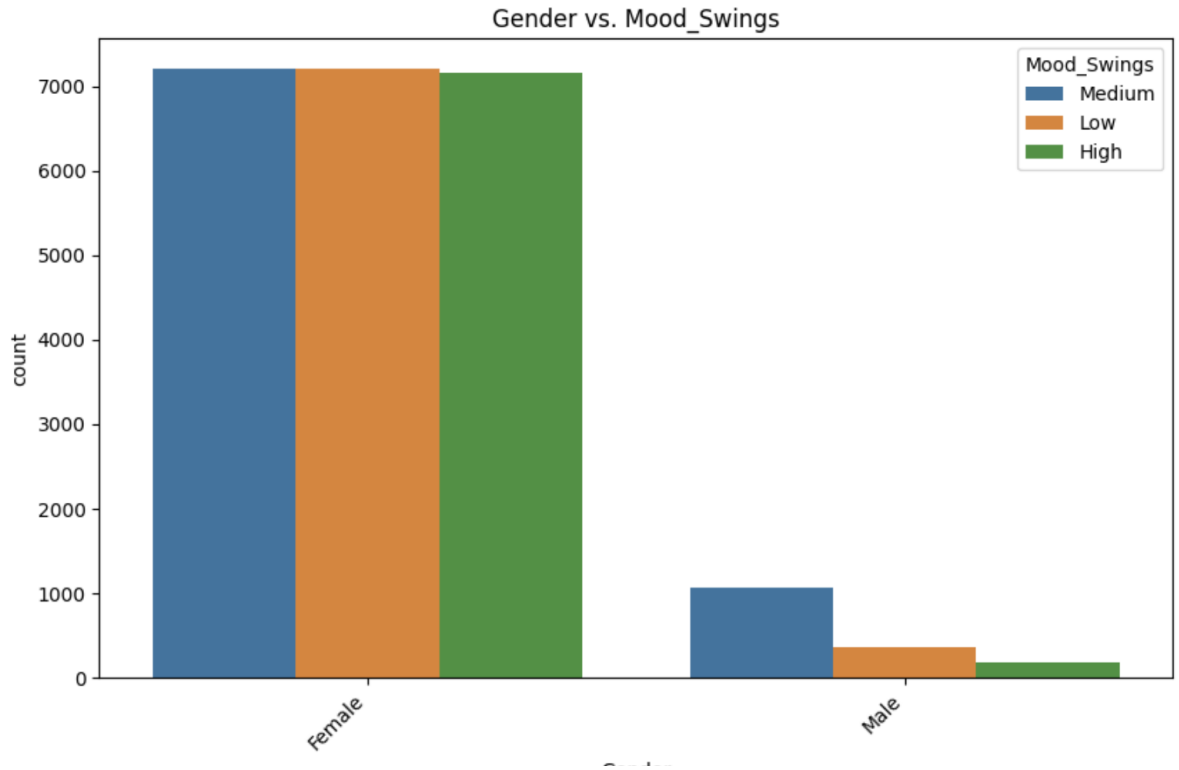


Fig. 2 *Comparison of gender with mood swing level*

Based on Fig. 2, it was reported that most samples with mood swings are women in all categories. It could be affected by the dominant number of female participants. However, it was suggested that based on the total samples of men the least group was found in a high level of mood swing.

Fig. 3 shows counts of individuals experiencing changes of habits (Changes_Habit = Yes) versus not experiencing habit change (Changes_Habit = No), further split by different categories of mood swing as the target variable. This highlights how the change of habit influences the outcome of mood swing level. The highest count found in the cohort of samples with habit change for medium level of mood swing (samples more than 3000).

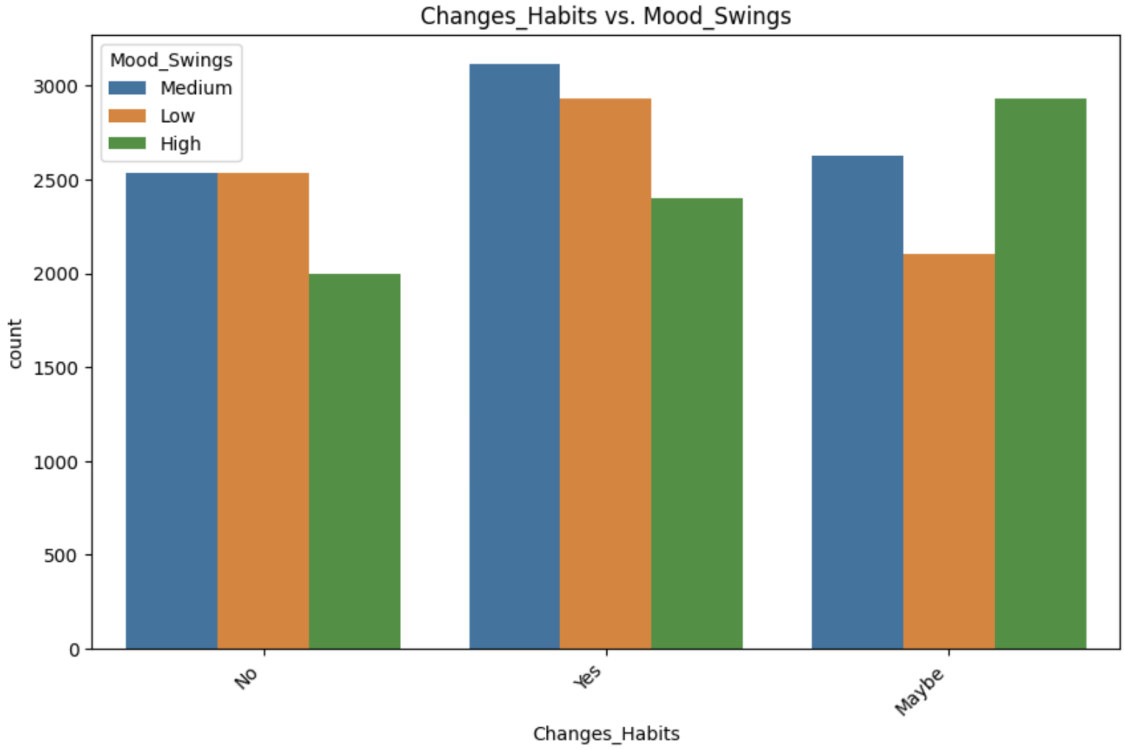


Fig. 3 *Comparison category of habit changes with different mood swing level outcome*

For the distribution of samples Mental_Health_History category, there are three groups (e.g., yes, no, maybe) are more likely to have high level of mood swing (as shown in Fig. 4). The mood swing high bar is consistently higher for categories representing maybe and no category of mental health history. However, the highest number was found in the group of samples with mental history and medium level of mood swing.

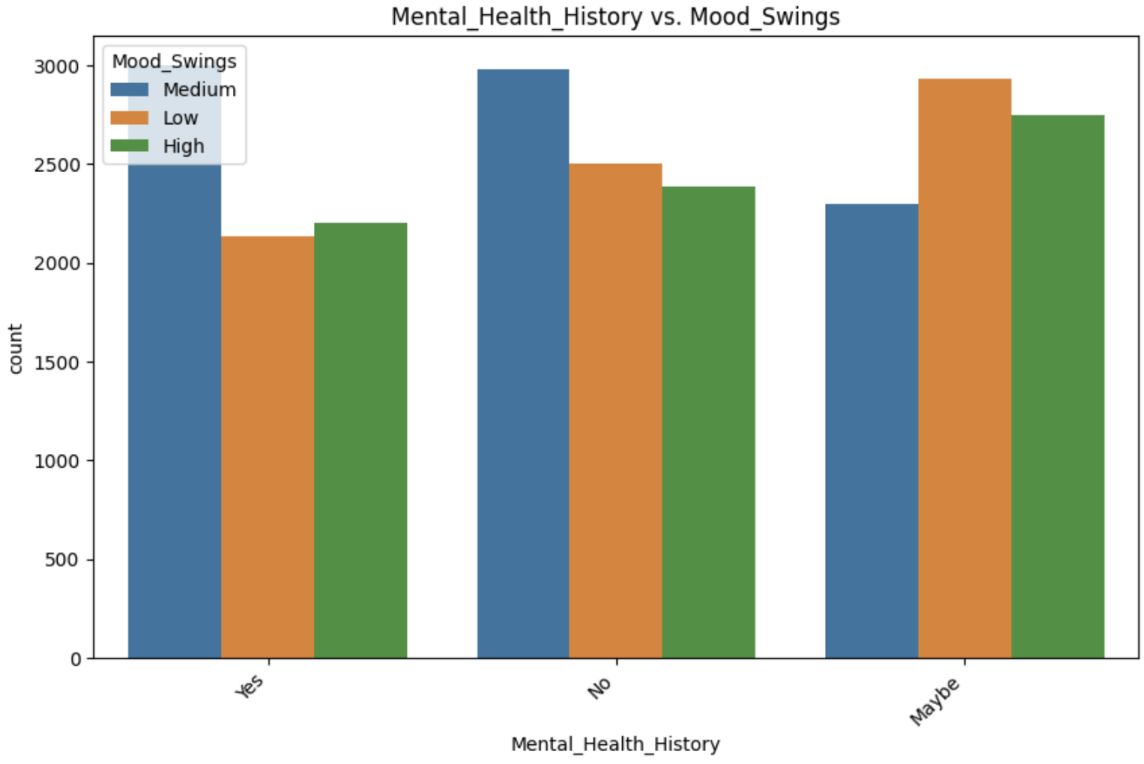


Fig. 4 *Comparison category of mental health with different mood swing level outcome*

Fig. 5 reported the comparison of samples with and without coping struggles towards outcome of mood swing. It was reported that samples without coping struggles reported to be higher in number for level of medium and high mood swing level (samples of 4000 or higher for each group).

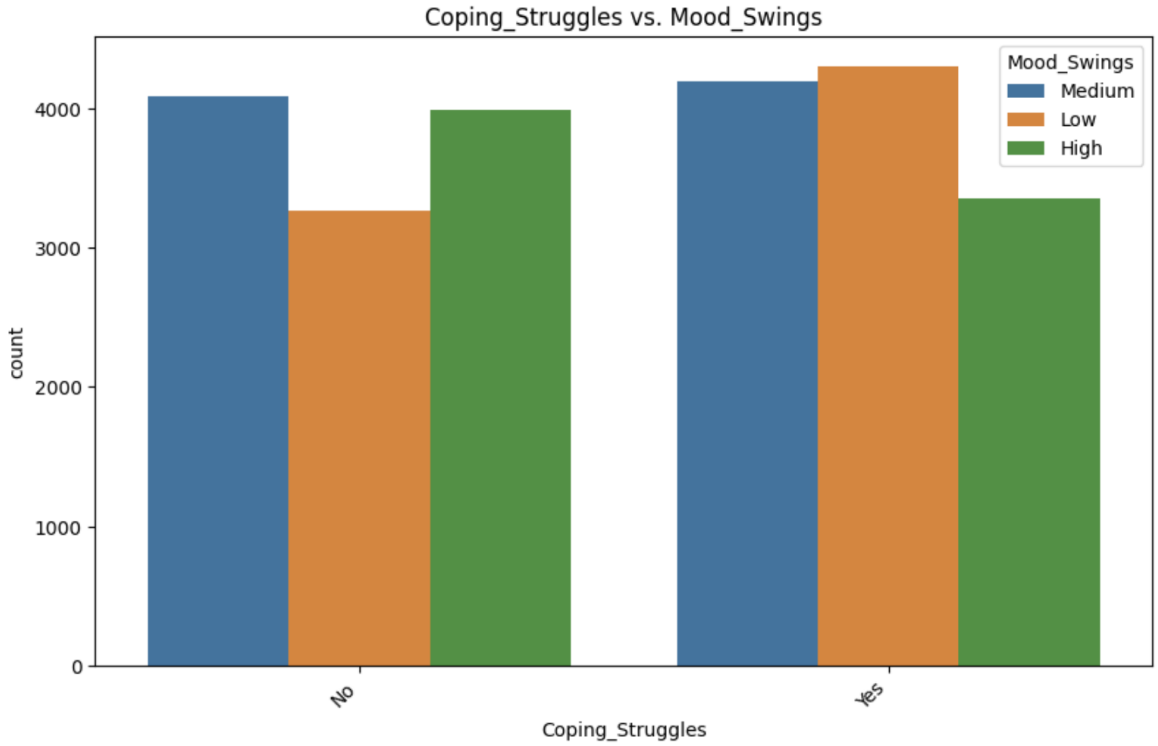


Fig. 5 *Comparison coping struggles status with different level of mood swing*

In mental health studies, chi-square tests can be applied to analyze associations between demographic factors (e.g., gender, occupation) and mood swings. A significant chi-square value indicates a strong correlation, suggesting that certain groups may be more vulnerable to specific mental health issues. This analysis is particularly useful in identifying patterns and risk factors, enabling targeted interventions and policy recommendations. Table 2 shows the cross-tabulation analysis result.

Table 2 *Cross-tabulation analysis result*

Variable	P-value	Chi square statistics (df=Degrees of Freedom)	Significant Association
Gender	<0.001	45.27 (2)	Yes
Self_employed	0.696	0.73 (2)	No
Family_history	0.387	1.90 (2)	No
Treatment	0.670	0.80 (2)	No
Days_Indoors	<0.001	982.31 (8)	Yes
Growing_Stress	<0.001	421.91 (4)	Yes
Changes_Habits	<0.001	724. 03 (4)	Yes
Mental_Health_History	<0.001	856.51 (4)	Yes
Coping_Struggles	<0.001	150.74 (2)	Yes
Work_Interest	<0.001	572.23 (4)	Yes
Social_Weakness	<0.001	716.18 (4)	Yes
Mental_health_interview	0.868	1.26 (4)	No
Care_options	0.977	0.46 (4)	No

The cross-tabulation comparison result was examined using Chi square analysis. It was shown that there were significant associations between gender, days of indoors, growing stress, changes in habits, mental history, coping struggles, work interest and social weakness towards mood swing (all $p<0.001$).

5. Data Modelling

The performance of four machine learning models, Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Decision Tree (DT), and Random Forest (RF), was evaluated using key classification metrics: accuracy, precision, recall, and F1 score (as shown in Table 3).

Table 3 *Performance comparison between the algorithms*

Algorithm	Accuracy	Precision	Recall	F1-score
SVM	0.9558	0.9562	0.9558	0.9558
KNN	0.9577	0.9589	0.9577	0.9577
Decision Tree	0.9501	0.9512	0.9501	0.9502
Random Forest	0.9501	0.9512	0.9501	0.9502

SVM achieved an accuracy of 95.58%, with a precision of 95.62%, a recall of 95.58%, and an F1 score of 95.58%. This indicates that SVM is highly effective in distinguishing between classes, maintaining a strong balance between precision and recall. The high F1 score suggests that the model performs well overall, making it a reliable classifier for the dataset. On the other hand, the KNN model outperformed the SVM model slightly, achieving an accuracy of 95.77%, the highest among all models. A precision value of 95.89% and a recall value of 95.77% indicate that KNN effectively classifies instances, particularly in scenarios where small variations in data points matter. The F1 score of 95.77% confirms its robustness, making it a strong candidate for classification tasks in mental health predictions.

Next, DT classifier demonstrated a slightly lower accuracy of 95.01% compared to SVM and KNN. Its precision (95.12%) and recall (95.01%) indicate that, while it effectively classifies data, it may be slightly more prone to overfitting given its deterministic nature. The F1 score 95.02% suggests a consistent, yet slightly less optimized performance compared to the top two models. Similarly, RF exhibited the same performance as the DT model, with an accuracy of 95.01%, precision of 95.12%, recall of 95.01%, and an F1 score of 95.02%. While RF generally improves classification by reducing variance through ensemble learning, its results here are identical to those of DT, possibly due to dataset characteristics or hyperparameter settings.

The study found that KNN performed best across all metrics, suggesting that a distance-based approach is well-suited to this dataset. SVM closely followed KNN, indicating that it effectively captures complex decision boundaries. DT and RF had slightly lower accuracy, likely due to overfitting or suboptimal hyperparameters. The high overall accuracy across all models suggests that the dataset is well-structured and that machine learning models can effectively classify mental health conditions based on the given features.

6. Conclusion

The findings of this study demonstrate significant associations between various demographic and behavioral factors with mood swings and mental health conditions. The chi-square analysis revealed that gender, days spent indoors, growing stress, changes in habits, mental health history, coping struggles, work interest, and social weaknesses have statistically significant relationships with mood swings. Additionally, machine learning models, including SVM, KNN, Decision Tree, and Random Forest, were evaluated for mental health prediction, with KNN achieving the highest accuracy (95.77%). In today's data-driven world, deriving insights from massive datasets is a competitive advantage that can drive success and expansion. As technology evolves, businesses should expect data mining techniques to become more sophisticated and useful, enabling them to stay ahead of the curve. These results highlight the effectiveness of AI-driven approaches in identifying mental health risks and predicting psychological conditions based on multiple factors. Future research should focus on integrating more diverse datasets to improve model generalizability and address potential biases in prediction. Additionally, enhancing model interpretability and explainability is crucial for real-world clinical applications. Developing AI-driven early intervention systems for mental health monitoring, incorporating real-time behavioral data, and expanding research on external factors such as social determinants of mental health will be valuable in advancing the field.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *NA, NAZ, HNZ, NZ, FDI;* ***data cleansing and modelling:*** *NAZ, HNZ, NZ, FDIR, FR;* ***analysis and interpretation of results:*** *NA, FR;* ***draft manuscript preparation:*** *NA, FR. All authors reviewed the results and approved the final version of the manuscript.*

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