



Explainable Machine Learning for Identifying Psychosocial Factors Associated with Mental Health Risk among Generation Z

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ABSTRACT

Mental health among Generation Z has become an increasing public health concern, while most previous studies have primarily focused on improving classification accuracy without explaining the factors influencing model predictions. This study aimed to identify the factors associated with mental health risk among Generation Z using an Explainable Machine Learning approach. **Methods:** A quantitative study was conducted using machine learning on data collected from 733 Indonesian Generation Z respondents selected through purposive sampling. Independent variables included demographic characteristics and all questionnaire items from DASS-21, STAI-T, and ACE, while the dependent variable was mental health risk status. Data preprocessing involved feature leakage removal, categorical encoding, missing value imputation, SMOTE-based class balancing, and feature standardization. Logistic Regression, Support Vector Machine, and Random Forest models were developed using hyperparameter optimization with Stratified 5-fold Cross Validation. Model interpretability was performed using SHapley Additive exPlanations (SHAP). **Results:** Logistic Regression and Support Vector Machine achieved the best performance with 93.6% accuracy, 100% recall, precision above 80%, an F1-score of 0.90, and ROC-AUC greater than 0.99. SHAP analysis identified the twenty most influential predictors, dominated by Adverse Childhood Experiences (45%), followed by DASS-21 (35%), STAI-T (15%), and demographic factors (5%). **Conclusion:** Logistic Regression was the most appropriate model for identifying mental health risk among Generation Z. Adverse childhood experiences were the strongest predictors, highlighting the importance of integrating early-life experiences into explainable machine learning-based mental health screening systems.

INTRODUCTION

Mental health is one of the most challenging public health issues worldwide. More than 970 million people experience mental disorders, with depression and anxiety disorders representing the largest contributors to the global burden of disease (Organization, 2022). Adolescents and young adults, particularly Generation Z, are among the most vulnerable populations due to academic pressure, social changes, economic uncertainty, and the increasing intensity of digital technology and social media use. These conditions significantly increase the risk of stress, anxiety, depression, and trauma-related disorders (World Health Organization, 2022) (Alzhanov et al., 2023).

A similar trend has been observed in Indonesia. According to the Indonesia National Adolescent Mental Health Survey (I-NAMHS), approximately one-third of Indonesian adolescents experienced at least one mental health problem within the previous year, while a proportion met the diagnostic criteria for a mental disorder (4). Early detection remains challenging because of the limited availability of mental health professionals, low public awareness, and the lack of rapid, objective, and accessible screening systems (Priya et al., 2020). This issue has also been identified among adolescents and university students in several Indonesian provinces, including West Java, DKI Jakarta, and Central Java, which constitute the study area of this research (Abdul Rahman et al., 2023).

Recent advances in machine learning have created new opportunities for developing automated mental health screening systems. Various algorithms have demonstrated promising performance in identifying individuals at risk of mental health problems using psychological and demographic data. Nevertheless, most previous studies primarily emphasized predictive performance, such as accuracy, precision, recall, and F1-score, while paying limited attention to model interpretability (Javaid et al., 2022), (Retnowati et al., 2026). Consequently, although these models achieve high classification accuracy, they provide limited explanation regarding the factors influencing prediction outcomes, (Christoph Molnar, 2022).

Furthermore, studies applying Explainable Artificial Intelligence (XAI) to mental health prediction remain limited, particularly in the Indonesian context. Existing research has rarely integrated standardized psychological instruments, including the Depression Anxiety Stress Scale (DASS-21), the State-Trait Anxiety Inventory (STAI), and





Adverse Childhood Experiences (ACE), within an explainable machine learning framework (Barnett, M. L., Sheldrick, R. C., Liu, S. R., Kia-Keating, M., & Negriff, 2021), (Kerz et al., 2023). This gap reduces the transparency and practical applicability of prediction models for supporting mental health professionals and policymakers.

Therefore, this study aims to develop an Explainable Machine Learning model to identify the factors influencing the risk of mental health tendencies among Generation Z using psychological assessment data and respondent characteristics. Several machine learning algorithms are compared to determine the best-performing classification model, which is subsequently interpreted using SHAP (SHapley Additive exPlanations). The findings are expected to contribute to the development of an accurate, transparent, and accessible mental health screening system that supports early detection and evidence-based intervention for Generation Z.

LITERATURE REVIEW

Mental health disorders among adolescents and young adults have become a major public health concern worldwide. Previous studies have consistently reported increasing prevalence rates of depression, anxiety, and stress among Generation Z, largely influenced by academic demands, socioeconomic uncertainty, and extensive digital technology use (World Health Organization, 2022). Early identification of individuals at risk is therefore essential to prevent more severe psychological disorders and improve access to timely intervention.

Machine learning has emerged as an effective approach for predicting mental health conditions because of its ability to analyze complex relationships among multiple psychological and demographic variables. Several algorithms, including Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and CatBoost, have demonstrated excellent predictive performance in mental health classification tasks (Aisyah, 2024), (Lina & Retnowati, 2024). These methods are capable of processing large datasets and identifying nonlinear patterns that are often difficult to detect using conventional statistical approaches.

Despite these advances, most existing studies have focused primarily on optimizing predictive accuracy using evaluation metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). While these metrics provide valuable information regarding model performance, they do not explain why a model produces a particular prediction. This limitation reduces model transparency and may hinder adoption in healthcare settings, where interpretability is essential for clinical decision-making (Christoph Molnar, 2022).

To address this limitation, Explainable Artificial Intelligence (XAI) has been introduced to improve the interpretability of machine learning models. One of the most widely adopted approaches is SHAP (SHapley Additive exPlanations), which quantifies the contribution of each feature to individual predictions and overall model behavior (Arrieta et al., 2020). SHAP enables researchers and practitioners to identify the most influential variables affecting prediction outcomes while maintaining high predictive performance.

Although explainable machine learning has gained increasing attention, its application to mental health risk identification among Indonesian Generation Z remains limited. Furthermore, few studies have simultaneously integrated standardized psychological assessment instruments such as DASS-21, STAI, and ACE into an explainable prediction framework (Barnett, M. L., Sheldrick, R. C., Liu, S. R., Kia-Keating, M., & Negriff, 2021). This study addresses this gap by combining multiple machine learning algorithms with SHAP-based interpretation to produce a transparent and clinically meaningful mental health prediction model for Generation Z in Indonesia.

METHOD

This research employed a quantitative approach with a cross-sectional design. The factors influencing the risk of mental health tendency among Generation Z were identified through the application of an Explainable Artificial Intelligence (XAI) approach. The study was conducted from January to June 2026 and involved Generation Z respondents from several provinces in Indonesia, including West Java, DKI Jakarta, and Central Java. Data were collected online via Google Forms, which had undergone an instrument trial process prior to distribution to respondents. Generation Z, defined as individuals aged 17 to 24 years, constituted the study subjects. A purposive sampling technique was employed, and respondents aged 17 to 24 years who were willing to participate provided informed consent and completed all research instruments in full. Following the data cleaning process, the study included 733 individuals who met the analytical inclusion criteria. This study obtained ethical approval from the Health Research Ethics Committee (Komite Etik Penelitian Kesehatan/KEPK) under approval number No. 1460/KEPK-FIK/VII/2025.

Research Variables

The dependent variable was the risk of mental health tendency, generated through the classification of psychological instruments employed in this study. The independent variables consisted of demographic characteristics (age, sex, occupation, province, place of residence, and educational major) as well as all items from the psychological instruments: the Depression Anxiety Stress Scale-21 (DASS-21), the State-Trait Anxiety Inventory-Trait (STAI-T), and the Adverse Childhood Experiences (ACE) questionnaire. The DASS-21 instrument consists of 21 items measured on a four-point Likert scale, assessing three dimensions: depression, anxiety, and stress. The STAI-T instrument comprises 20 items measuring trait anxiety tendencies. The ACE instrument consists of ten items assessing traumatic experiences





such as abuse, neglect, and family dysfunction.

Research Procedure

The research began with a data preprocessing stage to produce a dataset suitable for machine learning modeling. This stage included duplicate data checking, identification and handling of missing values, removal of attributes irrelevant to the research objectives, and transformation of categorical variables into numerical form through an encoding process. Subsequently, the data were divided into independent variables (X) and a dependent variable (Y). The independent variables comprised the encoded demographic characteristics along with all items from the DASS-21, STAI-T, and ACE instruments, while the dependent variable consisted of the mental health risk tendency label used as the classification target.

Then, the dataset was split into a training set (80%) and a testing set (20%) using the Stratified Train-Test Split method. This technique was selected to maintain a balanced class proportion between the training and testing sets, thereby preserving the representativeness of the data distribution. Given the class imbalance observed in the training set, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to generate synthetic samples for the minority class. SMOTE was applied exclusively to the training set to preserve the integrity of the testing set and to avoid the risk of data leakage.

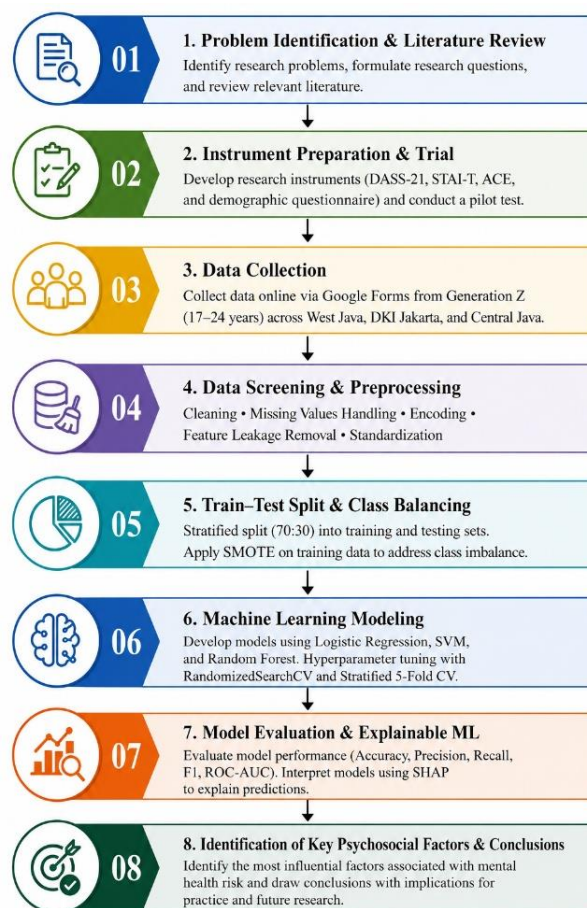


Figure 1. Research workflow for identifying psychosocial factors associated with mental health risk using explainable machine learning.

Machine Learning Model Development

Parameter optimization was performed using Randomized Search Cross Validation (RandomizedSearchCV) combined with five-fold Stratified K-Fold Cross Validation ($k = 5$). This strategy was employed to obtain the optimal parameter combination while enhancing the model's generalization capability. The optimized parameters included the regularization value (C) for Logistic Regression and SVM, whereas for Random Forest, the parameter search encompassed the number of trees (n_estimators), maximum tree depth (max_depth), minimum number of samples per leaf (min_samples_leaf), minimum number of samples required for splitting (min_samples_split), and the number of features considered at each split (max_features). The performance of each model was evaluated on the testing set using several classification metrics, namely Accuracy, Precision, Recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). The confusion matrix presented above contains four main cells, as illustrated in Figure 2 below.





		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Figure 2. Confusion Matrix

The confusion matrix (evaluation matrix) above is explained as follows:

True Positive (TP) : The number of samples correctly predicted as positive by the model.

False Negative (FN): The number of samples incorrectly predicted as negative by the model when they were actually positive.

False Positive (FP): The number of samples incorrectly predicted as positive by the model when they were actually negative.

True Negative (TN): The number of samples correctly predicted as negative by the model (Aisyah, 2024).

From the confusion matrix, various performance evaluation metrics can be calculated, such as accuracy, precision, recall, and F1-score. The formulas for these metrics are as follows:

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall (sensitivitas) = \frac{TP}{TP + FN}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The following explains the ROC-AUC evaluation metric, which assesses classification model performance, along with the figure illustrating the ROC curve:

The True Positive Rate (TPR), also known as sensitivity, represents the proportion of the positive class correctly predicted as positive by the model (Lina & Retnowati, 2024), calculated using the following equation:

$$TPR = \frac{TP}{TP + FN}$$

The False Positive Rate (FPR) represents the proportion of the negative class incorrectly predicted as positive by the model, calculated as follows:

$$FPR = \frac{FP}{FP + TN}$$

Explainable Machine Learning

To identify the factors contributing to the model's predictions, this study applied an Explainable Artificial Intelligence (XAI) approach using the SHapley Additive exPlanations (SHAP) method. The SHAP method calculates the contribution value of each variable to the prediction outcome based on the concept of Shapley values derived from game theory, thereby enabling the influence of each feature on the model's decision to be explained quantitatively. The contribution value of each feature is calculated using the following equation:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|! (M - |S| - 1)!}{M!} [f(S \cup \{i\}) - f(S)]$$



Where :

ϕ_i = the SHAP value of the i -th feature,

N = the total number of features,

S = a subset of features,

$f(S)$ = the model prediction before the i -th feature is added.

The results of the SHAP analysis were visualized using SHAP Summary Plots, SHAP Bar Plots, and SHAP Waterfall Plots to illustrate the magnitude and direction of each variable's contribution to the model's predictions. Subsequently, the SHAP values were used to rank the factors most influential on the risk of mental health tendency among Generation Z (Mirechelin Kristanaya, Melinda Putri Azzahra, Trimono, 2025).

RESULT

The results of the study indicate that 733 respondents met the analytical inclusion criteria following the data cleaning process. Respondents were drawn from several provinces in Indonesia, within the age range of 17–24 years, corresponding to the Generation Z cohort. Respondent characteristics showed variation in sex, educational level, occupation, place of residence, and academic major, such that the dataset used represented respondents across diverse demographic characteristics. This diversity provided a sufficient basis for constructing a predictive model of mental health risk tendency.

Data Preprocessing Results

Table 1. Summary of the Data Preprocessing Stages

Stage	Result
Final number of respondents	733 respondents
Initial number of variables	92
Variables removed	34
Variables used	58
Feature leakage removed	15 variables
Missing values	Imputed using the mean (numerical variables)
Encoding	Categorical variables converted to numerical form
Feature selection	Mutual Information

Based on Table 1, the preprocessing stage was carried out to improve data quality prior to modeling. The initial dataset consisted of 92 variables encompassing demographic characteristics and psychological indicators. Subsequently, potential feature leakage was identified, resulting in the removal of 15 variables that could compromise information integrity. Following feature selection and data cleaning, the number of variables used was reduced to 58. The preprocessing stage also included the imputation of missing values using the mean for numerical variables, the transformation of categorical variables into numerical form through encoding, and the evaluation of inter-variable relationships using Mutual Information. The analysis results indicated no inter-feature correlation exceeding the predetermined threshold, confirming that all remaining features were suitable for use in the classification process.

Comparison of Machine Learning Model Performance

Table 2. Comparison of Model Performance

Model	Accuracy (%)	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	93.6	0.83	1.00	0.90	0.995
Support Vector Machine	93.6	0.82	1.00	0.90	0.994
Random Forest	93.2	0.82	1.00	0.90	0.995

Based on the results above, the three classification algorithms—Logistic Regression, Support Vector Machine (SVM), and Random Forest—were developed using a 70:30 data split, stratified 5-fold cross-validation, hyperparameter optimization via GridSearchCV and RandomizedSearchCV, and class imbalance handling through class weighting and SMOTE. The evaluation results showed that all models achieved excellent performance, with accuracy values ranging between 93% and 94%. Logistic Regression and SVM achieved an accuracy of 93.6%, while Random Forest achieved 93.2%. All three models achieved a recall of 100%, indicating that all at-risk respondents were successfully identified. Based on the combination of accuracy, F1-score, ROC-AUC, and model complexity, Logistic Regression was selected as the best-performing model in this study.





Model Evaluation

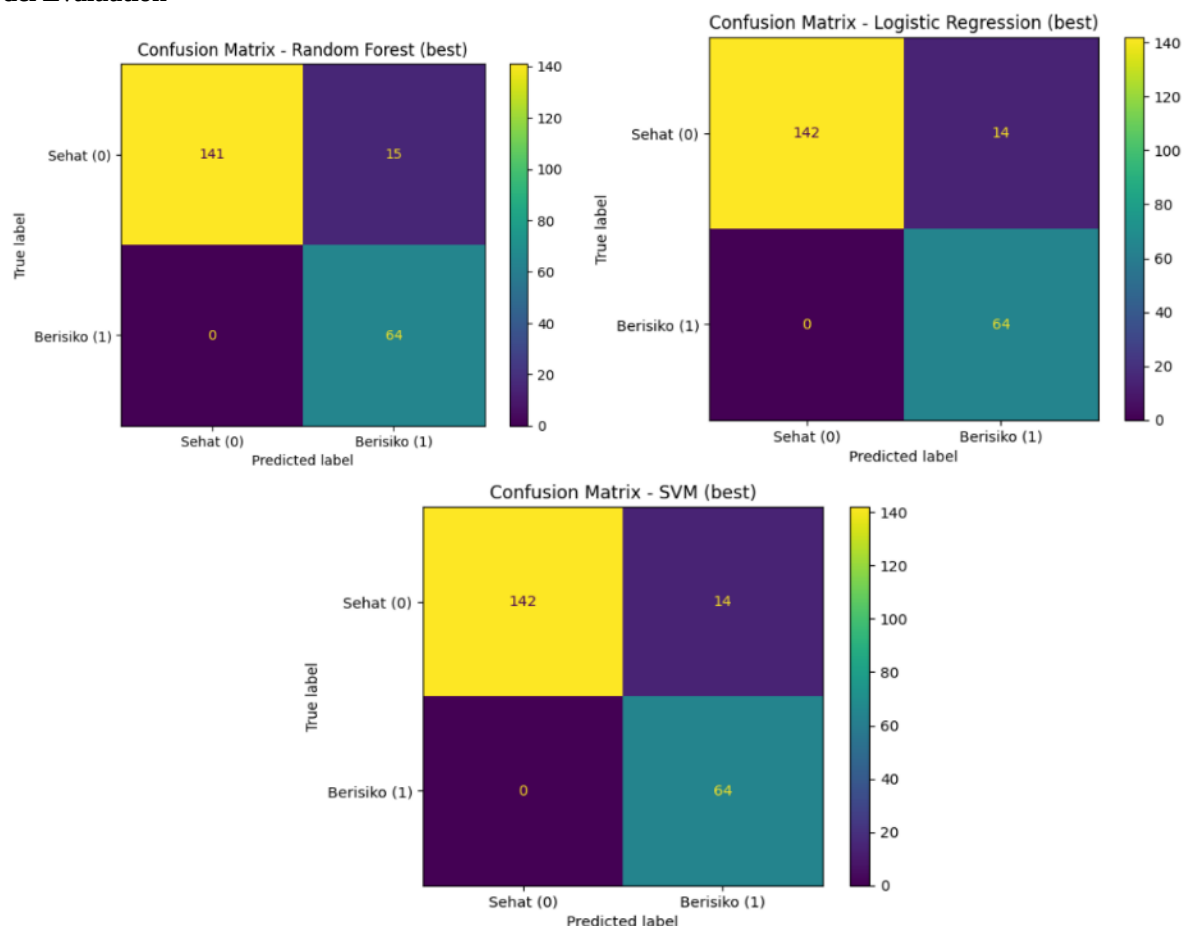


Figure 3. Confusion Matrix

Model evaluation using the confusion matrix showed that the Logistic Regression model was able to identify all respondents classified as at-risk without producing any false negatives. The model still generated a number of false positives healthy respondents predicted as at-risk—however, this outcome was considered more acceptable than failing to detect individuals who genuinely have a risk of mental health disorders. The dominance of predictions consistent with actual conditions indicates that the model possesses strong generalization capability when applied to previously unseen data.

Explainable Machine Learning

Table 3. Distribution of Contributions Based on SHAP Values

Domain	Number of Variables	Percentage
ACE	9	45%
DASS-21	7	35%
STAI-T	3	15%
Demographic	1	5%
Total	20	100%

Based on the results presented in Table 3, the SHapley Additive exPlanations (SHAP) method successfully identified twenty features with the greatest contribution to predicting mental health risk tendency among Generation Z. To obtain a more comprehensive interpretation, these features were subsequently grouped according to the instrument domains used in the study, namely Adverse Childhood Experiences (ACE), the Depression Anxiety Stress Scale-21 (DASS-21), the State-Trait Anxiety Inventory (STAI-T), and demographic characteristics. The distribution of dominant features by psychological domain is presented in Table 3.

Based on this grouping, the ACE domain constituted the most dominant group of variables, accounting for 45% (9 of 20 variables), followed by DASS-21 at 35% (7 variables) and STAI-T at 15% (3 variables), while demographic variables contributed only 5% (1 variable). This proportion indicates that the information most heavily utilized by the model in distinguishing at-risk from not-at-risk individuals originated from a history of adverse experiences during





childhood. In contrast, demographic characteristics contributed relatively little, playing a lesser role in enhancing the model's predictive capability compared to psychosocial factors measured through the psychological instruments.

Overall, the distribution of features by domain showed that 80% of the twenty most influential variables originated from psychological instruments, particularly ACE (45%) and DASS-21 (35%), while STAI-T contributed 15% and demographic factors only 5%. This finding confirms that the predictive model was more strongly influenced by psychosocial factors representing individuals' life experiences and emotional conditions than by demographic characteristics. Therefore, mental health screening approaches for Generation Z should not focus solely on currently manifesting psychological symptoms but should also incorporate childhood experience history as a key component in the early risk identification process.

DISCUSSION

This study demonstrates that a machine learning approach can achieve strong performance in identifying Generation Z individuals with a tendency toward mental health disorders based on a combination of psychological factors and demographic characteristics. The integration of multiple psychological instruments measuring both current emotional states and childhood life experiences produced a classification model capable of consistently distinguishing at-risk from not-at-risk individuals. These findings suggest that data-driven approaches have the potential to support mental health screening processes that are faster, more objective, and more efficient than conventional methods that rely solely on manual interpretation of questionnaire results.

Moreover, the results showed that Logistic Regression performed slightly better than Support Vector Machine and Random Forest. This finding suggests that the relationship between the predictor variables and mental health risk status in the study dataset tends to be linear, allowing it to be optimally learned by a model with lower complexity. Simpler models offer advantages of greater prediction stability, easier interpretability, and a lower risk of overfitting compared to more complex ensemble-based models. This finding indicates that increasing algorithmic complexity does not always improve performance when the data characteristics are relatively homogeneous and the relationships between variables are not overly complex.

Then, the model's ability to identify all individuals classified as at-risk represents an important finding in the context of public health. In mental health screening systems, failure to detect individuals who are genuinely at risk can result in delayed psychological intervention or necessary health services. Therefore, a model with high sensitivity is more appropriate for use as an initial screening tool, even though it may still generate several positive predictions for individuals who are not actually at risk. Such an approach is widely recommended in early detection systems, as the clinical consequences of false negatives are generally more severe than those of false positives (Abdul Rahman et al., 2023).

Additionally, the preprocessing stage made an important contribution to the quality of the resulting model. The removal of variables with potential feature leakage ensured that the model's learning process relied only on information available prior to prediction. In addition, the application of encoding, missing value imputation, feature selection using Mutual Information, and class imbalance handling via SMOTE helped improve the model's generalization capability. These steps are consistent with best practices in machine learning model development, as they help reduce bias, enhance model stability, and produce more representative evaluations of real-world conditions (Priya et al., 2020). One of the most notable findings of this study was obtained through Explainable Machine Learning analysis using SHAP. Unlike most previous studies that report only model accuracy, this study was able to explain the contribution of each variable to the model's decisions, thereby enhancing the transparency of the classification process. Interpretability is a critical aspect of machine learning implementation in the health sector, as prediction results are not only required to achieve high accuracy but must also be scientifically explainable to health practitioners and policymakers (Javaid et al., 2022).

The SHAP analysis revealed that most of the highly influential variables originated from the Adverse Childhood Experiences (ACE) domain. The dominance of ACE variables indicates that traumatic experiences during childhood contribute more strongly to the risk of mental health tendency than current emotional conditions or demographic characteristics measured at the time of the study. This finding reinforces the concept of life-course epidemiology, which posits that adverse experiences during early development can influence neurobiological function, emotional regulation, coping mechanisms, and vulnerability to psychological disorders into adulthood (Retnowati et al., 2026). The dominance of ACE variables also indicates that mental health risk among Generation Z is not solely influenced by current psychological conditions but represents an accumulation of life experiences since childhood. Exposure to verbal abuse, physical abuse, sexual abuse, emotional neglect, domestic violence, or a lack of family support has the potential to cause long-term changes in an individual's ability to manage stress and build social relationships. This condition explains why ACE variables obtained the highest contribution in the model's decision-making process. These results are consistent with various longitudinal studies reporting that higher exposure to traumatic experiences during childhood is associated with an increased risk of developing depression, anxiety disorders, stress disorders, and even suicidal behavior during adolescence and young adulthood.



In addition to ACE, the DASS-21 domain also contributed substantially to the model's predictions. This indicates that the levels of depression, anxiety, and stress reported by respondents at the time of completing the questionnaire remained an important indicator in the mental health risk identification process. The psychological symptoms measured through DASS-21 reflect respondents' current emotional state, thereby complementing the historical information obtained from the ACE instrument. Consequently, the combination of these two instruments allowed the model to capture both predisposing factors and the psychological manifestations currently experienced by individuals.

In contrast, the contribution of STAI-T variables was relatively lower than that of ACE and DASS-21. This result indicates that trait anxiety, as a personality characteristic, does influence the model's predictions, although its effect is not as substantial as that of traumatic experiences or current psychological symptoms. One possible explanation is the association between trait anxiety and symptoms of depression and stress, such that a portion of the information captured by STAI-T is already represented by other variables in the model. This finding suggests that while trait anxiety is an important psychological factor, measures of life experience and current emotional condition provide greater informational value for the mental health risk identification process. The relatively small contribution of demographic variables indicates that age, sex, education, occupation, and place of residence are not the primary factors distinguishing at-risk from not-at-risk individuals within this study population. This result suggests that psychological condition is more strongly influenced by individuals' life experiences and emotional responses than by demographic characteristics alone. This finding also indicates that the use of demographic data as a sole predictor is likely insufficient for developing a mental health screening system, underscoring the need to integrate psychological instruments to enhance the model's predictive capability.

Practically, the findings of this study imply that mental health screening programs for Generation Z should not focus solely on detecting symptoms of depression, anxiety, and stress, but should also consider a history of childhood traumatic experiences as a key component of the assessment process. Integrating the ACE and DASS-21 instruments has the potential to improve the effectiveness of identifying individuals in need of further intervention. Furthermore, the application of Explainable Machine Learning enables health practitioners to understand the reasoning behind model decisions, thereby increasing trust in the use of artificial intelligence within mental health services.

This study has several limitations that warrant consideration. The data were obtained using a cross-sectional survey approach, meaning that causal relationships between variables cannot be directly inferred. In addition, all information was obtained through self-report questionnaires, which may introduce perception bias or response bias. The study population was also limited to Generation Z in Indonesia, so the generalization of these findings to other populations should be made with caution. Future research is recommended to employ a longitudinal design, involve a larger number of respondents, integrate clinical data or biomarkers, and evaluate model performance across more diverse populations to enhance the external validity of the predictive model.

CONCLUSION

This study demonstrates that a machine learning approach can identify the risk of mental health tendency among Generation Z with high performance, with Logistic Regression selected as the best-performing model due to its balance between accuracy, generalization ability, and interpretability. Explainable Machine Learning analysis using SHAP revealed that the factors most influential on risk prediction were dominated by Adverse Childhood Experiences (ACE), followed by DASS-21, STAI-T, and demographic factors, indicating that adverse experiences during childhood are the primary determinant in the process of identifying mental health risk among Generation Z.

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