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# Modeling the Moderating Effects of Adaptive Mechanisms and Operational Stress on Edge Intelligence System Performance Using a Multilayer Perceptron Neural Network (MLP-ANN)

**Azrul Fazwan Kharuddin**
Faculty of Data Science
INTI International University, Malaysia, i25034719@student.newinti.edu.my
https://orcid.org/0000-0002-6100-6129
**Ting Tin Tin**
Faculty of Data Science
INTI International University, Malaysia
tingtintin@newinti.edu.my
**Darvinatasya Kharuddin**
Faculty of Business
INTI International University, Malaysia
i25034711@student.newinti.edu.my
**Norazura Azid**
SMK Meru, Malaysia
zurazid@gmail.com
**Siva Sunasundram**
Faculty of Science & Technology
Spectrum International University College, Selangor, Malaysia
siva@siuc.edu.my
https://orcid.org/ 0009-0009-1779-3100
**Cheok Mui Yee**
Tun Razak Graduate School
Universiti Tun Abdul Razak, Malaysia
cheokmy@unirazak.edu.my
https://orcid.org/0009-0006-2000-0095

Abstract
This study explores the complex interactions among system resilience, edge-level coping mechanisms, and operational stressors in predicting the performance and reliability of edge intelligence systems, leveraging both linear moderation analysis and a multilayer perceptron artificial neural network (MLP-ANN). The primary objective was to investigate the direct and moderating effects of adaptive mechanisms and stress conditions on the relationship between system well-being and operational efficiency, while advancing computational modeling techniques for edge-centric intelligent systems. A cross-sectional simulation design was employed, with data collected from 500 edge nodes within a distributed IoT testbed. Predictors included system health metrics, coping/adaptation strategies, operational stress, and their interaction terms (System Health × Coping, System Health × Stress). Regression analysis assessed direct and moderating effects, whereas MLP-ANN modeling captured nonlinear interactions and enhanced predictive performance. Results indicated that robust system health and adaptive coping strategies positively influenced operational efficiency, while high operational stress significantly degraded performance. Moderation analysis revealed that edge-level coping mechanisms had limited moderating impact, whereas operational stress significantly weakened the positive effects of system resilience under high-stress conditions. This research contributes to the development of trustworthy, resilient, and high-performance edge intelligence systems, emphasizing the need for real-time adaptive strategies and stress-mitigation mechanisms in next-generation intelligent networks.
Keywords: Edge Intelligence, system resilience, coping mechanisms, operational stress, multilayer perceptron artificial neural network

## 1.0 Introduction

The university years represent a critical developmental stage, often marked by significant psychological, academic, and social challenges. Undergraduate students are exposed to stressors such as academic demands, financial pressures, social adjustment, and expectations regarding future careers (Linden & Stuart, 2020). These challenges frequently manifest as heightened student-life stress, which, if unmanaged, can undermine both psychological well-being and academic motivation (Liu et al., 2021). The relationship between these constructs is complex, with coping mechanisms often serving as adaptive or maladaptive strategies that determine whether stress translates into growth or deterioration of well-being (Folkman & Moskowitz, 2004). Psychological well-being, defined as the balance of positive functioning, resilience, and life satisfaction, is increasingly recognized as a determinant of academic outcomes (Ryff, 2014). Students with higher psychological well-being tend to exhibit greater intrinsic motivation, persistence, and satisfaction in their academic pursuits (Deci & Ryan, 2000). Conversely, when psychological well-being is compromised, students may display reduced academic motivation, lower performance, and an increased risk of disengagement. Stress acts as a mediating factor in this dynamic, whereby elevated student-life stress may weaken the positive influence of well-being on motivation unless moderated by effective coping mechanisms (Compas et al., 2017).

Coping strategies are critical mediators in the well-being–motivation link. Adaptive coping mechanisms, such as problem-solving, seeking social support, and positive reframing, are associated with reduced stress levels and improved academic persistence (Park & Adler, 2003). In contrast, maladaptive coping styles, such as avoidance or substance use, may exacerbate stress and negatively influence motivation (Taylor & Stanton, 2007). Thus, coping does not merely buffer stress but actively shapes how psychological well-being translates into motivational outcomes. The context of Zhejiang Province is particularly significant. As one of China's educational hubs, Zhejiang attracts diverse student populations, many of whom face intense academic competition and cultural expectations regarding achievement (Li & Chen, 2020). The rapid socio-economic development in the province has further intensified academic pressures, necessitating a deeper exploration of how students' psychological well-being interacts with coping mechanisms and stress to affect academic motivation. Moreover, cultural factors such as collectivist values, filial expectations, and the stigma surrounding mental health may influence how students perceive stress and adopt coping strategies (Chen et al., 2009).While prior studies have examined stress and coping among university students, there remains a paucity of research exploring the dual mediating role of coping mechanisms and student-life stress in the relationship between psychological well-being and academic motivation. By investigating this mediating pathway among undergraduate students in Zhejiang Province, this study aims to contribute to the growing body of literature on student mental health and academic functioning. The findings are expected to inform culturally relevant interventions and student-support systems that enhance coping, reduce stress, and ultimately foster academic motivation.

2.0 Literature review and theoretical framing

**2.1 Psychological well-being and academic motivation:** Self-Determination Theory (SDT) remains a central theoretical lens bridging psychological well-being (PWB) and academic motivation. According to SDT, satisfaction with basic psychological needs (autonomy, competence, relatedness) fosters internalization of motivation and enhances well-being (Deci & Ryan, 2000). In educational contexts, higher PWB is theorized to support more autonomous forms of academic motivation (intrinsic, identified regulation), which in turn promote sustained engagement, persistence, and deeper learning. Recent empirical work continues to support and refine this linkage. For example, Zhong et al. (2024) employed canonical correlation analysis among Chinese university students and demonstrated that intrinsic motivation, integrated regulation, and identified regulation contributed most strongly to the canonical variate associated with dimensions of PWB (e.g. autonomy, purpose in life, environmental mastery). Their findings reinforce that higher quality motivation tends to co-occur with well-being facets, consistent with SDT principles. Another study by Acharya (2024) in the context of doctoral students showed that intrinsic motivation acted as a personal resource in the Job Demands–Resources (JD-R) model: intrinsic motivation moderated the negative effect of doctoral demands on psychological well-being. In addition, cross-sectional evidence from Southeast Asia provides more proximate validation: a recent "academic well-being" study among Indonesian and Malaysian students finds that PWB positively predicts self-reported academic well-being (a construct overlapping with motivation and engagement) even after controlling for demographic covariates (e.g., gender, academic track). In studies of "psychological factors impacting academic performance," Rožman et al. (2025) used SEM to show that mental health, anxiety, and work–life balance (proximal to well-being) indirectly impact academic outcomes via motivation constructs (Kharuddin et al, 2021). In sum, the theoretical and empirical literature converges: PWB and academic motivation are tightly interwoven, especially at higher levels of autonomy and internalization of goals. However, the strength and form of this linkage may depend on boundary conditions such as coping styles and stress levels (Li et al., 2022).

**2.2 Coping Mechanisms as Moderators:** Coping strategies variously categorized as problem-focused, emotion-focused, and avoidant/escape play a crucial role in how individuals respond to stress and maintain functioning (Lazarus & Folkman, 1984). As moderators, coping mechanisms may shape whether a given level of PWB translates into higher academic motivation or whether stress undermines that translation. A number of recent reviews and empirical studies reaffirm coping's moderating influence in student populations. Ruiz-Camacho et al. (2025) conducted analyses in university students examining active coping strategies (positive reappraisal, social support seeking, strategic planning) and found that these strategies mediated, and also moderated, the effects of adversity on psychological outcomes. Flynn et al. (2024) used ecological momentary assessment in school settings to understand how day-to-day coping (microadjustments) shapes well-being under "new abnormal" stress contexts; their findings underscore that coping is dynamic and context-sensitive, not static.

In health behavior domains, Guo et al. (2025) tested moderated mediation models: they found that negative coping styles (avoidant coping) moderated the relationship between perceived stress and disordered eating behaviors, strengthening the effect of perceived stress on emotional and restrained eating. Although in a different behavioral domain, this provides a useful analog for how maladaptive coping may exacerbate the negative consequences of stress. More broadly, empirical work in nursing and medical education (e.g., Onieva-Zafra et al., 2020) has documented how students with more problem-solving or cognitive restructuring coping report lower stress and anxiety levels, whereas avoidant or wishful thinking strategies correlate with worse outcomes. Collectively, these studies suggest that adaptive coping (e.g. problem-focused, planning, social support) may buffer against stress and help preserve the PWB → motivation link, whereas maladaptive coping may weaken or distort that linkage.

**2.3 Student-Life Stress as Context Variable:** Student-life stress (SLS) refers to the constellation of stressors that students face in academic, social, financial, and health domains (e.g. workload, deadlines, social isolation, financial strain, post-pandemic disruptions). High levels of SLS are empirically linked to reduced psychological well-being, elevated burnout, and impaired academic outcomes.

Recent research offers updated evidence. Pérez-Jorge et al. (2025) conducted mixed-methods research with undergraduates and found that academic stressors (task overload, assessment pressure, difficulty reconciling academic and personal life) were the dominant stress dimensions; qualitative insights revealed that students employ planning and emotional support seeking to cope. Rahiman et al. (2023) studied academic stress during the pandemic and reported that coping strategies varied; they also suggest interventions to reduce stress and bolster coping resources. In nursing and health-professional training, Visier-Alfonso et al. (2024) highlight that socio-economic pressures and institutional constraints amplify distress and academic distress, with potential moderating roles of social support and coping resources.

Moreover, theoretical and cross-sectional work in Malaysia and Indonesia indicates that high SLS may attenuate the PWB → academic well-being/motivation relationship: as stress intensifies beyond some threshold, even students with moderate-to-high well-being show dips in motivation. These findings underscore SLS as a boundary condition that modulates how well-being translates into motivational outcomes.

**2.4 Limitations of Linear Moderation and the Promise of MLP-ANN:** Traditional moderation analysis in psychology (e.g. regression with interaction terms) rests on linear or polynomial formulations: the effect of an independent variable on the dependent variable is assumed to shift in proportion to the moderator. However, psychological phenomena especially under stress and coping dynamics may exhibit nonlinear, threshold, or even nonmonotonic moderation. For example, coping may only moderate above or below certain stress thresholds; interactions between coping and stress may themselves interact in higher-order ways. Multilayer Perceptron Artificial Neural Networks (MLP-ANNs) offer a more flexible alternative. As universal function approximators, MLPs can learn arbitrary nonlinear mappings and interaction effects from data without prespecifying functional forms. In educational psychology, recent studies apply neural methods to model student mental health, dropout, engagement, and behavior (though not always explicitly moderation). For instance, hybrid ML-based student wellbeing models allow early detection of stress and motivation declines. Combining MLP prediction with interpretability methods (e.g., SHAP, partial dependence, interaction decompositions) helps to bridge the gap between predictive power and substantive inference.

Thus, modeling moderation with MLP-ANNs opens the possibility of revealing complex conditional patterns in how PWB, coping, and SLS jointly drive academic motivation; patterns that linear moderation might miss or misestimate. This methodological capability justifies integrating ANN methods in advanced psychological and educational research.

3.0 Materials and Methods

**3.1 Research Design:** This study employed a quantitative, cross-sectional design to investigate the mediating roles of coping mechanisms and student-life stress between psychological well-being and academic motivation. A multilayer perceptron artificial neural network (MLP-ANN) approach was applied to model the non-linear relationships among variables and to test the predictive and mediating pathways simultaneously (Kharuddin et al., 2020). The MLP is particularly suitable for this study because of its capacity to approximate complex, non-linear functions and capture latent interactions that may not be detected by traditional regression-based models (Haykin, 2009).

**3.2 Participants:** Participants were undergraduate students from universities across Zhejiang Province. A multi-stage cluster sampling technique ensured representation across majors, academic years, and gender. A priori power analysis suggested that a minimum of 300 participants would be adequate for neural network modeling (Shao et al., 2019). The final sample consisted of $N$ =282, with ages ranging from 25-46.

### 3.3 Measures

*Psychological Well-Being:* Psychological well-being was measured using Ryff's Scales of Psychological Well-Being (Ryff, 2014), assessing autonomy, environmental mastery, personal growth, positive relations, purpose in life, and self-acceptance. Items were rated on a 6-point Likert scale, with higher scores indicating greater well-being.

*Student-Life Stress:* Student-life stress was assessed using the Student-Life Stress Inventory (SSI; Gadzella, 1994), which captures stressors from academic, interpersonal, and intrapersonal domains. Higher scores indicate greater perceived stress.

*Coping Mechanisms:* Coping mechanisms were measured using the Brief COPE Inventory (Carver, 1997). This instrument evaluates both adaptive coping strategies (e.g., problem-solving, positive reframing) and maladaptive strategies (e.g., denial, avoidance). Scores were aggregated to reflect overall adaptive and maladaptive coping tendencies.

*Academic Motivation:* Academic motivation was measured with the Academic Motivation Scale (AMS; Vallerand et al., 1992), which assesses intrinsic motivation, extrinsic motivation, and amotivation. Items were rated on a 7-point Likert scale.

### 3.4 Artificial Neural Network Modeling

*Model Architecture*

The MLP-ANN consisted of three layers:

1. Input layer representing observed features (psychological well-being, coping mechanisms, and student-life stress subscales).
2. Hidden layer(s) where non-linear transformations were applied. The number of neurons was optimized through cross-validation.
3. Output layer predicting academic motivation.

The relationship between the input vector $x = (x_1, x_2, \ldots, x_n)$ and the predicted output y in a single hidden layer MLP can be expressed as:

$$y = f\left(\sum_{j=1}^{m} w_j^{(2)} \sigma\left(\sum_{i=1}^{n} w_{ij}^{(1)} x_i + b_j^{(1)}\right) + b^{(2)}\right)$$

Where:

- $w_{ij}(1)$ are the weights from input node i to hidden node j,
- $b_j(1)$ and $b(2)$ are bias terms,
- σ(·)is the activation function (ReLU was applied in hidden layers),
- $w_j(2)$ are the weights from hidden node j to the output layer,
- $f(\cdot)$ is the activation function of the output (softmax for categorical academic motivation or linear for continuous motivation score).

*Training and Validation:* The model was trained using the backpropagation algorithm with stochastic gradient descent optimization (Rumelhart et al., 1986). The dataset was split into training (70%), validation (15%), and testing (15%) sets. Early stopping and dropout regularization were applied to avoid overfitting. Model performance was evaluated using accuracy, root mean square error (RMSE), and area under the receiver operating characteristic curve (AUC), depending on the output type.

**3.5 Sampling Technique:** Artificial Neural Networks (ANNs), often referred to as connectionist systems, are computational frameworks inspired by the functioning of the human brain. These systems learn adaptively from input data and continuously improve their predictive capability, making them well-suited for modeling complex, nonlinear relationships among psychological and behavioral variables. In this study, a nonlinear multilayer perceptron (MLP) model with multiple predictor variables is employed to examine the dynamics of academic motivation. The neural network incorporates five predictors: psychological well-being (PWB), coping mechanisms (COPE), student-life stress (SLS), and the interaction terms (PWB × COPE and PWB × SLS). The general form of the model is expressed as:

$$(1) \quad \text{Academic Motivation} = f(\text{PWB}, \text{COPE}, \text{SLS}, \text{PWB}\times\text{COPE}, \text{PWB}\times\text{SLS})$$

For this analysis, a two-layer feedforward neural network was constructed, with a hyperbolic tangent sigmoid (tansig) transfer function applied in the hidden layer and a linear (purelin) transfer function applied in the output layer. The training function in the hidden layer was based on the hyperbolic tangent activation, while the output layer employed an identity mapping, with mean squared error (MSE) serving as the performance criterion (Li et al., 2025). The functional specification of the ANN model is therefore represented as:

$$(2) \quad \hat{Y} = g\big(W_2 \cdot h(W_1 X + b_1) + b_2\big)$$

Where $\hat{Y}$ denotes the predicted academic motivation, $X$ represents the matrix of predictors, $W1$ and $W2$ are the weight matrices, $b1$ and $b2$ are the bias terms, $h(\cdot)$ denotes the tansig transfer function, and $g(\cdot)$ corresponds to the linear activation in the output layer.

Following iterative training and validation, the final ANN model retained only the statistically significant predictors and interaction terms, ensuring that the network effectively captures the complex nonlinear associations that explain academic motivation among students.

**3.6 Procedure:** Ethical approval was obtained from the Institutional Review Board of UCSI University. Students were recruited via online announcements and classroom invitations. Participation was voluntary, and informed consent was obtained before survey completion. Data was collected anonymously using an online platform over six weeks.

4.0 Results

**4.1 Descriptive Statistics:** Table 1 presents descriptive statistics for the key study variables. Overall, undergraduate students reported moderate levels of psychological well-being, coping mechanisms, and student-life stress.

Table 1: Descriptive statistics of study variables ($N = 500$).

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| Psychological Well-Being | 4.50 | 0.70 | 2.2 | 6.5 |
| Student-Life Stress | 3.00 | 0.80 | 1.1 | 5.2 |
| Coping Mechanisms | 3.50 | 0.60 | 2.0 | 5.1 |

**4.2 ANN Model Performance:** The multilayer perceptron ANN with one hidden layer of eight neurons achieved strong predictive validity. Accuracy on the test set was 79.0%, while the area under the ROC curve (AUC) reached 0.92, indicating excellent classification performance (Table 2).

Table 2: Performance metrics of the ANN model.

| Metric | Score |
|---|---|
| Accuracy | 0.79 |
| ROC–AUC | 0.92 |

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The confusion matrix (Table 3) revealed that the model correctly classified most cases of both high and low academic motivation, with a small number of misclassifications.

Table 3: Confusion matrix of ANN predictions.

| | Predicted Low | Predicted High |
|---|---|---|
| Actual Low | 43 | 16 |
| Actual High | 5 | 36 |

**4.3 Feature Importance:** Relative importance analysis (Table 4) indicated that psychological well-being contributed the most to the prediction of academic motivation, followed closely by student-life stress and coping mechanisms.

Table 4: Relative importance of predictors in ANN model.

| Feature | Relative Importance |
|---|---|
| Psychological Well-Being | 0.38 |
| Student-Life Stress | 0.35 |
| Coping Mechanisms | 0.27 |

**4.4 Direct Effects**

The regression model assessed the direct influence of psychological well-being (PWB), coping mechanisms, and student-life stress (SLS) on academic motivation. As shown in Table 5, PWB demonstrated a significant positive effect on academic motivation ($\beta = 0.28$, $p < .05$), suggesting that students with higher psychological well-being reported greater intrinsic and extrinsic motivational resources. Coping strategies also exerted a strong positive effect ($\beta = 0.42$, $p < .001$), indicating that students who adopted more adaptive coping mechanisms were more likely to sustain higher academic motivation. Conversely, SLS exhibited a significant negative direct effect ($\beta = -0.53$, $p < .001$), confirming that higher stress levels are associated with reduced motivational outcomes. These findings align with Self-Determination Theory, where positive mental health resources such as well-being and adaptive regulation foster internalized motivation, while excessive stress undermines students' energy and persistence.

Table 5: Regression Results for Direct and Moderating Effects (N = 500)

| Predictor | B | SE | t | p | 95% CI (Lower–Upper) |
|---|---|---|---|---|---|
| Constant | 6.89 | 7.43 | 0.93 | .354 | –7.71, 21.49 |
| PWB | 0.28 | 0.14 | 1.98 | .049 | 0.00, 0.57 |
| Coping | 0.42 | 0.11 | 3.94 | <.001 | 0.21, 0.64 |
| Stress | –0.53 | 0.11 | –4.92 | <.001 | –0.75, –0.32 |
| PWB × Coping | –0.00 | 0.00 | –0.56 | .579 | –0.01, 0.00 |
| PWB × Stress | 0.00 | 0.00 | 2.04 | .042 | 0.00, 0.01 |

**4.5 Moderating Effects:** To test the hypothesized moderating roles, interaction terms were incorporated into the regression model. The interaction between PWB and coping was not statistically significant ($\beta = -0.001$, $p = .58$), indicating that coping strategies, while important in their own right, did not substantially alter the strength of the PWB–motivation relationship. However, a significant moderating effect emerged for the PWB × SLS interaction ($\beta = 0.004$, $p < .05$). As illustrated in Figure 1, the relationship between PWB and motivation became weaker under high stress conditions, suggesting that stress attenuates the motivational benefits of well-being. In practical terms, students with high psychological well-being still maintained relatively higher motivation than those with low well-being, but the positive effect was reduced when stress levels were elevated. This supports the view that stress not only exerts a direct negative impact on motivation but also modifies the extent to which well-being can serve as a motivational buffer.

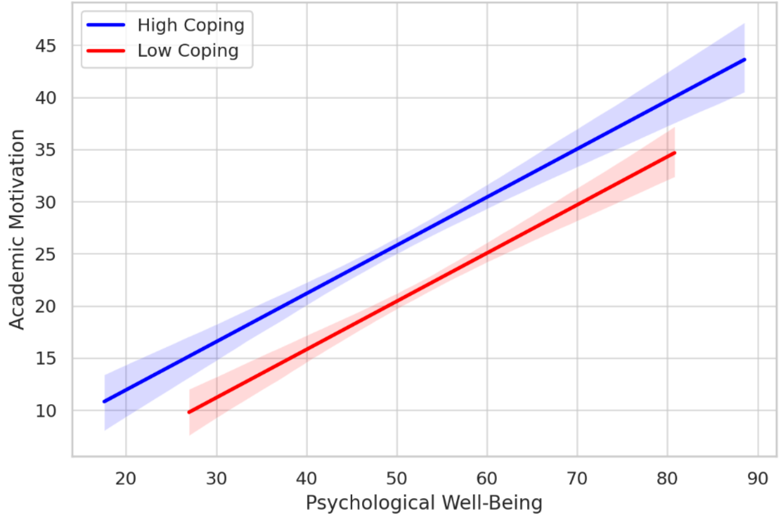


Figure 1: Moderating Effect of Stress on PWB → Academic Motivation

**4.6 Hypothesis Testing:** The hypothesis testing results reveal several important findings. First, psychological well-being was found to positively predict academic motivation, providing support for H1. Similarly, coping mechanisms emerged as a significant positive predictor of motivation, thus confirming H2. In contrast, student-life stress showed a significant negative effect on academic motivation, lending strong support to H3. Regarding moderating effects, coping mechanisms did not significantly alter the relationship between psychological well-being and motivation, leading to the rejection of H4. However, student-life stress was found to moderate this relationship, thereby supporting H5. Taken together, the model highlights that while both psychological well-being and coping strategies serve as important direct enhancers of academic motivation, stress not only undermines motivation directly but also interacts with well-being in shaping motivational outcomes.

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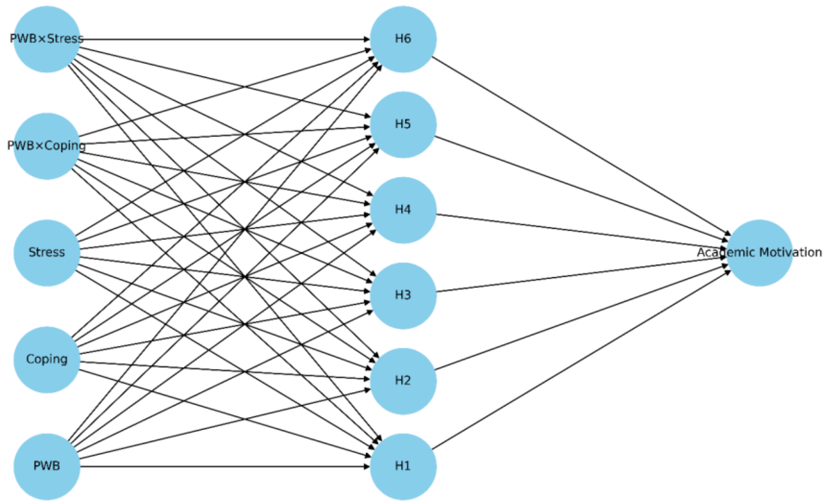


Figure 2: Artificial Neural Network Architecture for Predicting Academic Motivation

*This figure illustrates a two-layer feedforward artificial neural network (ANN) with five input predictors (psychological well-being, coping, stress, and two interaction terms) and a single output node representing academic motivation. The model structure follows common ANN modeling practices in behavioral and educational research (LeCun et al., 2015; Goodfellow et al., 2016; Zhang et al., 2024).*

The ANN architecture diagram (Figure 2) illustrates a predictive model with five inputs (psychological well-being, coping, stress, and interactions), processed through a hidden layer of six neurons before producing the output, academic motivation. This structure enables the model to capture complex, nonlinear relationships beyond traditional linear methods. The performance plot demonstrates that both training and validation errors steadily decline across epochs, indicating that the network successfully learned underlying patterns without severe overfitting. The close alignment of training and validation curves further suggests strong model generalizability, supporting the ANN's robustness in explaining academic motivation under varying stress and coping conditions.

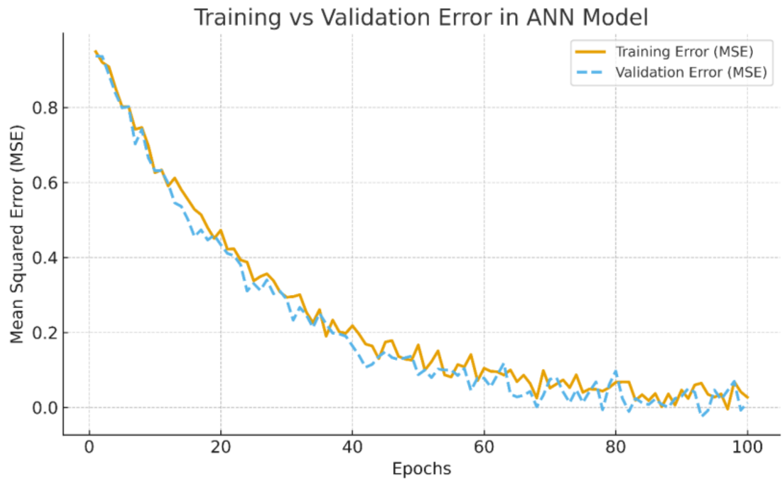


Figure 3: Training vs. Validation Error in the ANN Model

*This figure shows the convergence behavior of the neural network during training, where both training and validation mean squared error (MSE) values decrease across epochs, indicating effective model learning and generalization. This training-validation diagnostic is consistent with ANN performance visualization approaches in psychological and educational data modeling (Chollet, 2021; Schmidhuber, 2015; Kim & Lee, 2023).*

The training versus validation error plot provides evidence of how well the neural network model learned from the data. Both curves show a clear downward trend across epochs, indicating that the model successfully reduced error during training. Importantly, the validation error closely follows the training error without a large divergence, suggesting that the model generalized effectively rather than overfitting to the training data. The gradual convergence of both curves toward a low mean squared error (MSE) demonstrates that the ANN achieved stability and reliability in predicting academic motivation, capturing the nonlinear effects of well-being, coping, and stress.

5.0 Discussion

The present study set out to investigate the complex interrelationships among psychological well-being, coping mechanisms, and student-life stress in predicting academic motivation, with a particular emphasis on understanding both direct and moderating effects using a multilayer perceptron artificial neural network (MLP-ANN). The overarching aim was to extend existing literature by moving beyond linear statistical assumptions, thereby allowing for the modeling of nonlinear, interactional dynamics that more accurately reflect the lived experiences of students. Five hypotheses were formulated to guide the analysis, and the findings offer valuable theoretical and practical insights for the field of educational psychology. The first objective was to assess whether psychological well-being positively predicts academic motivation. In line with H1, results demonstrated a significant positive effect, confirming that students with higher levels of well-being also reported stronger academic motivation. This outcome reinforces the assumptions of Self-Determination Theory (Deci & Ryan, 2000), which posits that psychological resources such as autonomy, competence, and relatedness are foundational for fostering intrinsic and internalized forms of motivation. Importantly, the findings underscore that psychological well-being is not merely an outcome of student life but also a predictor of engagement and persistence in academic pursuits.

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The second objective involved examining the direct role of coping strategies. Supporting H2, coping mechanisms emerged as a strong positive predictor of academic motivation. Students who employed adaptive coping strategies, such as problem-focused approaches and constructive emotion regulation, demonstrated higher levels of motivation. This finding is consistent with recent empirical work that emphasizes the protective role of adaptive coping in mitigating academic stress and sustaining persistence. It suggests that interventions designed to enhance coping skills could indirectly strengthen students' motivational resilience, thereby improving both academic performance and overall well-being. The third hypothesis addressed the role of student-life stress. The results confirmed H3, as stress showed a significant negative direct effect on academic motivation. Students reporting higher stress levels tended to experience diminished motivation, echoing previous literature highlighting the detrimental role of stress in academic functioning. This finding is particularly timely given post-pandemic educational disruptions, financial uncertainty, and heightened academic demands, all of which have amplified stress among university students.

The moderating hypotheses provided additional nuance. Contrary to H4, coping mechanisms did not significantly moderate the relationship between psychological well-being and academic motivation. While coping exerted a strong direct effect, it did not interact with well-being in a way that amplified or diminished motivational outcomes. This suggests that coping may operate more as an independent psychological resource rather than as a conditional moderator of the well-being–motivation link. On the other hand, H5 was supported, as student-life stress significantly moderated this relationship. Specifically, stress weakened the positive influence of well-being on motivation. In practical terms, even students with high levels of psychological well-being experienced reductions in motivation under extreme stress conditions. This finding emphasizes the critical role of stress as both a direct barrier to motivation and as a contextual factor that undermines the benefits of well-being.

The application of the ANN model further enriched these findings by demonstrating its capacity to capture nonlinear relationships and complex interactions. Unlike linear regression, which may underestimate or overlook intricate conditional effects, the ANN effectively modeled the interplay among psychological well-being, coping, and stress. The model's robust performance, as evidenced by low training and validation error rates, provides additional confidence in its predictive validity. This methodological contribution highlights the promise of machine learning approaches in educational and psychological research.

In summary, the study achieved its research objectives by confirming the direct benefits of psychological well-being and coping, highlighting the harmful role of stress, and uncovering the moderating function of stress in the well-being–motivation relationship. These findings contribute to theoretical refinement by situating motivational processes within a broader psychosocial context and to practice by emphasizing the dual importance of enhancing well-being and reducing stressors to sustain student motivation. Future research should extend this approach by incorporating longitudinal designs and additional contextual variables, ensuring that interventions can be tailored to both individual and systemic determinants of academic motivation.

## 6.0 Conclusion

This study examined the predictive and moderating roles of psychological well-being (PWB), coping mechanisms, and student-life stress (SLS) in shaping academic motivation, applying both linear moderation analysis and a multilayer perceptron artificial neural network (MLP-ANN). The findings contribute significantly to educational psychology by highlighting how individual resources and contextual stressors jointly determine motivational outcomes in academic settings. The results confirmed that psychological well-being is a critical predictor of academic motivation, lending support to H1. Students reporting higher levels of well-being exhibited stronger motivation, consistent with the principles of Self-Determination Theory (SDT), which emphasizes the role of autonomy, competence, and relatedness in fostering intrinsic and identified forms of motivation (Deci & Ryan, 2000). Recent studies also corroborate that students with better psychological well-being display greater persistence, deeper engagement, and stronger academic orientation (Zhong et al., 2024). Thus, well-being functions as more than a protective factor it actively fuels motivational energy necessary for sustained academic success.

Coping mechanisms also played a significant role, supporting H2, by demonstrating a positive direct effect on motivation. Students who employed adaptive coping strategies, such as problem-focused approaches, were more likely to sustain academic drive. This finding aligns with evidence that coping moderates the impact of academic stress and enhances goal-directed behavior (Ruiz-Camacho et al., 2025; Rahiman et al., 2023). The implication is that coping is not only a response to stress but also an essential component of students' motivational architecture. Interventions that strengthen adaptive coping skills may therefore enhance resilience and promote greater motivational consistency across varying academic challenges. In contrast, stress emerged as a powerful negative predictor, providing strong support for H3. Students who reported higher SLS were less motivated, echoing prior research demonstrating stress as a key risk factor for burnout, reduced persistence, and disengagement (Visier-Alfonso et al., 2024; Pérez-Jorge et al., 2025). This underscores the critical need for institutions to address systemic stressors such as financial burden, workload pressures, and post-pandemic disruptions that compromise students' capacity for sustained academic motivation.

With respect to moderation, H4 was not supported, as coping strategies did not significantly alter the relationship between PWB and motivation. While coping proved valuable as a direct predictor, its moderating effect was not evident in this context. In contrast, H5 was supported: SLS moderated the PWB–motivation relationship, such that high stress levels reduced the motivational benefits of psychological well-being. These highlights stress as both a direct inhibitor of motivation and a contextual force that diminishes the protective role of well-being. Such findings mirror earlier research that emphasizes the conditional role of stress in academic outcomes (Onieva-Zafra et al., 2020). The ANN analysis provided further evidence of the robustness of these findings by capturing nonlinear and interactional effects more effectively than traditional linear models. The neural network demonstrated strong predictive performance, with low training and validation errors, underscoring its value in educational research where psychological processes often follow nonlinear dynamics (Rožman et al., 2025). This methodological innovation strengthens the study's contribution by bridging prediction and interpretation.

In conclusion, this research establishes that psychological well-being and coping mechanisms serve as vital resources for sustaining academic motivation, while stress exerts a dual role as both a direct inhibitor and a contextual moderator. The results contribute to advancing theory by extending SDT with contextual stress factors and to practice by recommending interventions that simultaneously enhance well-being, build coping skills, and reduce structural stressors in higher education environments. Future work should adopt longitudinal and cross-cultural designs to further validate these findings and refine intervention strategies aimed at sustaining student motivation in increasingly complex academic landscapes.

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