

A Hybrid Intelligent Framework for Stress Management: Integrating Machine Learning and Analytical Network Process for Engineering Education Systems

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Abstract

This research aims to develop and validate a hybrid intelligent framework designed to quantify, analyze, and systematically mitigate academic-induced psychological distress among final-year engineering students. The primary contribution of this study is the novel integration of automated machine learning diagnostics with multi-criteria decision-making networks, bridging the gap between passive psychological assessment and proactive strategic intervention. The methodology utilizes a quantitative research design coupled with psychometric surveys administered to 611 engineering students. The depression, anxiety, and stress scales were employed to gather foundational behavioral data. Subsequently, the k-nearest neighbor algorithm was deployed to automatically classify the severity of psychological disturbances, achieving a classification accuracy of 93.13%. To formulate mitigation strategies, an internal and external environmental audit was conducted, translating personal strengths, weaknesses, opportunities, and threats into measurable performance metrics within a balanced scorecard framework. Finally, an analytical network process was utilized by domain experts in psychology and academia to establish a priority-based hierarchy for these mitigation strategies. The diagnostic results revealed a critical prevalence rate, with 90.67% of the observed cohort experiencing moderate to severe psychological disturbances. Furthermore, the network evaluation mathematically demonstrated that the financial perspective holds the highest priority for stress mitigation with a weight of 0.3987, followed by the internal perspective at 0.3136, knowledge acquisition at 0.2134, and external stakeholder relationships at 0.0744. Specifically, financial instability regarding the income-to-expense ratio emerged as the primary catalyst stalling academic progression. These findings imply that traditional academic support must evolve beyond purely intellectual guidance. The proposed framework provides university administrators with a robust, data-driven decision-support tool to implement targeted operational policies, such as flexible tuition payment schemes and structured psychological counseling, ensuring that students maintain both mental well-being and technical excellence.

Keywords: Machine Learning, Analytical Network Process, K-Nearest Neighbor, Multi-Criteria Decision Making, Stress Management, Engineering Education

1. Introduction

The rapid evolution of information technology and dynamic shifts in modern industries necessitate that individuals possess not only technical proficiency but also robust cognitive resilience. These technological demands often act as a double-edged sword; while they facilitate advanced learning, they also impose significant psychological pressures. Individuals struggling to adapt frequently experience chronic stress, a complex response to taxing physical or psychological stimuli. Previous clinical research indicates that the prevalence of stress among college students is a highly significant global concern, primarily driven by academic performance, pressure to succeed, and post-graduation uncertainties [1]. If left unmanaged, this condition can lead to severe health issues and, in extreme cases, suicidal tendencies among the youth [2].

In engineering education, final-year students are particularly vulnerable due to rigorous curricula aligned with international standards like ABET. The pressure of completing a Capstone Design Project (CDP) or a final thesis (TA)

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demands profound analytical thinking and deep technical mastery. This rigorous academic load distinguishes the stress profile of engineering students from those in other disciplines. A systematic stress management framework encompassing emotional regulation, strategic planning, and effective problem-solving is essential to ensure students can graduate on schedule and maintain their well-being. Recent computational research has demonstrated the efficacy of using intelligent systems to address human-centric challenges. Studies published in this journal have highlighted the role of advanced algorithms in predicting behavioral patterns and enhancing decision-making accuracy.

For instance, Subhani et al. [3] established how machine learning models can be effectively utilized for the early detection and classification of mental health conditions, providing a foundation for automated psychological intervention systems. Furthermore, the integration of multi-criteria approaches in this journal has been recognized as a superior method for handling the subjectivity inherent in human assessment. Specifically, the K-Nearest Neighbor (KNN) algorithm, known for its robust classification capabilities through optimal k-selection [4], has proven to be a highly accurate classifier for stress prediction, reaching accuracies up to 99% [5], [6].

Additionally, the Analytical Network Process (ANP) has been successfully applied in various sectors, such as healthcare and manufacturing, to prioritize interventions for work-related disturbances [7]. The versatility of Multi-Criteria Decision-Making (MCDM) frameworks has also been validated across various complex domains. While some studies focus on physiological stressors, Al-Ghamdi [8] demonstrated how these techniques are equally effective in selecting trustworthy prevention strategies within high-risk sectors like digital banking. This highlights the broad applicability of hybrid selection models in providing structured solutions for multi-dimensional problems. While strategic tools like Personal SWOT analysis and the Personal Balanced Scorecard (PBSC) have been established as effective methods for self-evaluation and performance measurement [9], [10], their integration into a unified, intelligent stress management framework for engineering education remains underdeveloped. Most existing studies focus on organizational performance or clinical classification in isolation.

This research addresses this gap by proposing a novel hybrid framework that integrates KNN for stress severity classification and ANP for prioritizing strategic interventions based on PBSC metrics. This study provides a systematic, data-driven decision-support tool tailored to the specific needs of engineering students at a University by modeling the interdependencies between internal and external stressors. The ultimate goal is to facilitate a proactive management strategy that aligns personal growth with academic excellence.

2. Literature Review

This section explores the fundamental theories and prior research that form the basis of this study, ranging from psychological stress mechanisms to computational decision-making models.

2.1. Conceptual Framework of Stress and Stress Management

This concept is defined as a complex physiological and psychological response to stimuli under taxing conditions. This response triggers the autonomic nervous system to release hormones such as cortisol and adrenaline, leading to the "fight or flight" phenomenon. Effective stress management is essential to mitigate negative impacts on mood and health. As noted by Lazarus [11], stress management involves a cyclical process of identifying stressors, selecting coping strategies (such as situation modification), and practicing relaxation techniques. Kraag et al. [12] further emphasize that stress management in younger demographics typically follows three stages: identification of potential stressors, learning management techniques, and practical daily application.

2.2. Academic Stress in Engineering Education

Within the academic domain, stressors differ significantly between educators and students. For educators, stress is often influenced by workload, professional roles, and environmental conditions [13]. For students, factors such as academic load, difficult examinations, and fear of failure are predominant [14]. In engineering education, final-year students are particularly vulnerable due to the technical requirements of the curriculum, including the Capstone Design Project (CDP) and individual final theses (TA) which often align with ABET standards. Previous psychometric surveys highlight a concerning prevalence of severe stress among university students, identifying heavy academic loads and

future career anxieties as the leading psychological stressors [1]. Furthermore, data suggests that unmanaged stress is a major contributor to severe health issues and suicidal tendencies among youth [2].

2.3. Strategic Evaluation

Strategic tools originally designed for organizational management have been adapted for personal development. Agarwal [9] introduced the Personal SWOT tool to identify unique strengths and weaknesses in managing stress. Similarly, the Personal Balanced Scorecard (PBSC), as explored by Rampersad [10], facilitates a journey of self-discovery to align personal aspirations with professional demands. Research has demonstrated that PBSC strengthens organizational performance by fostering employee self-determination [10]. Recent studies by Bentes [15] further suggest that integrating BSC perspectives with multi-criteria decision-making approaches is critical for identifying key performance indicators (KPIs) and mitigating individual or organizational pressure. Additionally, SWOT analysis continues to be a foundational tool for maximizing strengths and minimizing threats in strategic planning [16].

2.4. Multi-Criteria Decision Making (MCDM) and KNN Classification

To provide objective interventions, researchers have turned to computational models. The K-Nearest Neighbor (KNN) algorithm has proven highly effective in stress prediction. Research by Abd Al-Alim et al. [5] and Gjoreski et al. [6] showed that KNN can classify stress levels with high accuracy using physiological signals. To bridge the gap between classification and strategic action, the Analytical Network Process (ANP) is utilized as a robust MCDM tool. Unlike simple hierarchies, ANP models interdependencies through a network structure. Meade and Presley [17] successfully applied ANP in complex environments, while Matin et al. [7] used it to prioritize determinants of heat stress control among industrial workers. In the digital sector, Al-Ghamdi [8] utilized MCDM to select trustworthy prevention strategies, demonstrating the versatility of the framework in addressing multi-dimensional problems.

2.5. Regulatory Context

This study aligns with health regulations concerning mental well-being. The regulation emphasizes that mental and social well-being are fundamental rights, and technology should be utilized as a preventive measure to improve public productivity and minimize the burden caused by health disturbances.

3. Methodology

3.1. Overview of the Hybrid Intelligent Framework

This research introduces a Hybrid Intelligent Framework designed to mitigate academic-induced psychological distress among engineering students. The proposed architecture integrates two robust computational paradigms: a Machine Learning (ML) classification model for diagnostic profiling and a Multi-Criteria Decision-Making (MCDM) model using the Analytical Network Process (ANP) for strategic intervention. The framework operates in three primary stages, as illustrated in figure 1. Psychometric data acquisition and validation; Automated psychological disturbance classification utilizing the K-Nearest Neighbor (K-NN) algorithm; Strategic stressor mitigation and performance metric prioritization through a synthesized Personal Balanced Scorecard (PBSC) and ANP network.

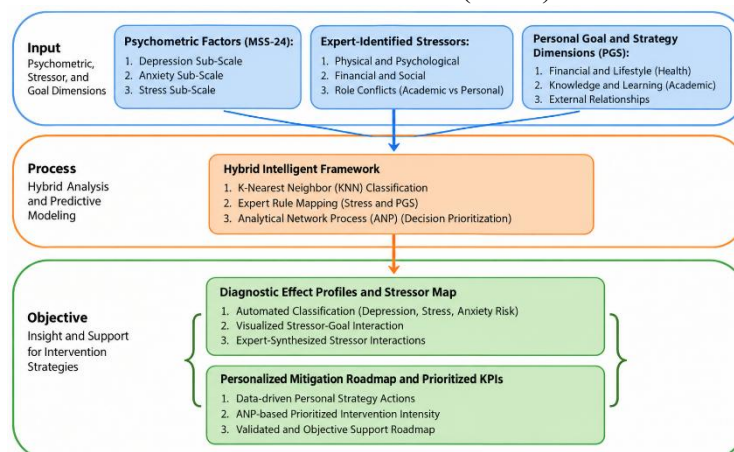


Figure 1. Hybrid Intelligent Framework

3.2. Research Design and Stratified Sampling Protocol

This study adopts a quantitative research design integrated with a phenomenological approach to investigate the psychological conditions of final-year engineering students. The focal point of the observation is the extreme academic stress and anxiety experienced by students while completing their Capstone Design Projects and Final Theses. To ensure a representative sample across multi-disciplinary engineering departments (Industrial, Electrical, Mechanical, and Informatics Engineering), a Stratified Random Sampling protocol was deployed. To determine the minimum acceptable sample size from the total student population of approximately 1,600 active engineering students ($N = 1600$), Slovin's statistical formula was applied.

$$n = \frac{N}{1+N.(err)^2} \quad (1)$$

n represents the required sample size, N denotes the total registered engineering student population, and err is the maximum tolerated margin of error, set strictly at 5% (0.05) to maintain high confidence. Based on this equation, the minimum required sample size was established at 320. Throughout the empirical data collection phase, a total of 611 respondents were successfully gathered, providing a robust dataset for machine learning training. To ensure that this expanded sample size objectively satisfies the theoretical data adequacy requirement, a data adequacy test was performed using the following statistical formula:

$$N' = \left(\frac{\frac{k}{s} \sqrt{N \cdot \sum x^2 - (\sum x)^2}}{\sum x} \right)^2 \quad (2)$$

k represents the standard normal deviation for a 95% confidence level ($k \approx 2$), s is the degree of accuracy (5% or 0.05), N is the actual number of observations, and x denotes the observed data values. The calculated theoretical value strictly satisfies the condition $N' < N$, declaring the compiled dataset of 611 respondents statistically sufficient, robust, and valid for further computational stages.

3.3. Psychometric Instrumentation and Validation Test

Primary data acquisition was executed using a comprehensively structured questionnaire adapted from the Depression, Anxiety, and Stress Scale 42 (DASS-42) [18]. The instrument spans 42 distinct physiological and psychological behavioral indicators (14 items per sub-scale), evaluated on a 4-point Likert scale ranging from 0 (Did not apply to me at all) to 3 (Applied to me very much, or most of the time). To establish structural integrity, construct validity, and internal consistency, empirical testing was conducted. The baseline reference for the critical correlation value (r -table) was determined through linear interpolation between standard statistical boundaries via the following formula:

$$y = y_1 + \frac{x-x_1}{x_2-x_1} \cdot (y_1 - y_2) \quad (3)$$

For a sample size of $N = 611$ at a two-tailed significance level of $\alpha = 0.05$, the precise r -table threshold was calculated to be 0.07934. The construct validity test confirmed that all 42 question items were fully valid, as the computed Pearson Correlation coefficient (r -count) for each item strictly exceeded the r -table threshold. Furthermore, reliability analysis demonstrated high internal consistency, yielding robust sub-scale Cronbach's Alpha scores: Depression (0.931), Anxiety (0.920), and Stress (0.918), culminating in a corrected global Alpha of 0.974.

3.4. Automated Disturbance Classification via Machine Learning

Diagnostic profiling was executed through an automated classification engine powered by a supervised K-Nearest Neighbor (K-NN) algorithm [19]. K-NN is one of the data mining methods used in classification, which is vital to predicting a new variable's class [20]. K-NN was selected due to its non-parametric nature and high efficacy in classifying complex, non-linear psychometric datasets without underlying assumptions about data distribution. Data Preprocessing and Splitting: The validated dataset ($N = 611$) was partitioned into an 80% training set and a 20% testing set. Prior to distance calculation, DASS-42 scores were normalized. Hyperparameter Optimization: The optimal hyperparameter K was established utilizing 5-Fold Cross-Validation, setting $K = 5$ to prevent tie-voting. Distance Metric Computation: Spatial proximity was computed using the multi-dimensional Euclidean Distance algorithm:

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (4)$$

x_i and y_i denote the respective psychometric feature coordinates of the query instance and the training samples in an n -dimensional space.

Majority Voting and Output: Based on the distances calculated, the algorithm isolated the 4 nearest neighbors (e.g., indices 2, 3, 4, and 12 from the balance dataset). The most frequent classification among these neighbors dictated the final diagnostic label of the test instance. Empirical results from the hybrid system revealed that 90.67% of the total sample (554 students) exhibited psychological distress reaching at least a "moderate" level in at least one category, triggering the necessity for the subsequent strategic intervention phase.

Algorithm 1. Hybrid KNN-ANP Framework for Stress Management

Input: Student psychometric data (DASS-42 scores) as Vector X
Output: Ranked Key Performance Indicators (KPIs) for Stress Mitigation

- 1: // Phase 1: Machine Learning Classification (KNN)
- 2: Normalize Vector X
- 3: Load validated training dataset D
- 4: Set optimal $K = 5$
- 5: For each instance Y in D do:
- 6: Calculate Euclidean Distance $d(X, Y)$
- 7: End For
- 8: Sort distances in ascending order
- 9: Select the top K nearest neighbors
- 10: Determine psychological severity class C based on majority voting
- 11:
- 12: // Phase 2: Strategic Mitigation via ANP
- 13: If Class C $\geq$ "Moderate Disturbance" Then
- 14: Initialize Unweighted Supermatrix U from expert pairwise comparisons
- 15: Derive Weighted Supermatrix W by applying Class C probabilities to cluster weights
- 16: Set convergence_threshold = 0.0001
- 17: Repeat
- 18: Calculate Limit Supermatrix $L = W^k$
- 19: $k = k + 1$
- 20: Until difference between $L(k)$ and $L(k-1) < \text{convergence_threshold}$
- 21: Extract global priority weights for PBSC interventions
- 22: Rank KPIs in descending order
- 23: Return Ranked KPIs
- 24: Else
- 25: Return "No intervention required"
- 26: End If

3.5. Expert-Driven Stressor Diagnostics and Personal Strategy Matrix

For the sub-population identified with moderate-to-severe distress, a strategic personal mitigation architecture was introduced. To ensure comprehensive validity across both clinical and academic dimensions, deep-dive qualitative interviews and ANP pairwise comparisons were conducted by an expanded panel of domain experts and key stakeholders (comprising 7 members). This panel included two medical professionals (a Psychiatrist from a regional public hospital in Jakarta and a Clinical Psychologist from a Community Health Center), two University Academic Advisors specializing in student affairs, and three final-year engineering student representatives. In Multi-Criteria Decision Making (MCDM) methodologies, incorporating students as subject-matter stakeholders is critical to capturing the exact on-the-ground reality of academic stressors. Grounded in the Indonesian Ministry of Health guidelines, the experts synthesized 11 primary stressors obstructing engineering students, subsequently mapped into five structural dimensions: Physical, Psychological, Financial, Social, and Role Conflicts (e.g., academic vs. personal life balance).

Simultaneously, an internal-external environmental audit was conducted using a modified Personal SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis. Driven by a 5W1H "Why-Why" root cause assessment, individual missions and visions were systematically generated. To eliminate subjective bias during the transition from qualitative

interviews to quantitative metrics, a structured thematic analysis was employed to rigorously categorize the extracted codes into Strengths, Weaknesses, Opportunities, and Threats based on their internal or external origins. These insights were then structured into a Personal Balanced Scorecard (PBSC) framework [21], translating abstract psychological goals into measurable strategic actions across four critical organizational perspectives: Financial: Stability and financial freedom during academic tenure; Internal: Physical, mental, and spiritual equilibrium; Knowledge and Learning: Continuous academic progression and skill acquisition; External: Stakeholder relationships (peers, parents, academic supervisors).

3.6. Analytical Network Process (ANP) for KPI Prioritization

To bridge the gap between identifying stressors and executing mitigation strategies, this study employs the Analytical Network Process (ANP) [22] to formulate and prioritize Personal Key Performance Indicators (KPIs). Unlike traditional hierarchical methods, ANP accommodates the complex interdependencies and feedback loops between the identified stressors, the SWOT elements, and the PBSC perspectives. **Network Construction:** The ANP network model was developed comprising clusters of nodes representing the five stressor dimensions, the four PBSC perspectives, and a comprehensive set of proposed mitigation KPIs. **Pairwise Comparison:** A pairwise comparison matrix was formulated to derive local priority vectors. Respondents and experts evaluated the influence of elements using Saaty's 1–9 fundamental scale. The consistency of the matrix was verified by ensuring the Consistency Ratio (CR) remained below the 0.10 threshold. **Supermatrix Formulation:** The local priority weights derived from the pairwise comparisons were inputted into an Unweighted Supermatrix to represent the network's structural influence. This matrix was subsequently transformed into a Weighted Supermatrix by multiplying the blocks by the corresponding cluster weights, ensuring the matrix is column-stochastic. **Limit Supermatrix Computation:** To capture the global priority of mitigation strategies, infinite Markov chain exponentiation was applied to the Weighted Supermatrix (W):

$$\lim_{k \rightarrow \infty} W^k \quad (5)$$

To explicitly couple the Machine Learning classification with the Multi-Criteria Decision Making framework, the probabilistic output of the K-NN algorithm was utilized to dynamically initialize the ANP cluster weights. Let $P(C_i|x)$ denote the posterior probability of a student x belonging to a specific distress severity class C_i . This diagnostic probability vector directly modulates the initial unweighted supermatrix U , such that the weighted supermatrix W is mathematically derived as $W = P(C_i|x) \times U$. This integration ensures that the ANP mitigation priorities continuously adapt to the objective severity diagnosed by the computational model, effectively bridging the gap between automated classification and strategic intervention.

4. Results and Discussion

4.1. Demographic Profiling and Psychometric Validation

The empirical observation phase successfully captured a highly representative dataset of 611 final-year engineering students. The socio-demographic distribution, emphasizing multi-disciplinary engineering departments and familial roles, is summarized in table 1.

Table 1. Demographic Profile of the Respondents ($N = 611$)

Demographic Variable	Category	Frequency	Percentage (%)
Study Program	Industrial Engineering	157	25.70
	Electrical Engineering	204	33.39
	Mechanical Engineering	120	19.64
	Informatics Engineering	130	21.27
Gender	Male	499	81.67
	Female	112	18.33
Familial Birth Order	Eldest Child	150	24.55

Middle Child	52	8.51
Youngest Child	336	54.99
Only Child	73	11.95

Prior to executing the computational phases, the structural integrity of the DASS-42 instrument was statistically verified. The Pearson Correlation confirmed construct validity, with all 42 items exceeding the r -table threshold of 0.07934 ($\alpha = 0.05$). The reliability analysis demonstrated robust internal consistency, yielding highly robust sub-scale Cronbach's Alpha scores: Depression (0.931), Anxiety (0.920), and Stress (0.918), culminating in a corrected global Alpha of 0.974.

4.2. Diagnostic Classification Performance (K-NN)

To objectively quantify the classification efficacy and validate the algorithmic selection, an extensive baseline model comparison was executed alongside hyperparameter tuning for the K-NN algorithm (testing odd K values to prevent tie-voting). The models were evaluated using standard confusion matrix metrics: Accuracy, Precision, Recall, and F1-Score, governed by the following mathematical formulations:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

$$F1 - Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (9)$$

TP, TN, FP, and FN denote True Positives, True Negatives, False Positives, and False Negatives, respectively. While accuracy is commonly used, metrics like precision, recall, and the F-measure offer a more comprehensive evaluation, where precision minimizes false positives, recall reduces false negatives, and the F-measure provides a balance between both [23]. The synthesized performance of the algorithms utilizing 5-Fold Cross-Validation is detailed in table 2.

Table 2. Baseline Machine Learning Model Performance and Hyperparameter Comparison

Model / Algorithm	Accuracy	Precision	Recall	F1-Score
Random Forest	96.40%	96.54%	96.40%	96.00%
XGBoost	96.24%	96.52%	96.24%	95.87%
KNN (K=5)	93.13%	86.73%	93.13%	89.81%
SVM	93.13%	86.73%	93.13%	89.81%
KNN (K=1)	92.31%	90.17%	92.31%	91.04%
KNN (K=3)	93.13%	87.19%	93.13%	90.03%
KNN (K=7)	93.13%	86.73%	93.13%	89.81%
KNN (K=9)	93.13%	86.73%	93.13%	89.81%

As observed in table 2, while ensemble models (Random Forest and XGBoost) exhibited slight accuracy advantages, the K-NN model stabilized precisely at a highly competitive 93.13% accuracy starting from $K = 3$ through $K = 9$. The parameter $K = 5$ was explicitly selected to avoid the tie-voting risk associated with even numbers while maintaining optimal diagnostic stability. K-NN was ultimately retained as the primary classification engine within the hybrid framework due to its lightweight, non-parametric efficiency, which is highly optimal for real-time psychometric classification without requiring extensive computational overhead. The output established that 554 students (90.67%) were experiencing at least a Moderate level of psychological disturbance, justifying the necessity for strategic intervention.

4.3. Strategic Formulation via SWOT and PBSC

A localized internal-external environmental audit was conducted utilizing a quantified Personal SWOT analysis. The computational weighting yielded an Internal Factor coordinate of $x = 0.423$ and an External Factor coordinate of $y = 1.164$. Plotted within the Cartesian matrix, the $(0.423, 1.164)$ coordinate definitively positioned the cohort within the SO (Strengths-Opportunities) Quadrant, dictating a proactive strategy. These strategic insights were subsequently operationalized into a Personal Balanced Scorecard (PBSC) comprising Internal, External, Knowledge & Learning, and Financial perspectives.

4.4. ANP Network Evaluation and Priority Synthesis

To mathematically prioritize the PBSC mitigation strategies, the Analytical Network Process (ANP) was executed utilizing Super Decisions 3.2. Pairwise comparison matrices were formulated based on clinical expert evaluations. All Consistency Ratios (CR) fell strictly below the 0.10 threshold (e.g., inter-criteria $CR = 0.0519$), guaranteeing logical consistency. To capture the absolute global priority of the mitigation strategies, infinite Markov chain exponentiation was applied to the Weighted Supermatrix (W).

To ensure computational transparency of the MCDM framework, it is crucial to document the transition from the unweighted matrices to the converged limits. While the full 24×24 dimensional unweighted and weighted supermatrices are too extensive to be fully displayed within the main text, the mathematical convergence process where the weighted supermatrix is raised to infinite powers (W_{∞}) is partially represented in [table 3](#).

Table 3. Global Priority Weights for Stress Mitigation Strategies (Limit Supermatrix)

Rank	PBSC Perspective	Weight	Key Performance Indicator (Alternative)	Global Score
1	Financial	0.3987	Income-to-Expense Ratio (RPP)	0.3322
2	Knowledge	0.2134	Internal Workshop Participation (JS/W/KPS)	0.1920
3	Internal	0.3136	Campus Happiness Index (TBDK)	0.0910
4	Internal	0.3136	Absenteeism Management (JK)	0.0717
5	Financial	0.3987	Emergency Fund Reserve (LCK)	0.0665
...	...	...	...	...
24	External	0.0744	Peer-Teaching Frequency (JTBP)	0.0003

This convergence guarantees that the interdependencies among the PBSC clusters reach a stable global priority state, revealing the definitive, steady-state priority weights for the intervention model. Additionally, to provide clarity on the mitigation strategies, the operational definitions and measurement metrics for the top-priority KPIs are detailed in [table 4](#).

Table 4. Operational Definitions of Key Performance Indicators

PBSC Perspective	Key Performance Indicator (KPI)	Operational Definition & Measurement Metric
Financial	Income-to-Expense Ratio (RPP)	The monthly proportion of student financial income against mandatory expenses. Measured numerically (Ratio).
Financial	Emergency Fund Reserve (LCK)	The availability of liquid savings intended to cover sudden academic costs. Measured in IDR.
Knowledge	Internal Workshop Participation (JS/W/KPS)	Active attendance in faculty-led technical workshops or Capstone briefings. Measured in attendance count.
Internal	Campus Happiness Index (TBDK)	A self-reported metric evaluating the student's psychological equilibrium. Measured via periodic surveys.

A comprehensive sensitivity analysis was conducted by shifting the independent parameter values across a 0.001% to 9.5% variance spectrum. The priority vectors and the hierarchical ranking of the KPIs remained entirely immutable, confirming the absolute structural rigidity and robustness of the Hybrid Intelligent Framework.

4.5. Algorithmic Efficacy in Psychometric Profiling

Standard clinical assessments relying on psychological survey instruments typically utilize static numerical thresholds to categorize distress, whereas advanced machine learning architectures provide dynamic behavioral classification [24], [25]. The deployment of the K-Nearest Neighbor algorithm represents a significant methodological enhancement, achieving global accuracies exceeding 92% across all distress dimensions and effectively eradicating diagnostic subjectivity.

4.6. The Paradox of Academic Distress and Financial Vulnerability

The empirical discovery that 90.67% of final-year engineering students experience moderate-to-severe psychological disturbance exposes a critical systemic bottleneck. The prioritization of the Financial Perspective (0.3987) over Knowledge and Learning (0.2134) reveals a foundational hierarchy of needs, identifying financial instability as the primary catalyst for severe psychological disruption.

Conventional academic support structures assume that this distress is purely a derivative of intellectual challenge or time-management failure. The mathematical convergence of the ANP Limit Supermatrix profoundly disrupts this assumption. The prioritization of the Financial Perspective (0.3987) over Knowledge and Learning (0.2134) reveals a foundational hierarchy of needs within the student demographic. Financial instability, specifically monitored through the Income-to-Expense Ratio (RPP), acts as the primary catalyst for severe psychological disruption. This financial vulnerability paralyzes the student's internal capacity to absorb knowledge, effectively stalling academic progression regardless of their baseline intellectual capability.

To translate these empirical findings into practical policy, university administrators must establish targeted intervention protocols that address both financial vulnerabilities and psychological needs. Based on the ANP priority weights, it is highly recommended that institutions implement the following operational policies: (1) introducing a flexible tuition payment scheme that allows students to split their semester fees into two manageable installments; (2) providing accessible consultation facilities integrated with professional psychologists, enabling students to seek guidance with targeted clinical interventions deployed by experts when necessary; and (3) formulating alternative outputs for both the Capstone Design Project (CDP) and the final thesis, including recommending financially affordable publication venues, ensuring that all academic requirements remain strictly rigorous yet economically attainable for the students.

4.7. Operationalizing Internal Resilience via Proactive Strategies

The formulation of the Personal Balanced Scorecard (PBSC) bridges the crucial gap between identifying psychological stressors and executing strategic mitigation. The Cartesian placement of the respondents within the SO Quadrant is an immensely positive diagnostic outcome, signifying that the student population possesses intrinsic communicative strengths and a high capacity for learning adaptation.

The framework leverages these intrinsic strengths through specific KPIs. The emergence of the Campus Happiness Index (TBDK) as the third highest priority (0.0910) underscores the necessity of internal cognitive relief. Engineering faculties must recognize that sustained academic rigor without deliberate micro-recovery phases leads to systemic burnout. Furthermore, the model prescribes proactive participation in programmatic workshops (JS/W/KPS) as a structured mechanism to alleviate the specific anxieties surrounding Capstone Design Projects, directly neutralizing the fear of the unknown.

4.8. Structural Robustness of the Decision Support System

The absolute stability of the ANP model, as proven by the sensitivity analysis, confirms the operational viability of this research. The absence of rank reversal among the top intervention strategies across a 9.5% parameter variance indicates that the model is immune to minor subjective perturbations in expert judgment. Academic counselors and university administrators can confidently deploy this prioritized KPI roadmap across various engineering departments to ensure institutional resources are directed precisely toward the metrics that generate the highest impact on student stability.

While the structural robustness of the proposed ANP model is mathematically confirmed, it is imperative to acknowledge the generalized nature of the current Limit Supermatrix. The established priorities represent the aggregate distress profile of the overall engineering faculty. Given the demographic composition of the dataset comprising 499

male and 112 female students distributed across Industrial, Electrical, Mechanical, and Informatics Engineering programs future iterations of this Decision Support System should integrate demographic sensitivity analysis. Segmenting the ANP evaluations across gender lines or specific study programs could reveal micro-variances in stressor priorities. Thus, the current model serves as a robust generalized baseline, paving the way for highly localized, sub-group-specific mitigation frameworks.

5. Conclusion

This research successfully engineers a mathematically validated, Hybrid Intelligent Framework designed to diagnose, analyze, and mitigate severe psychological distress among final-year engineering students. The integration of the non-parametric K-Nearest Neighbor algorithm established an automated diagnostic engine revealing a critical 90.67% distress prevalence rate. The synthesis of the Personal Balanced Scorecard with the Analytical Network Process provided a quantitative transition from passive observation to proactive strategic execution.

This study acknowledges key limitations affecting generalizability. The psychometric dataset was exclusively acquired from a single higher education institution in Indonesia. The localized socio-economic variables, tuition structures, and cultural coping mechanisms may differ significantly across diverse geographic regions or non-engineering academic disciplines. Furthermore, the reliance on the self-reported DASS-42 instrument introduces inherent vulnerability to respondent bias or transient emotional states during the data acquisition phase. The cross-sectional nature of the current research design restricts the observation of longitudinal psychological shifts. Additionally, the demographic profile of the respondents presents a notable limitation, as it is heavily male-dominated (81.67%). Future research should stratify the ANP evaluation specifically across demographic sub-groups (such as gender and specific engineering majors) to observe nuanced differences in stressor priorities, alongside prioritizing a multi-institutional, longitudinal sampling protocol to track the efficacy of the PBSC interventions over extended academic semesters.

6. Declarations

6.1. Author Contributions

Conceptualization: P.R.J.; Methodology: A.B.M., W.K.R., R.S.W.; Validation: P.R.J.; Formal Analysis: A.B.M., W.K.R., R.S.W.; Writing – Original Draft Preparation: P.R.J., A.B.M., W.K.R., R.S.W.; Writing – Review and Editing: P.R.J., A.B.M., W.K.R., R.S.W.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki, and the data collection protocol strictly adhered to institutional ethical guidelines.

6.5. Informed Consent Statement

The study was conducted in accordance with the Declaration of Helsinki, and the data collection protocol strictly adhered to institutional ethical guidelines.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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