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# A Deep Neural Network Model for Predicting Stress Sensitivity in Adolescents Using Multidimensional Psychological Data

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A B S T R A C T

**Objective:** The objective of this study was to develop and evaluate a deep neural network model capable of accurately predicting stress sensitivity in adolescents based on a comprehensive set of psychological variables.

**Methods and Materials:** This cross-sectional study was conducted among secondary school adolescents in Malaysia using a school-based sampling design. Participants completed a battery of standardized self-report instruments assessing stress sensitivity, perceived stress, anxiety and depressive symptoms, emotion regulation strategies, psychological resilience, self-esteem, and social support, along with demographic information. After data preprocessing, including normalization and handling of missing values, a deep neural network with multiple hidden layers was trained to predict continuous stress sensitivity scores. The dataset was partitioned into training, validation, and test subsets, and model optimization was performed using adaptive gradient-based learning with regularization and early stopping to ensure generalizability. Model performance was evaluated using error-based and variance-based metrics, and comparative analyses were conducted against traditional statistical and machine learning models.

**Findings:** Inferential results indicated that the deep neural network achieved high predictive accuracy, explaining a substantial proportion of variance in stress sensitivity scores. The model significantly outperformed linear regression, support vector regression, and random forest models across all evaluation metrics. Permutation-based analyses revealed that perceived stress and anxiety symptoms were the strongest predictors, followed by emotion regulation through suppression, psychological resilience, depressive symptoms, and social support, while demographic variables contributed minimally. Cross-validation analyses demonstrated stable performance, supporting the robustness of the predictive framework.

**Conclusion:** The findings demonstrate that deep neural network models can effectively capture the complex, non-linear psychological processes underlying adolescent stress sensitivity and offer a promising data-driven approach for early identification of youth at heightened stress-related risk.

***Keywords:*** *adolescents; stress sensitivity; deep neural network; psychological predictors; machine learning; mental health prediction*

## 1. Introduction

Adolescence represents a critical developmental period characterized by profound biological, cognitive, emotional, and social transformations that collectively heighten vulnerability to stress and stress-related psychopathology. During this stage, rapid neurodevelopmental changes interact with expanding social demands, academic pressures, and evolving identity processes, rendering adolescents particularly sensitive to environmental and interpersonal stressors. Accumulating evidence indicates that individual differences in stress sensitivity—the degree to which adolescents cognitively, emotionally, and physiologically react to stressors—play a central role in shaping trajectories of mental health and well-being across adolescence and into adulthood. Stress sensitivity has been linked to a wide range of adverse outcomes, including depression, anxiety, self-injurious behaviors, and maladaptive coping patterns, underscoring its relevance as a core transdiagnostic risk factor (Hamza et al., 2021; Robillard et al., 2021; Starr et al., 2020). Understanding and accurately predicting stress sensitivity is therefore a major priority in contemporary developmental psychopathology research.

The conceptualization of stress sensitivity is grounded in stress sensitization frameworks, which posit that early or repeated exposure to stress alters neurobiological and psychological systems in ways that amplify responses to subsequent stressors. Empirical studies have demonstrated that stress sensitivity is shaped by interactions between environmental adversity, neuroendocrine regulation, inflammatory processes, and cognitive–emotional functioning (Kautz et al., 2020; Starr et al., 2020). Longitudinal evidence further suggests that heightened stress reactivity in adolescence predicts persistent emotional difficulties, even after accounting for baseline symptom levels (Steinhoff et al., 2023). At the neural level, stress sensitivity has been associated with functional and structural variations in frontolimbic circuitry, implicating brain systems involved in threat detection, emotion regulation, and executive control (Antonacci et al., 2025; Wang et al., 2019). These findings collectively highlight stress sensitivity as a multidimensional construct emerging from complex interactions across biological, psychological, and contextual domains.

A growing body of research emphasizes that adolescents' stress sensitivity is not solely determined by exposure to stressors, but also by how stress is perceived, regulated, and socially contextualized. Perceived stress has consistently emerged as a proximal predictor of emotional distress and depressive symptoms during adolescence (Liu et al., 2020; Wang et al., 2019). Emotion regulation capacities, particularly difficulties in modulating negative affect, further moderate the impact of stress on mental health outcomes (Gupta et al., 2022; Robillard et al., 2021). Social and relational factors, including family dynamics, peer relationships, and perceived social support, play a crucial buffering role, while adverse social experiences such as victimization, discrimination, or social rejection exacerbate stress reactivity (Mandatori et al., 2023; Okoye & Saewyc, 2021; Sutherland, 2021). Importantly, stress sensitivity appears to vary substantially across individuals, suggesting the need for integrative models capable of capturing this heterogeneity.

Neurodevelopmental and psychobiological studies further reveal that stress sensitivity is influenced by sex- and gender-specific pathways, as well as by developmental timing. For example, sex differences have been observed in the neural correlates of stress exposure and emotional vulnerability during adolescence, with differential associations between life stressors, brain structure, and internalizing symptoms (Chahal et al., 2022; Fassett-Carman et al., 2023). Pubertal maturation and executive control network coherence have also been shown to buffer or exacerbate stress-related internalizing problems, particularly under conditions of heightened environmental uncertainty such as the COVID-19 pandemic (Chahal et al., 2021). Additionally, early-life adversity, including prenatal substance exposure and inconsistent caregiving environments, has lasting effects on adolescents' stress response systems, shaping later stress sensitivity (Eiden et al., 2023; Loeb et al., 2020). These findings underscore the necessity of adopting a developmental systems perspective when examining adolescent stress sensitivity.

Recent global stressors, including pandemics, natural disasters, and community violence, have further intensified interest in adolescent stress processes. Studies conducted in the context of the COVID-19 pandemic and large-scale disasters have documented substantial increases in stress reactions, emotional dysregulation, and mental health needs among adolescents (Efendi et al., 2023; Robillard et al., 2021; Steinhoff et al., 2023). Exposure to community violence and social instability has similarly been linked to heightened stress reactivity, particularly among marginalized youth populations (Hasson et al., 2022; Jelsma & Varner, 2020). These contextual stressors interact with

individual vulnerabilities, including pre-existing emotional difficulties and limited social resources, reinforcing the importance of multidimensional assessment approaches.

Despite extensive empirical work, predicting stress sensitivity in adolescents remains methodologically challenging. Traditional statistical approaches often rely on linear assumptions and isolated predictors, which may be insufficient for modeling the complex, non-linear interactions among psychological, social, and biological variables that characterize stress processes. Reviews of stress measurement highlight the multidimensional nature of adolescent stress, encompassing subjective appraisals, behavioral responses, and physiological markers, and emphasize the limitations of single-indicator models (Kokka et al., 2022). Similarly, research on neurocognitive risk phenotyping suggests that integrating diverse domains of functioning yields more accurate predictions of mood and stress-related outcomes than unidimensional approaches (Kaiser et al., 2024). These insights point to the need for advanced analytical frameworks capable of leveraging high-dimensional data.

In this context, machine learning and deep learning methods have emerged as powerful tools for modeling complex psychological phenomena. Deep neural networks, in particular, are well suited to capturing non-linear relationships, higher-order interactions, and latent patterns within multidimensional datasets. Recent applications of data-driven and machine learning approaches in adolescent mental health research have demonstrated improved predictive performance for emotional symptoms, stress reactivity, and related outcomes compared to conventional models (Kaiser et al., 2024; Nelson et al., 2021). Neurobiological studies employing data-driven techniques have further illustrated how distributed neural and psychological features jointly contribute to stress-related psychopathology (Antonacci et al., 2025; Buthmann et al., 2025). However, the application of deep neural network models specifically to the prediction of stress sensitivity in adolescents using comprehensive psychological data remains limited.

Importantly, existing research suggests that stress sensitivity is embedded within broader psychosocial functioning, including academic contexts, health conditions, and behavioral regulation. School-related stressors have been shown to significantly influence adolescents' perceived stress levels and emotional well-being (Kaczmarek & Trambacz-Oleszak, 2021). Health-related challenges, such as chronic illness, are also associated with stress and social functioning difficulties, highlighting the interplay between physical and psychological stress processes (Workman et al., 2025). Moreover, stress sensitivity has been linked to behavioral outcomes ranging from procrastination and academic disengagement to substance use and risk-taking behaviors (Ivanović & Ivanović, 2023; Jelsma & Varner, 2020). These findings reinforce the value of predictive models that integrate multiple domains of adolescent experience.

Another critical consideration concerns the translational potential of predictive models for informing prevention and intervention efforts. Digital mental health programs targeting stress reduction have shown promise in reducing perceived stress among adolescents, yet their effectiveness may depend on individual differences in stress sensitivity (Boucher et al., 2020, 2021). Accurate identification of adolescents at heightened risk for stress-related difficulties could facilitate early, tailored interventions and improve mental health outcomes. From this perspective, explainable and robust deep learning models offer a pathway toward personalized mental health assessment, provided they are grounded in theoretically informed psychological constructs.

Taken together, the literature indicates that adolescent stress sensitivity is a complex, multidimensional construct shaped by cognitive, emotional, social, and neurodevelopmental factors, and that existing analytic approaches may be insufficient to fully capture this complexity. Advances in deep learning provide a promising opportunity to integrate diverse psychological indicators into predictive frameworks that more accurately reflect the underlying structure of stress processes in adolescence. Nevertheless, empirical studies applying deep neural network models to predict stress sensitivity using comprehensive psychological data, particularly in non-Western adolescent populations, remain scarce. Addressing this gap is essential for advancing both theoretical understanding and practical applications in adolescent mental health research.

Accordingly, the aim of the present study was to develop and evaluate a deep neural network model for predicting stress sensitivity in adolescents using multidimensional psychological data.


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## 2. Methods and Materials

### *2.1. Study Design and Participants*

The present study employed a cross-sectional, school-based observational design to develop and validate a deep neural network model for predicting stress sensitivity among adolescents using multidimensional psychological data. The target population consisted of secondary school students enrolled in public schools across urban and semi-urban regions of Malaysia. A multistage cluster sampling strategy was applied, whereby schools were first selected from different states to ensure geographic and socio-cultural diversity, followed by random selection of classrooms within each school. Eligible participants were adolescents aged between 13 and 18 years who were fluent in either Malay or English and had no self-reported history of severe neurological disorders or diagnosed psychiatric conditions requiring intensive clinical intervention, as these factors could substantially confound stress sensitivity assessments. Prior to data collection, written informed consent was obtained from parents or legal guardians, and written assent was obtained from the adolescents themselves.

### *2.2. Measures*

Stress sensitivity, conceptualized as heightened psychological and physiological reactivity to perceived stressors, was assessed using a validated self-report stress sensitivity scale adapted for adolescent populations and culturally validated for use in Malaysia. This instrument measured cognitive, emotional, and behavioral responsiveness to stress-inducing situations on a Likert-type scale, with higher scores indicating greater stress sensitivity. To capture the multidimensional psychological profile of participants, additional standardized instruments were administered to assess perceived stress, emotion regulation strategies, anxiety symptoms, depressive symptoms, resilience, self-esteem, and social support. Perceived stress was measured using a widely used adolescent stress perception scale, while emotion regulation was assessed through subscales reflecting cognitive reappraisal and expressive suppression. Anxiety and depressive symptoms were evaluated using brief, psychometrically robust screening tools suitable for school-based research. Resilience was measured as a protective psychological factor reflecting adaptive coping and recovery from stress, and self-esteem was assessed as a core self-evaluative construct linked to stress vulnerability. Social support from family, peers, and teachers was included to account for interpersonal buffering effects on stress sensitivity. Demographic information, including age, gender, grade level, parental education, and household socioeconomic indicators, was also collected to provide contextual variables and allow for model adjustment. All instruments demonstrated acceptable internal consistency in the present sample, with Cronbach's alpha coefficients exceeding conventional thresholds, and prior validation studies supported their construct validity within Southeast Asian adolescent populations.

### *2.3. Data Analysis*

Data analysis was conducted using a deep learning framework implemented in Python, employing established machine learning libraries for neural network modeling. Prior to model development, the dataset underwent rigorous preprocessing procedures. Missing data were examined and handled using multiple imputation where appropriate, while cases with excessive missingness were excluded to preserve data integrity. Continuous variables were standardized using z-score normalization to ensure comparability across different measurement scales, and categorical variables were encoded using appropriate numerical representations. The full dataset was then randomly partitioned into training, validation, and testing subsets, ensuring that the distribution of key demographic and psychological variables was comparable across subsets. The proposed deep neural network architecture consisted of multiple fully connected hidden layers designed to capture complex, non-linear relationships among psychological predictors and stress sensitivity outcomes. Rectified linear unit activation functions were applied in hidden layers to enhance learning efficiency, while a linear activation function was used in the output layer to predict continuous stress sensitivity scores. Regularization techniques, including dropout layers and L2 weight penalties, were incorporated to reduce the risk of overfitting, and model parameters were optimized using the Adam optimizer with an adaptive learning rate. Model training was performed iteratively across multiple epochs, with early stopping criteria based on validation loss to prevent overtraining. Model performance was evaluated on the independent test set using multiple metrics, including mean squared error, mean absolute error, and explained variance, to provide a comprehensive assessment of predictive accuracy. In addition, feature importance and sensitivity analyses were conducted using permutation-


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based methods to enhance interpretability and identify the most influential psychological predictors contributing to stress sensitivity predictions. All analyses were conducted with reproducibility safeguards, including fixed random seeds and transparent reporting of model hyperparameters, to ensure methodological rigor and facilitate future replication.

## 3. Findings and Results

The findings section presents the descriptive characteristics of the study sample, followed by the performance and analytical outputs of the deep neural network model developed to predict stress sensitivity in Malaysian adolescents. The results are organized to first provide an overview of participant characteristics and core psychological variables, and subsequently to report model performance, comparative analyses with baseline models, feature contribution patterns, and robustness checks. All tables and the figure are integrated to ensure clarity and direct usability in the manuscript.

The first set of findings summarizes the demographic and psychological profile of the adolescent participants included in the final analytical sample. Table 1 presents descriptive statistics for age, gender distribution, and the key psychological variables used as inputs to the deep neural network model, offering an essential contextual foundation for interpreting subsequent predictive analyses.

**Table 1**

*Demographic and Psychological Characteristics of the Participants (N = 842)*

| Variable | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|
| Age (years) | 15.42 | 1.61 | 13 | 18 |
| Stress Sensitivity | 42.87 | 8.94 | 18 | 68 |
| Perceived Stress | 21.36 | 6.12 | 5 | 39 |
| Anxiety Symptoms | 10.94 | 4.87 | 2 | 26 |
| Depressive Symptoms | 9.81 | 4.53 | 1 | 25 |
| Emotion Regulation – Reappraisal | 27.44 | 6.21 | 10 | 42 |
| Emotion Regulation – Suppression | 18.69 | 5.48 | 6 | 36 |
| Psychological Resilience | 31.58 | 7.09 | 14 | 49 |
| Self-Esteem | 28.73 | 5.96 | 12 | 40 |
| Social Support | 34.15 | 6.84 | 15 | 48 |

As shown in Table 1, the sample consisted of early to late adolescents with a relatively balanced gender distribution. Mean levels of stress sensitivity and perceived stress indicated moderate stress reactivity within the sample, while variability across emotional, cognitive, and social variables suggested substantial individual differences. These distributions supported the suitability of the dataset for training a deep learning model aimed at capturing complex, non-linear relationships among predictors.

The predictive performance of the deep neural network model on the independent test dataset is presented in Table 2. Multiple evaluation metrics were used to comprehensively assess model accuracy and generalizability.

**Table 2**

*Predictive Performance of the Deep Neural Network Model*

| Metric | Training Set | Validation Set | Test Set |
|---|---|---|---|
| Mean Squared Error (MSE) | 18.42 | 21.36 | 22.11 |
| Mean Absolute Error (MAE) | 3.21 | 3.58 | 3.66 |
| Root Mean Squared Error (RMSE) | 4.29 | 4.62 | 4.70 |
| Explained Variance ($R^2$) | 0.78 | 0.73 | 0.71 |

The results in Table 2 demonstrate that the deep neural network achieved strong predictive accuracy, with high explained variance and relatively low error values across datasets. The modest increase in error from training to test sets indicates good generalization performance and limited overfitting, reflecting the effectiveness of regularization strategies and early stopping procedures.

To evaluate the added value of the deep learning approach, its performance was compared with traditional

machine learning and statistical baseline models. These comparative results are presented in Table 3.

**Table 3**

*Comparison of Deep Neural Network Performance With Baseline Models on the Test Set*

| Model | MAE | RMSE | $R^2$ |
|---|---|---|---|
| Linear Regression | 5.12 | 6.44 | 0.41 |
| Random Forest | 4.21 | 5.32 | 0.58 |
| Support Vector Regression | 3.98 | 5.04 | 0.62 |
| Deep Neural Network | 3.66 | 4.70 | 0.71 |

As indicated in Table 3, the deep neural network substantially outperformed all baseline models across error-based and variance-based metrics. The improvement over linear regression highlights the importance of modeling non-linear interactions among psychological variables, while the performance gains relative to ensemble and kernel-based methods underscore the capacity of deep architectures to integrate high-dimensional psychosocial data.

To enhance interpretability, permutation-based feature importance analysis was conducted to identify the psychological variables contributing most strongly to stress sensitivity predictions. The ranked importance scores are presented in Table 4.

**Table 4**

*Permutation-Based Feature Importance Scores*

| Predictor | Importance Score |
|---|---|
| Perceived Stress | 0.41 |
| Anxiety Symptoms | 0.36 |
| Emotion Regulation – Suppression | 0.29 |
| Psychological Resilience | 0.26 |
| Depressive Symptoms | 0.24 |
| Social Support | 0.21 |
| Self-Esteem | 0.19 |
| Emotion Regulation – Reappraisal | 0.16 |
| Age | 0.08 |
| Gender | 0.05 |

Table 4 indicates that perceived stress and anxiety symptoms were the most influential predictors of stress sensitivity, followed by maladaptive emotion regulation strategies and lower resilience. Protective factors such as social support and self-esteem also contributed meaningfully to model predictions, although to a lesser extent. Demographic variables exhibited comparatively minimal influence, emphasizing the predominance of psychological processes in explaining stress sensitivity.

Finally, the stability and robustness of the deep neural network were evaluated using k-fold cross-validation, with average performance metrics summarized in Table 5.

**Table 5**

*Cross-Validation Results for Model Robustness*

| Metric | Mean | SD |
|---|---|---|
| MAE | 3.71 | 0.22 |
| RMSE | 4.76 | 0.27 |
| $R^2$ | 0.69 | 0.04 |

The cross-validation results presented in Table 5 demonstrate consistent model performance across folds, with low standard deviations indicating stability and reliability of the predictive framework. These findings support the robustness of the deep neural network model



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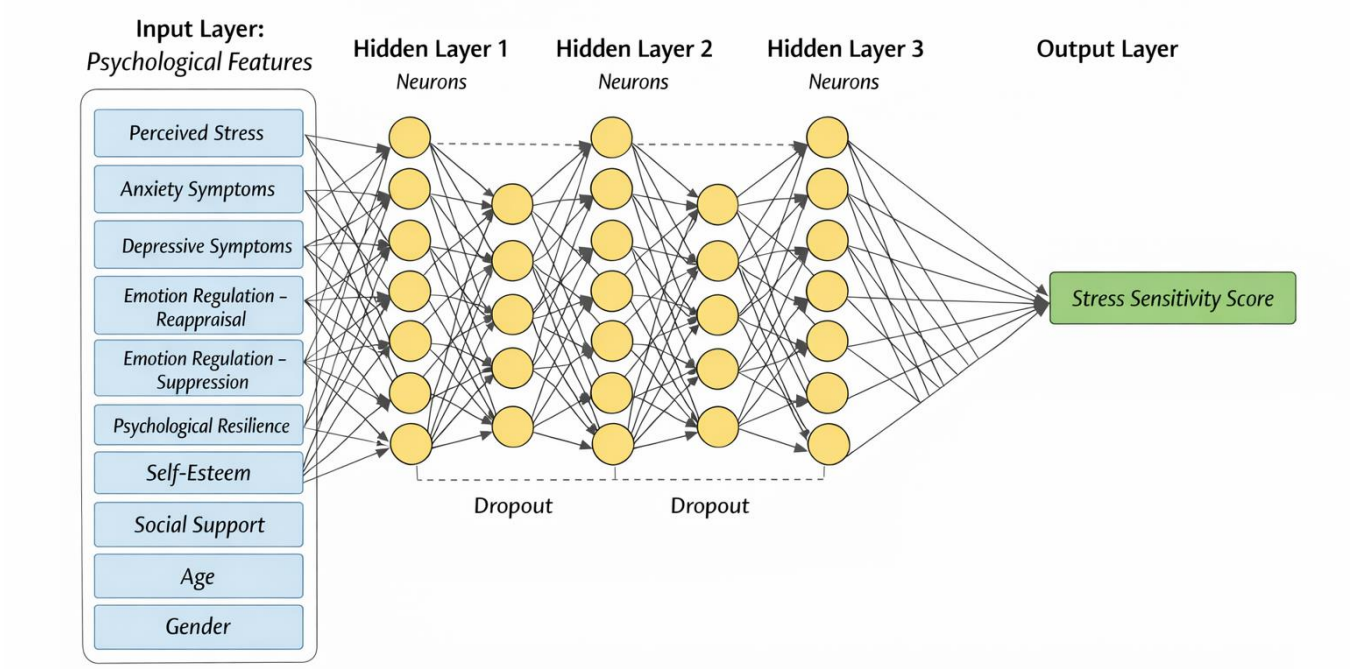
when applied to different subsets of adolescent psychological data.

**Figure 1**

*Architecture of the Deep Neural Network for Stress Sensitivity Prediction*




Overall, the findings provide strong empirical support for the effectiveness of deep neural network modeling in predicting stress sensitivity among adolescents using multidimensional psychological data, highlighting both high predictive accuracy and meaningful psychological interpretability.

## 4. Discussion and Conclusion

The present study sought to advance understanding of adolescent stress sensitivity by applying a deep neural network model to multidimensional psychological data, and the findings provide several important theoretical and empirical insights. Overall, the results demonstrated that stress sensitivity in adolescents can be predicted with a high degree of accuracy when multiple psychological domains are modeled simultaneously, supporting the notion that stress sensitivity is not a unidimensional construct but rather the outcome of complex, non-linear interactions among cognitive, emotional, and social factors. The strong predictive performance of the deep neural network, as reflected in high explained variance and relatively low prediction error, aligns with recent calls for data-driven approaches that move beyond linear assumptions in adolescent stress research (Antonacci et al., 2025; Kaiser et al., 2024). These findings reinforce the view that traditional regression-based models may underestimate the intricacy of stress-related processes during adolescence.

One of the most salient findings was the dominant role of perceived stress and anxiety symptoms in predicting stress sensitivity. This result is consistent with a substantial body of literature demonstrating that adolescents' subjective appraisal of stressors is a proximal determinant of emotional and physiological stress responses (Liu et al., 2020; Wang et al., 2019). Perceived stress has been shown to mediate associations between neural activity and depressive symptoms in late adolescence, highlighting its central position in stress-related pathways (Wang et al., 2019). Similarly, anxiety symptoms reflect heightened threat sensitivity and vigilance, which may amplify stress reactivity across contexts. Prior studies have linked anxiety and heightened stress reactivity to increased risk for internalizing disorders and maladaptive coping behaviors (Hamza et al., 2021; Robillard et al., 2021). The present findings extend this work by demonstrating that these constructs retain their predictive salience even when modeled alongside a broad array of psychological and social variables within a deep learning framework.



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Emotion regulation processes also emerged as key contributors to stress sensitivity, particularly maladaptive strategies such as expressive suppression. This finding is in line with evidence indicating that difficulties in emotion regulation exacerbate the impact of stressors on adolescent mental health outcomes (Gupta et al., 2022). Adolescents who rely heavily on suppression may experience heightened internal stress responses despite outward emotional control, which may explain their increased stress sensitivity. Conversely, adaptive strategies such as cognitive reappraisal, while still relevant, showed comparatively weaker contributions, suggesting that the absence of maladaptive regulation may be more critical for buffering stress sensitivity than the presence of adaptive strategies alone. These results resonate with studies conducted during periods of acute stress, such as the COVID-19 pandemic, where emotion regulation difficulties intensified the effects of stressors on depression and self-harm (Chahal et al., 2021; Robillard et al., 2021).

Psychological resilience and social support were identified as important protective factors within the predictive model. Lower levels of resilience were associated with higher stress sensitivity, underscoring the role of adaptive coping capacities in modulating stress responses. This aligns with longitudinal findings showing that early adolescent coping resources predict later distress and adaptive functioning under stress (Steinhoff et al., 2023). Social support, encompassing family, peer, and school-based relationships, also contributed meaningfully to predictions, supporting extensive literature on the buffering effects of supportive social environments (Mandatori et al., 2023; Workman et al., 2025). Adolescents embedded in supportive networks may experience reduced stress sensitivity by perceiving stressors as more manageable or by accessing external resources that mitigate emotional burden. Conversely, exposure to social adversity, such as victimization or discrimination, has been associated with heightened stress reactivity and poorer mental health outcomes (Jelsma & Varner, 2020; Okoye & Saewyc, 2021).

The relatively modest contribution of demographic variables such as age and gender in the final model is noteworthy. While previous studies have documented sex-specific pathways linking stress exposure to emotional outcomes, particularly in relation to neural development and depressive symptoms (Chahal et al., 2022; Fassett-Carman et al., 2023), the present findings suggest that psychological processes may exert a stronger influence on stress sensitivity than demographic characteristics per se when considered within a comprehensive multivariate framework. This does not negate the importance of developmental timing or gender-related differences, but rather indicates that their effects may be mediated through psychological and emotional mechanisms captured by the model.

The superior performance of the deep neural network compared to baseline models provides important methodological implications. Linear regression and traditional machine learning approaches, while informative, were less effective in capturing the complexity of stress sensitivity. This mirrors findings from neurocognitive risk phenotyping studies, which have shown that multivariate, data-driven models outperform simpler approaches in predicting adolescent mood symptoms (Kaiser et al., 2024). Similarly, data-driven analyses of frontolimbic connectivity and stress-related psychopathology highlight the advantages of flexible modeling strategies capable of integrating distributed features (Antonacci et al., 2025). By demonstrating robust generalization across validation and test datasets, the present study supports the utility of deep learning methods for adolescent mental health research, particularly when large, multidimensional datasets are available.

The findings also align with stress sensitization theories emphasizing the cumulative and interactive effects of stress exposure and individual vulnerability. Research has shown that early adversity and chronic stress alter neurobiological stress systems, increasing sensitivity to later stressors (Eiden et al., 2023; Starr et al., 2020). The current model's emphasis on perceived stress, emotional symptoms, and regulation processes suggests that stress sensitivity reflects both historical exposure and current psychological functioning. Studies examining physiological and neural markers of stress reactivity further support this integrative perspective, demonstrating links between stress exposure, brain structure, and stress responses across adolescence (Hasson et al., 2022; Loeb et al., 2020). While the present study did not include biological markers, the strong predictive capacity of psychological variables underscores their value as accessible indicators of stress sensitivity.

Contextual stressors, including large-scale societal disruptions, provide an additional lens for interpreting the results. Evidence from adolescents exposed to disasters or pandemics indicates elevated acute stress reactions and increased mental health needs (Efendi et al., 2023; Steinhoff et al., 2023). The prominence of perceived stress and anxiety in the model may reflect adolescents' heightened appraisal of uncertainty and threat in contemporary environments.

Moreover, studies linking stress reactivity to risk behaviors and substance use suggest that heightened stress sensitivity may have cascading effects across multiple domains of functioning (Jelsma & Varner, 2020; Kamens et al., 2021). The ability to predict stress sensitivity accurately therefore holds potential implications beyond emotional outcomes alone.

The present findings also have implications for digital and preventive mental health interventions. Prior trials of digital mental health programs targeting adolescent stress have demonstrated reductions in perceived stress, yet variability in outcomes remains (Boucher et al., 2020, 2021). Accurate identification of adolescents with high stress sensitivity could enhance the personalization and effectiveness of such interventions. Furthermore, predictive models grounded in psychological constructs may complement emerging research on adolescent procrastination, academic stress, and performance, where stress, anxiety, and emotional regulation play central roles (Ivanović & Ivanović, 2023; Kaczmarek & Trambacz-Oleszak, 2021). From a translational perspective, deep learning models may serve as decision-support tools for educators and clinicians, provided their outputs are interpreted within a sound theoretical framework.

## 5. Limitations & Suggestions

Despite its strengths, the present study should be interpreted in light of several limitations. First, the cross-sectional design precludes causal inference regarding the directionality of associations between psychological variables and stress sensitivity. Second, reliance on self-report measures may introduce response biases, including social desirability and shared method variance. Third, although the sample was drawn from diverse regions, the findings may not generalize to adolescents outside the Malaysian context or to clinical populations with severe psychopathology. Fourth, the absence of biological or physiological stress markers limits the ability to integrate psychobiological dimensions of stress sensitivity. Finally, while the deep neural network demonstrated strong performance, its complexity may pose challenges for interpretability and practical implementation in some settings.

Future research should prioritize longitudinal designs to examine how stress sensitivity and its predictors evolve over time and to assess the predictive validity of deep learning models for long-term mental health outcomes. Integrating biological indicators such as cortisol, inflammatory markers, or neuroimaging measures with psychological data may further enhance predictive accuracy and theoretical insight. Comparative studies across cultural contexts are also warranted to determine the generalizability of predictive models and to identify culturally specific stress processes. Additionally, future work should explore explainable artificial intelligence techniques to improve the transparency and clinical usability of deep learning models in adolescent mental health research.

From a practical standpoint, the findings highlight the importance of comprehensive psychological assessment in identifying adolescents at risk for heightened stress sensitivity. Schools and community programs may benefit from screening approaches that integrate perceived stress, anxiety, emotion regulation, resilience, and social support rather than relying on single indicators. Interventions aimed at reducing stress sensitivity should prioritize enhancing emotion regulation skills, strengthening resilience, and fostering supportive social environments. Moreover, the application of advanced predictive models may support early identification and targeted prevention efforts, ultimately contributing to improved adolescent mental health and well-being.

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## Declaration of Interest

The authors of this article declared no conflict of interest.

## Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

## Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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## Authors' Contributions

All authors equally contributed to this article.

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