Interpretation of the Main Academic Stress Triggers in Informatics Students Using SHAP Waterfall Plots

Ahmad Jihad Al Fayed, Muhammad Iqbal

Abstract

Final-year university students, particularly in their seventh semester, frequently experience complex psychological pressures due to the transition toward thesis writing and workforce preparation. Early detection efforts by educational institutions often rely on static historical data or demographics, which fail to accurately capture real-time psychological conditions. This study aims to classify and transparently interpret the primary triggers of academic stress using an Explainable Artificial Intelligence (XAI) approach. The dataset was gathered through primary questionnaires comprising 10 academic and psychological burden indicators from student respondents. Classification modeling was constructed using the Random Forest algorithm, while model transparency was evaluated using global SHAP (SHapley Additive exPlanations) methods. Experimental testing results demonstrate that the Random Forest model achieves an accuracy of 82% (with a macro average precision of 0.81, recall of 0.81, and F1-score of 0.81). Based on the SHAP Global Summary Plot and Feature Importance analysis, it is revealed that Cemas_Karir (career anxiety with a mean magnitude of +0.15) and Tekanan_Skripsi (thesis pressure with a value of +0.13) are the two most dominant factors driving high academic stress risks among students. These findings prove that the combination of Random Forest and global SHAP analysis can serve as a reliable, accurate, and transparent early warning system for institutions to formulate targeted advisory interventions.

***Keywords**:* Academic Stress, Psychological, Random Forest, Explainable AI, SHAP Waterfall Plot.

Ahmad Jihad Al Fayed [1]
[1]Magister Teknologi Informasi, Universitas Pembangunan Panca Budi, Indonesia
e-mail: jihadahmad000@gmail.com [1]

Muhammad Iqbal [2]
e-mail: muhammadiqbal@dosen.pancabudi.ac.id [2]
[2]Magister Teknologi Informasi, Universitas Pembangunan Panca Budi, Indonesia
2nd International Conference on Islamic Community Studies (ICICS)
Theme: History of Malay Civilisation and Islamic Human Capacity and Halal Hub in the Globalization Era
https://proceeding.pancabudi.ac.id/index.php/ICIE/index

Introduction

Entering the final year of study, particularly upon reaching the seventh semester, students frequently face severe psychological pressure [1]. The burden of transitioning from regular classroom routines to thesis work often triggers mental fatigue [5]. Unfortunately, higher education institutions' efforts to predict their students' academic conditions still frequently rely on historical variables—such as admission pathways or initial entrance exam scores [5]. In reality, such static data is no longer relevant for capturing students' real-time psychological conditions during ongoing coursework [1]. Recent studies confirm that academic stress is dynamic and heavily influenced by daily campus ecology, such as exam pressure, family expectations, and career anxiety, thus requiring real-time evaluation instruments based on primary data [1], [7].

On the other hand, the use of machine learning to detect academic stress levels or psychological risks in students has proven highly robust [6], [8]. To process ordinal-scale tabular data (such as Likert-scale questionnaire results), decision tree-based ensemble algorithms, particularly Random Forest [7], [18], [19], are often the primary choice [2], [11]. Its ability to combine hundreds of decision trees through a bagging mechanism makes it highly accurate and resistant to overfitting when mapping the non-linear relationships of students' psychological conditions [2], [11], [12].

However, the high accuracy of ensemble models such as Random Forest comes at the cost of lost transparency, with the system operating as a "black box" [4], [9]. Faculty members often struggle to formulate interventions because they do not understand why the system labels a student as being in a state of high stress [4]. Addressing this gap, this study offers an Explainable Artificial Intelligence (XAI) approach through the SHAP (SHapley Additive exPlanations) Global Summary Plot and Feature Importance methods [3]. This approach has been proven in various recent studies to enhance educators' reliability and trust in AI systems [11], [13], [14]. This XAI approach is applied to transparently dissect the Random Forest algorithm—which in this study successfully achieved an 82% accuracy rate—in order to identify the specific questionnaire factors that weigh most heavily on students' minds (such as career anxiety and thesis pressure), enabling campus interventions to be much more precisely targeted.

Literature Review

Academic pressure goes beyond merely maintaining a Grade Point Average (GPA); it is an accumulation of curriculum demands, family expectations, financial constraints, and anxiety regarding post-graduation career realities [7]. This complex condition requires measurement instruments that directly address students' daily grievances [1], [10]. A study on student mental health prediction using machine learning demonstrates that specific complaints gathered from self-administered questionnaires are significantly more accurate in detecting stress levels compared to static demographic data [10].

This research utilizes the reliability of the Random Forest algorithm, which is an advancement over the Decision Tree method [2], [12]. Random Forest operates on the principle of bagging, constructing numerous independent decision trees from bootstrapped random samples and subsequently aggregating final decisions through majority voting [2]. This ensemble algorithm group is highly suitable for processing ordinal data derived from Likert-scale questionnaires due to its capability to map complex patterns without requiring intricate data structure modifications [5], [11]. Educational Data Mining research affirms that Random Forest consistently delivers high and stable classification performance in predicting student vulnerability [5], [11], [16].

The concept of XAI is essential for dissecting black-box algorithm decisions so that predictive results can be logically interpreted by humans [4], [9], [14]. Unlike conventional correlation visualizations, the SHAP framework—built upon the concept of Shapley values

from game theory—unravels the contribution of each feature to model predictions both locally and globally [3]. Through the SHAP Summary Plot and Feature Importance, this tool specifically maps how the magnitude and direction of push from each questionnaire response collectively influence students' stress level assessments [3], [15]. The application of SHAP has proven capable of bridging the gap between computational accuracy and interpretive needs for educational institution stakeholders [12], [14]

Research Methodology

This study employs a quantitative approach focusing on the analysis of numerical questionnaire data processed through statistical, machine learning, and Explainable Artificial Intelligence (XAI) methods to interpret the primary triggers of academic stress among Informatics students [21]. As illustrated in Fig. 1, the research workflow consists of seven sequential stages: literature study, data collection using an academic stress questionnaire, data processing and encoding, model training and optimization, model evaluation, SHAP interpretability analysis utilizing waterfall plots, and results and reporting.

3.1 Data Collection Scenario

Data was collected primarily through the distribution of questionnaires to active seventh-semester students (with a total of 300 verified respondents) in the Computer Science program at Satya Terra Bhinneka University. To ensure that the analysis accurately reflects current academic pressures, the dataset was intentionally excluded from attributes related to college admission scores or high school academic records.

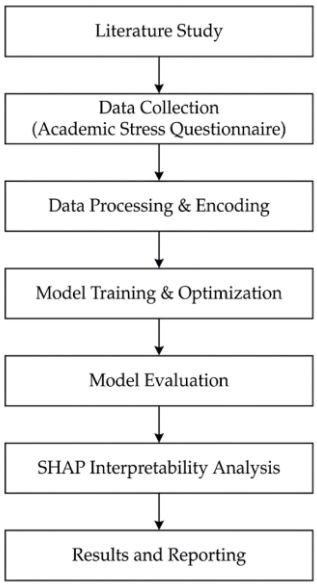


Figure 1. Research methodology framework

Initially, a literature study is conducted to review and analyze scientific literature, international journals, reference books, and prior studies related to student mental health, triggers of academic stress in higher education—particularly within computer science and informatics disciplines—and the application of Explainable Artificial Intelligence (XAI) techniques, specifically SHapley Additive exPlanations (SHAP), in predictive modelling [21], [24]. This stage aims to establish a solid theoretical foundation, identify relevant research variables, and select the most appropriate machine learning algorithms and interpretability methods [21]. Following this, data are collected by distributing a structured questionnaire to Informatics students, designed around comprehensive psychological and academic indicators including daily assignment burden, comprehension of advanced course material, thesis writing pressure, post-graduation career anxiety, time management, GPA expectations, and social support, with the target label representing the students' academic stress risk status [22]. Because raw data gathered from the questionnaire are often not immediately ready for computational

modeling, a data processing and encoding stage is subsequently performed to clean the dataset of outliers or invalid entries, handle missing values through statistical imputation (median or mode), and apply normalization alongside feature encoding to convert categorical variables into numerical formats compatible with machine learning algorithms [23].

Once the dataset is cleaned and structured, the workflow proceeds to model training and optimization, which involves building and training predictive models using ensemble or decision-tree-based classification algorithms such as Random Forest or XGBoost. The dataset is partitioned into training and testing sets, and the training process incorporates hyperparameter optimization—such as Grid Search—to achieve optimal and accurate performance in recognizing student academic stress risk patterns [23]. The trained models are then rigorously evaluated using an independent testing set to measure their generalization capability. This model evaluation is performed quantitatively using standard classification metrics, including Accuracy, Precision, Recall, and F1-Score, alongside confusion matrix analysis to ensure high model reliability prior to the interpretation stage [23].

The core novelty of this study lies in the SHAP interpretability analysis, which applies Explainable Artificial Intelligence (XAI) using SHapley Additive exPlanations values rather than treating the predictive model merely as a black box [24], [25]. This method calculates the marginal contribution of each feature to the model's predictions, generating visualizations in the form of SHAP Waterfall Plots to diagnose and thoroughly break down how specific factors—such as thesis pressure or assignment burden—drive or suppress the probability of academic stress risk both globally across all students and locally for individual students [25]. Finally, the research workflow concludes with results and reporting, which involves compiling a comprehensive report presenting the experimental findings, SHAP Waterfall Plot visualizations, feature importance rankings, and scientific conclusions to serve as an objective empirical reference for educational institutions in formulating early intervention policies, counseling services, and curriculum improvements to mitigate academic stress among Informatics students [21], [24].

3.2 Measurement Instrument

Questionnaire parameters were measured using a Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Independent feature indicators (X_1 to X_{10}) encompass various dimensions of students' mental burdens:

Table 1. Operational Definitions of the Academic Stress Questionnaire Measurement Instruments

Variabel Name	Measurement Scale	Definition & Questionnaire Item Description
Assignment Burden *(Beban_Tugas)*	Likert Scale (1 – 5)	Daily assignments and practical work given currently feel far beyond my capacity.
Advanced Material *(Materi_Lanjut)*	Likert Scale (1 – 5)	I often feel overwhelmed trying to absorb advanced lecture materials in the seventh semester.
Thesis Pressure *(Tekanan_Skripsi)*	Likert Scale (1 – 5)	Thinking about the topic, proposal, and thesis writing process makes me extremely stressed.

Variabel Name	Measurement Scale	Definition & Questionnaire Item Description
Career Anxiety *(Cemas_Karir)*	Likert Scale (1 – 5)	Thoughts about job market competition after graduation make me excessively anxious.
Time Management *(Manajemen_Waktu)*	Likert Scale (1 – 5)	My time is entirely consumed by university matters, sacrificing my rest and personal life.
GPA Expectations *(Tuntutan_IPK)*	Likert Scale (1 – 5)	The expectation to graduate with high grades or a high GPA has become a mental burden.
Lecturer Communication *(Komunikasi_Dosen)*	Likert Scale (1 – 5)	I often feel reluctant or afraid when consulting and discussing with lecturers.
Campus Infrastructure *(Infrastruktur)*	Likert Scale (1 – 5)	Inadequate campus facilities often cause delays in completing my coursework and assignments.
Financial Issues *(Finansial)*	Likert Scale (1 – 5)	Tuition payment problems and daily living costs severely disrupt my study concentration.
Social Support *(Dukungan_Sosial)*	Likert Scale (1 – 5)	When going through difficult academic times, I feel I am struggling alone without peer support.
Academic Stress Label *(Label_Stres)*	Binary (0 / 1)	Classification of student stress risk status (0 = Controlled Stress, 1 = High Stress Risk).

3.3 Random Forest Modeling Scheme

The gathered dataset was partitioned into an 80% training set (240 samples) and a 20% testing set (60 samples). Modeling steps were executed using the Random Forest classification algorithm (n_estimators=100, max_depth=5, class_weight='balanced') [2], [12], [17], [18]. Model performance was evaluated using standard evaluation metrics comprising Accuracy, Precision, Recall, and F1-Score [15], [19].

3.4 XAI Explanation Extraction (SHAP Global Analysis)

Once the Random Forest model was successfully trained, its decision-making logic was explored using the TreeExplainer module from the SHAP library [3]. Analysis focused on global interpretation via the SHAP Summary Plot (beeswarm plot) to examine feature impact distributions and SHAP Global Feature Importance (mean absolute SHAP value) to rank the most dominant stress-triggering variables at the population level [3], [15].

Results

Based on experimental testing results across 60 test samples, the Random Forest model successfully achieved an accuracy rate of 82% [23]. Detailed classification metric evaluations indicated stable performance in recognizing class groups (0: Controlled Stress and 1: High Stress Risk.

Class 0 (Controlled Stress) with Precision 0.86, Recall 0.83, F1-score 0.85 (based on a support of 36 samples). Class 1 (High Stress Risk) with Precision 0.76, Recall 0.79, F1-score 0.78 (based on a support of 24 samples), The macro average stood at 0.81, while the weighted average metrics for Precision, Recall, and F1-Score were consistently at 0.82. This achievement confirms that the Random Forest algorithm is highly effective in managing the complexity of ordinal questionnaire data without experiencing overfitting [2], [11], [16].

```
=== Performance of the Random Forest Model ===
Accuracy: 0.82
Precision (Weighted): 0.82
Recall (Weighted): 0.82
F1-Score (Weighted): 0.82

Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.83      0.85        36
           1       0.76      0.79      0.78        24

    accuracy                           0.82        60
   macro avg       0.81      0.81      0.81        60
weighted avg       0.82      0.82      0.82        60
```

Figure 2. Performance of the Random Forest Model

To address the black-box issue [4], [9], analysis proceeded by extracting feature contributions utilizing the SHAP Global Summary Plot and Bar Plot [3]. Based on the SHAP graphical visualizations:

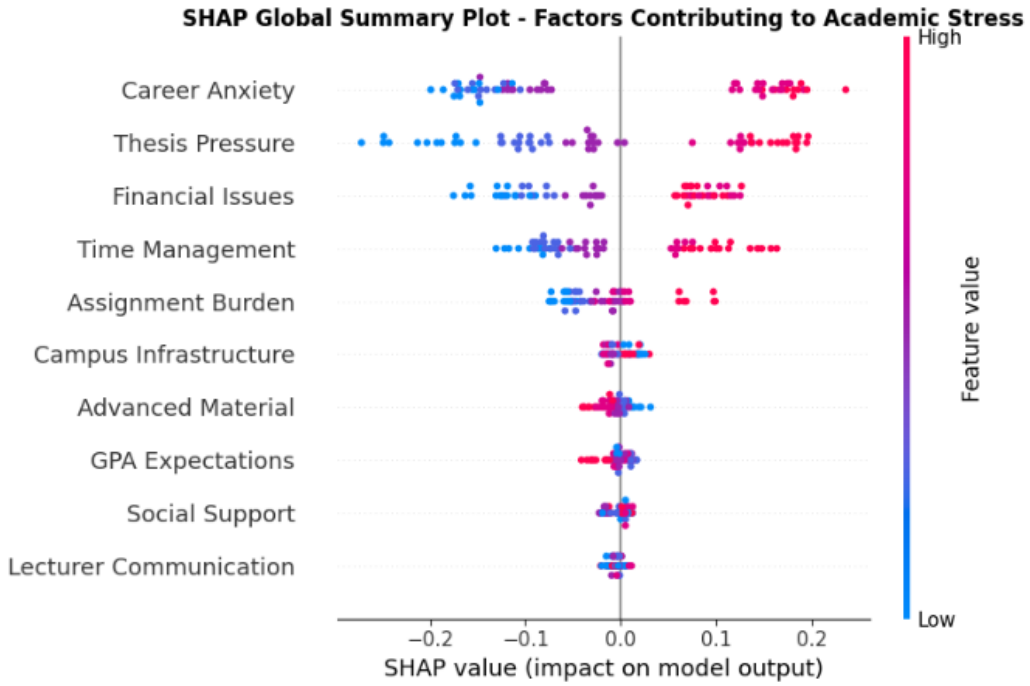


Figure 3. SHAP Global Summary Plot - Factors Contributing to Academic Stress

Ranked at the top as the most dominant variable with a mean absolute SHAP magnitude value of +0.15. Red dots spreading toward the positive side of the x-axis in the Summary Plot indicate that higher levels of student career anxiety consistently drive increased probabilities of entering the high stress risk category [3], [20]. Ranked second with a magnitude value of +0.13. The burden of proposal and final project preparation proved to be a significant mental catalyst for seventh-semester students.

Followed sequentially by Financial Issues (magnitude of +0.09), Time Management (magnitude of +0.08), and Assignment Burden (magnitude of +0.04) [25]. Meanwhile, factors such as Campus Infrastructure, Advanced Material, GPA Expectations, Social Support, and Lecturer Communication demonstrated a very minimal impact (+0.01) on model predictions.

These findings deliver practical implications for higher education institutions indicating that counseling guidance and career service programs must be prioritized over merely enforcing administrative academic sanctions or warnings.

Conclusion

This study successfully implemented the Random Forest algorithm integrated with an Explainable Artificial Intelligence (XAI) approach via the SHAP framework to analyze the primary triggers of academic stress among final-year students. This Educational Data Mining approach demonstrated that the Random Forest algorithm is highly robust in modeling ordinal-scale questionnaire data, evidenced by achieving an accuracy rate of 82% with balanced classification metric performance and no indication of overfitting. Furthermore, the application of the SHAP Global Summary Plot and Feature Importance effectively resolved the black-box limitation of ensemble models by providing transparent visual explanations. Based on the extraction of mean SHAP magnitude values, anxiety regarding career prospects (Career Anxiety) and the heavy burden of final project preparation (Thesis Pressure) were identified as the two most dominant factors driving students into the high stress risk category. Conversely, variables such as campus infrastructure adequacy and GPA achievement demands proved to have no significant impact on students' stress fluctuations during this phase. Practically, these findings recommend that higher education policymakers proactively optimize psychological counseling services and early career preparation programs. For future research, it is highly recommended to expand the respondent demographic scope across various faculties and apply advanced hyperparameter tuning techniques, such as Grid Search, to explore further improvements in model sensitivity.

References

[1] R. Al-Shabandar, A. Jaddoa, P. Liatsis, and A. Hussain, "An explainable machine learning framework for academic stress classification among university students: a comparative multi-dataset study with ablation analysis and statistical significance testing," *Frontiers in Computer Science*, 2026.

[2] L. Breiman, "Random Forests," *Machine Learning*, vol. 45, pp. 5-32, 2001.

[3] S. M. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," in *Proc. 31st Conf. Neural Inf. Process. Syst. (NIPS)*, Long Beach, CA, USA, 2017.

[4] H. Khosravi, S. B. Shum, G. Chen, C. Conati, Y. S. Tsai, J. Kay, and D. Gašević, "Explainable Artificial Intelligence in education," *Computers and Education: Artificial Intelligence*, vol. 3, p. 100074, 2022.

[5] R. Asif, A. Merceron, S. A. Ali, and N. G. Pathan, "Analyzing undergraduate students' performance using educational data mining," *Computers & Education*, vol. 113, pp. 177–194, 2017.

[6] A. B. Shatte, D. M. Hutchinson, and S. J. Teague, "Machine learning in mental health: a scoping review of methods and applications," *Psychological Medicine*, vol. 49, no. 9, pp. 1426–1448, 2019.

[7] K. J. Reddy, K. R. Menon, and A. Thattil, "Academic stress and its sources among university students," *Biomedical and Pharmacology Journal*, vol. 11, no. 1, pp. 531–537, 2018.

[8] El Morr, M. Jammal, I. Bou-Hamad, S. Hijazi, D. Ayna, M. Romani, and R. Hoteit, "Predictive Machine Learning Models for Assessing Lebanese University Students' Depression, Anxiety, and Stress During COVID-19," *J. Prim. Care Community Health*, vol. 15, pp. 1-12, 2024.

[9] C. Molnar, *Interpretable Machine Learning: A Guide for Making Black Box Models Explainable*, 2nd ed. Leanpub, 2022.

[10] M. S. Oyaj and A. Islam, "Predicting Academic Stress Levels Among Students Using Structured Data Analysis," *Department of Computer Science and Engineering, International Islamic University Chittagong, Chattogram, Bangladesh*, 2026.

[11] W. Hidayatulloh, F. Mahardika, and D. I. Junaedi, "Explainable artificial intelligence-based model for student academic performance prediction," *Journal of Information System Exploration and Research*, vol. 4, no. 1, pp. 31–40, 2026.

[12] R. Cernechez, S. E. Hosseini, M. Nadeem, S. Pervez, M. Salah, and M. Shahbaz, "Explainable Machine Learning for Predicting Student Depression Risk," *Bioengineering*, vol. 13, no. 9, Art. no. 1083, Sep. 2026.

[13] S. Thorat and R. B. Kulkarni, "Explainable AI for Student Performance Prediction," *Recent Trends in Information Technology and its Application*, vol. 9, no. 3, pp. 67–74, 2026.

[14] Y. Rothacher and C. Strobl, "Identifying Informative Predictor Variables With Random Forests," *Journal of Educational and Behavioral Statistics*, vol. 49, no. 4, pp. 595–629, 2024.

[15] C. B. Sucahyo *et al*., "Performance Analysis of Random Forest on Quartile Classification Journal," *Applied Engineering and Technology*, vol. 3, no. 1, pp. 1–17, 2024.

[16] M. Kumar *et al*., "Utilizing Random Forest and XGBoost Data Mining Algorithms for Anticipating Students' Academic Performance," *International Journal of Modern Education and Computer Science*, vol. 16, no. 2, pp. 29–44, 2024.

[17] A. Ernawati, Khairul, Z. Sitorus, M. Iqbal, dan D. Nasution, "Penerapan Data Mining Untuk Klasifikasi Penduduk Miskin Di Kabupaten Labuhanbatu Menggunakan Random Forest Dan K-Nearest Neighbors," *Bulletin of Information Technology (BIT)*, vol. 6, no. 2, pp. 23-35, Jun. 2025.

[18] A. P. U. Siahaan, A. G. Nainggolan, K. Putra, N. Nahampun, dan D. M. Sibarani, "Perbandingan Algoritma Linear Regression dan Random Forest Dalam Menganalisis Hubungan Perilaku Antara Kesehatan Mental dan Media Sosial," *Jurnal Sistem Informasi TGD*, vol. 4, no. 6, pp. 1376-1383, Nov. 2025.

[19] R. Hermawan, M. Iqbal, dan M. I. Sarif, "Analisis Prediksi Kesesuaian Lulusan Dengan Dunia Kerja Menggunakan Model Ensemble Random Forest dan XGBoost Berdasarkan Data Tracer Study Universitas Royal," *JUKTISI (Jurnal Komputer Teknologi Informasi Sistem Komputer)*, vol. 5, no. 2, pp. 1513-1522, Sep. 2026.

[20] S. Darma, M. I. Sarif, A. J. Alfayed, A. Syahdewa, dan K. Tyas, "IT Career Navigation: Performance Evaluation of KNN and Naïve Bayes in Career Path Recommendations for Computer Science Students (Case Study: Battuta University)," *Journal of Science and Social Research*, vol. 9, no. 2, pp. 2838-2847, Apr. 2026.

[21] C. Romero and S. Ventura, "Educational data mining and learning analytics: An updated survey," *WIREs Data Mining and Knowledge Discovery*, vol. 10, no. 3, Art. no. e1355, May 2020, doi: 10.1002/widm.1355.

[22] A. J. Al Fayed, S. Darma, M. H. Aqsha, S. M. P. Pardede, and M. Amin, "Perbandingan kinerja algoritma machine learning dalam memprediksi tingkat stres mahasiswa berdasarkan faktor akademik dan non-akademik," *Journal of Science and Social Research*, vol. 9, no. 1, pp. 483–490, 2026, doi: 10.54314/jssr.v9i1.5805.

[23] F. Pedregosa *et al.*, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, Oct. 2011.

[24] R. Cernechez, S. E. Hosseini, M. Nadeem, S. Pervez, M. Salah, and M. Shahbaz, "Explainable Machine Learning for Predicting Student Depression Risk," *Bioengineering*, vol. 13, no. 9, Art. no. 1083, Sep. 2026, doi: 10.3390/bioengineering13091083.

[25] S. M. Lundberg *et al.*, "From local explanations to global understanding with explainable AI for trees," *Nature Machine Intelligence*, vol. 2, no. 1, pp. 56–67, Jan. 2020, doi: 10.1038/s42256-019-0138-9.