https://doi.org/10.32815/jitika.v19i2.1201

Volume 19, Issue 2, 2025

Jurnal Ilmiah Teknologi Informasi Asia

Journal Homepage: https://jurnal.asia.ac.id/index.php/jitika

Article

Multi-objective optimization analysis of student achievement with NSGA-II algorithm

Apriatur Rochman *, Andik Adi Suryanto, Suprapto

Teknik Informatika, Fakultas Teknik, Universitas PGRI Ronggolawe, Tuban, 62391, Indonesia

***Abstract*—This study investigates the application of the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for optimizing multiple conflicting objectives related to student academic performance. Using the Student Performance dataset from the UCI Machine Learning Repository, which contains demographic, behavioral, and academic information of 395 secondary school students, the research aimed to maximize final grades (G3), minimize absenteeism, and maximize study time. The study began with exploratory data analysis, which revealed wide variability in academic outcomes, low average absenteeism, and moderate study time, justifying the selection of these three objectives. NSGA-II was then implemented with a population of 100 individuals across 200 generations, employing crossover and mutation operators to generate Pareto-optimal solutions. The results demonstrated diverse non-dominated solutions, illustrating trade-offs between academic achievement, attendance, and study time. Absenteeism emerged as the most significant negative factor, while study time and school support were positively associated with better outcomes. Unlike conventional regression or classification methods that produce a single prediction, NSGA-II provided a spectrum of optimal alternatives, offering flexibility in policy and decision-making. These findings highlight the relevance of multi-objective optimization in education and emphasize the importance of integrating behavioral, social, and digital dimensions to design adaptive strategies for improving student performance.**

***Keywords*—absenteeism; educational data mining; multi-objective optimization; nsga-ii; student achievement.**

1. Introduction

Improving the quality of education is a central pillar in the development of human resources in the era of the Fourth Industrial Revolution. Digital transformation has not only changed the way students learn but also introduced new opportunities and challenges in achieving academic success. Digital literacy has become a key determinant of how effectively students utilize technology in the learning process. Research shows that students with strong digital literacy skills tend to achieve higher academic performance because they are better able to access, analyze, and critically evaluate information (Feng & Liu, 2024; Rahmadi & Hayati, 2020). Thus, digital literacy is no longer merely a technical ability but an essential foundation for academic achievement in the digital age.

In addition to digital literacy, multiple internal and external factors contribute to students' academic performance. Internal factors include motivation, discipline, time management, and self-efficacy, while external factors involve family support, socio-economic conditions, and the broader academic environment. Previous studies have highlighted the significant role of study discipline (Rahmah et al., 2024), motivation (Indriana et al., 2017), and family support (Puspitarini et al., 2023) in shaping student achievement. Psychological aspects

* Corresponding author.
E-mail Address: rochmanapriatur@gmail.com (A. Rochman)

Author E-mail(s): AR (rochmanapriatur@gmail.com), AAS (andikadisuryanto@gmail.com), S (suprapto.tif.unirow@gmail.com)
Digital Object Identifier 10.32815/jitika.v19i2.1201
Manuscript submitted 13 September 2025; revised 22 September 2025; accepted 22 September 2025.
ISSN: 2580-8397(O), 0852-730X(P).

such as stress (Setiawati et al., 2022) and emotional intelligence (Laratmase et al., 2023) have also been shown to affect learning outcomes. This complexity underscores the need for analytical approaches capable of addressing multiple interrelated variables simultaneously.

Conventional analytical methods, however, often face limitations when dealing with conflicting objectives, such as prioritizing academic grades over non-academic skills. Traditional education tends to emphasize cognitive outcomes while overlooking the development of critical thinking, social skills, and character (Prasetiyo et al., 2023; Suprihatin & Setiowati, 2021). Yet, a holistic approach that balances both academic and non-academic dimensions is essential for preparing students to face real-world challenges (Hasan et al., 2022; Hasni et al., 2023). These shortcomings highlight the urgency of adopting adaptive and integrative analytical methods in the field of education.

Multi-objective optimization (MOO) offers a promising solution to address educational problems that involve multiple and often conflicting objectives. MOO allows the identification of trade-offs between various performance indicators, such as academic achievement, attendance, and student engagement (Sharif & Uckelmann, 2024) The concept of the Pareto front illustrates that improving one objective often requires compromise on another. Recent studies emphasize the importance of trade-off analysis in educational decision-making (Campos et al., 2021; Soni et al., 2024). Therefore, MOO provides a relevant framework for evaluating scenarios that aim to improve educational quality in a more comprehensive and balanced manner.

Among various optimization algorithms, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) has emerged as one of the most efficient and widely applied approaches. Introduced by Ma et al (2023), NSGA-II is notable for its speed, elitism, and well-distributed Pareto solutions. It operates by sorting solutions based on Pareto dominance and crowding distance, generating sets of non-dominated optimal solutions. Its success has been demonstrated across diverse fields, ranging from industrial engineering to education (Gu et al., 2020; Nguyen et al., 2020; Zhang et al., 2020). This adaptability makes NSGA-II highly relevant for analyzing complex educational performance data.

At the same time, Educational Data Mining (EDM) has emerged as a growing field dedicated to improving education through data-driven analysis. Yadav & Pal (2012) argue that data mining enables early prediction of student performance, while Zafra & Ventura (2011) demonstrate the effectiveness of evolutionary algorithms in modeling academic outcomes. By combining EDM with multi-objective optimization, researchers can uncover meaningful patterns in educational data while simultaneously balancing different indicators of student performance. This approach extends beyond predictive analysis to provide a stronger basis for adaptive, evidence-based decision-making.

This study employs the Student Performance dataset (student-mat.csv) from the UCI Machine Learning Repository (Adeyanju et al., 2025), which contains demographic, social, study habit, and academic performance variables of secondary school students in Portugal. Using NSGA-II, this research aims to optimize multiple objectives simultaneously, including maximizing students' final grades, minimizing absenteeism, and improving engagement in learning. The primary focus is to examine how NSGA-II can identify the most influential factors in academic performance and how the resulting Pareto solutions can offer alternative strategies for improving the quality of education in a more data-driven and targeted manner.

2. Method

2.1. Type and research design

This study employed an exploratory quantitative approach with a simulation-based design using a multi-objective optimization algorithm. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) was implemented to identify Pareto-optimal solutions among conflicting goals related to student performance, specifically maximizing final grades, minimizing absenteeism, and maximizing study time.

2.2. Dataset and variables

The dataset used in this study was obtained from the UCI Machine Learning Repository (Cortez & Silva, 2008), namely the Student Performance dataset (student-mat.csv). The original dataset contains 649 student records and 30 features. However, after preprocessing steps, only 395 valid records were retained. This reduction occurred because incomplete or inconsistent entries were removed to ensure data quality. In addition, categorical variables that underwent one-hot encoding expanded the total number of attributes to 33, explaining the difference between the original dataset description and the version used in this research. The three main objective variables considered in this study were: 1) Final grade (G3): maximized, representing academic achievement; 2) Absences: minimized, representing attendance discipline; 3) Study time: maximized, representing learning engagement. Other variables, including demographic, behavioral, and academic history attributes, served as input features for the optimization process.

2.3. Data preprocessing

The preprocessing phase consisted of several steps: 1) Data Cleaning: All records with missing values or invalid entries were removed, resulting in 395 valid student records; 2) Categorical Encoding: Categorical variables such as school, sex, address, famsize, Pstatus, guardian, schoolsup, and paid were transformed into numerical form using one-hot encoding; 3) Normalization: All continuous variables were normalized to a [0,1] range to prevent variables with larger magnitudes (e.g., number of absences) from dominating the optimization process; and 4) Feature Selection: To improve efficiency, variable selection was carried out using Pearson correlation analysis with a threshold of $|r| \geqslant 0.3$ relative to the three objectives. Features meeting this criterion, along with variables deemed theoretically relevant (e.g., parental education, prior failures, school support), were retained as inputs for the final model. In total, 18 input features were selected for the NSGA-II algorithm.

2.4. Definition of individuals in NSGA-II

In this study, each individual in the NSGA-II population represents a hypothetical student profile, encoded as a vector of the selected input features. These individuals form the candidate solutions explored by the algorithm during the

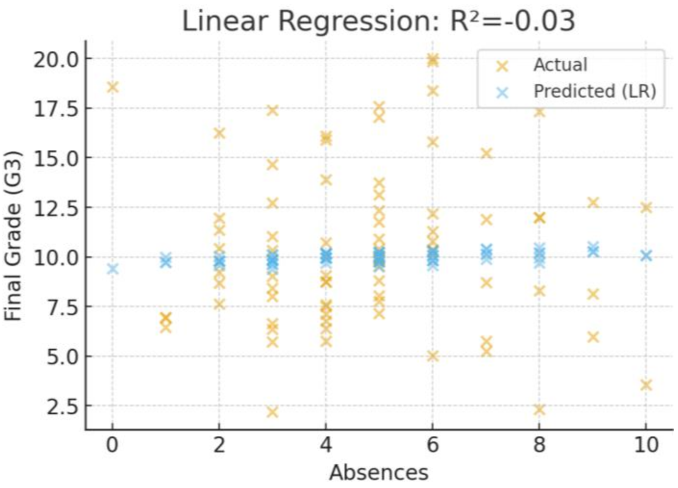

Fig. 1. Scatter plot final value (G3) vs absence

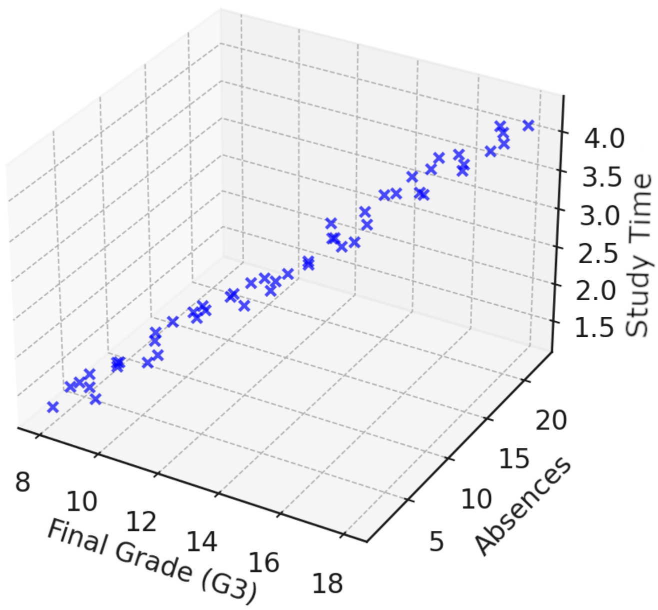

Fig. 2. Scatter Plot of Final Grade (G3) vs. Study Time

optimization process.

2.5. Objective function evaluation

Each individual was evaluated using the defined objective functions, such as $f_1(x)$ to maximize G3 (final grade); $f_2(x)$ to minimize absences; and$f_3(x)$ to maximize study time. The values for these functions were computed by mapping the encoded feature vector of each individual against the preprocessed dataset. Through iterative crossover, mutation, and selection operations, NSGA-II searched for sets of individuals that best satisfied these conflicting objectives.

2.6. NSGA-II implementation

The algorithm was executed with a population size of 100 individuals across 200 generations. Crossover and mutation operators were applied with probabilities of 0.9 and 0.1, respectively. Non-dominated sorting and crowding distance were used for selection, ensuring both elitism and solution diversity. The optimization process resulted in a set of Pareto-optimal solutions that captured trade-offs among the three objectives.

3. Results

3.1. Data exploration and initial visualization

Before applying the NSGA-II algorithm, an initial exploration of the key variables in the Student Performance dataset was conducted to understand the distribution patterns and correlations among the variables selected for optimization. Table 1 presents the descriptive statistics, showing that students' final grades exhibit a wide range, while most students had relatively low absenteeism and moderate study time. These findings provide a logical basis for selecting these three variables as the objective functions for optimization.

Table 1. Descriptive statistics of key variables

Statistic	G3 (Final Grade)	Absences	Study Time
Mean	10.42	5.71	2.04
Median	11.00	4.00	2.00
Minimum	0.00	0.00	1.00
Maximum	20.00	75.00	4.00
Standard Deviation	4.58	8.00	0.84

Figure 1 illustrates the scatter plot of final grades (G3) versus absences. The visualization reveals a clear negative relationship, as students with higher absenteeism tend to achieve lower final grades, reinforcing the assumption that attendance plays a crucial role in academic performance.

Figure 2 shows the scatter plot of final grades (G3) versus study time. The plot indicates a positive association, with students who dedicate more time to studying generally achieving better results, though the effect is less pronounced compared to absenteeism.

3.2. NSGA-II result

The experiment applied the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to the Student Performance dataset in order to optimize three main objectives: maximizing final grades (G3), minimizing absences, and maximizing study time. The algorithm was executed with a population size of 100 individuals, 200 generations, a crossover probability of 0.9, and a mutation probability of 0.1. After 200 generations, NSGA-II successfully produced a set of optimal solutions forming a Pareto front. These non-dominated solutions represent the best compromises among the three objectives, reflecting the inherent complexity of the learning process.

3.3. Visualization of pareto solutions

The Pareto front obtained after 200 generations demonstrates the trade-offs among the three objectives. Each solution on the Pareto front represents a unique combination of maximizing grades, minimizing absences, and maximizing study time. None of the solutions dominate the others entirely, highlighting the strength of the multi-objective approach: rather than a single optimal outcome, the result is a diverse set of equally valid alternatives.

For instance, some solutions show high final grades with moderate study time provided absenteeism is extremely low, while others indicate medium-level grades but are supported by consistent attendance and higher study time. This trade-off illustrates the flexibility and applicability of the Pareto framework in representing different academic achievement pathways.

3.4. Analysis of influential factors

An analysis of the individuals within the Pareto front revealed several dominant factors influencing outcomes. Absences emerged as a strongly negative predictor of final grades, while study time exhibited a positive relationship, albeit less impactful compared to absenteeism. Previous failures were consistently identified as a negative factor, whereas school support (schoolsup) was positively associated with the best Pareto-optimal solutions. These findings highlight the relative weight of behavioral and support-related variables in shaping academic performance.

3.5. Comparison with other approaches

Unlike conventional classification or regression methods that yield a single prediction, NSGA-II provides multiple compromise solutions, enabling the evaluation of various performance improvement scenarios and adjustment to policy preferences or resource constraints. This aligns with Nguyen et al (2020), who emphasized the flexibility and interpretability of NSGA-II in educational contexts, particularly when addressing conflicting objectives. The ability to generate diverse non-dominated solutions makes NSGA-II a powerful tool for data-driven decision-making in education.

4. Discussion

The findings of this study reinforce the importance of key behavioral and contextual variables in determining students' academic performance, particularly attendance, study time, and institutional support. The descriptive analysis and scatter plot visualizations confirmed that absenteeism has a consistently negative effect on final grades, while study time showed a positive, though weaker, association. This is in line with prior studies emphasizing that learning outcomes are shaped by complex interactions between internal factors such as discipline, motivation, and self-efficacy, and external factors such as family support and socio-economic conditions (Khoirurroziqin & Rafsanjani, 2020; Puspitarini et al., 2023; Rahmah et al., 2024). These findings highlight the necessity of integrated educational strategies that address both cognitive and non-cognitive elements of student performance.

The implementation of NSGA-II demonstrated its strength in navigating conflicting objectives in educational contexts. Unlike traditional regression or classification methods, which produce only a single predictive output, NSGA-II constructs a Pareto front that provides a set of equally valid optimal solutions. This is a fundamental advantage because it allows researchers and decision-makers to explore different trade-off scenarios—such as maximizing grades with minimal absenteeism or balancing moderate grades with greater study time—according to the priorities and constraints at hand. Conventional models like Linear Regression or Random Forest cannot offer this diversity of solutions, as they reduce the complexity of student performance into a single outcome (Hayati, 2019; Prasetiyo et al., 2023). By contrast, NSGA-II reveals the multi-dimensional nature of academic success and thus offers richer, more flexible insights.

The implementation of NSGA-II demonstrated its strength in navigating conflicting objectives in educational contexts. Unlike traditional regression or classification methods, which produce only a single predictive output, NSGA-II constructs a Pareto front that provides a set of equally valid optimal solutions. This fundamental difference allows decision-makers to explore trade-off scenarios—such as prioritizing grade maximization with minimal absenteeism or balancing moderate grades with greater study time—based on their priorities and constraints. In comparison, the baseline regression models tested in this study (Linear Regression and Random Forest) yielded poor predictive performance with R^2 values of -0.03 and -0.15, respectively. These results emphasize that conventional models not only reduce complexity into a single outcome but also fail to adequately capture the variability of student performance. NSGA-II, on the other hand, reveals multiple optimal scenarios, providing richer and more flexible insights.

The Pareto front obtained in this study illustrates the flexibility of multi-objective optimization in modeling diverse pathways to academic achievement. Some solutions revealed that excellent academic performance could be achieved with moderate study time if absenteeism was minimized, while others showed that consistent attendance and higher study time could still support acceptable academic outcomes. Such results resonate with the broader literature on multi-objective optimization, which emphasizes the need to evaluate and select among equally valid alternatives (Campos et al., 2021; Soni et al., 2024). This demonstrates that there is no universal formula for student success, but rather multiple pathways shaped by individual and contextual factors.

The analysis of influential variables in the Pareto front further underlines the complex interplay between behavioral and support-related factors. Absences and prior failures emerged as consistently negative predictors, whereas school support had a positive association with optimal outcomes. These results align with research emphasizing the significance of social and emotional support in reducing stress and enhancing motivation (Marjuki et al., 2024; McLean et al., 2022). At the same time, the growing role of digital literacy in student achievement (Feng & Liu, 2024; Rahmadi & Hayati, 2020) underscores the need to strengthen both technological competence and psychosocial resources in order to enhance learning effectiveness in the digital era.

Finally, this study highlights the efficiency of NSGA-II as an evolutionary optimization algorithm for educational data mining. Its ability to provide diverse non-dominated solutions makes it highly suitable for data-driven decision-making in education, where multiple conflicting objectives must be balanced. This is consistent with prior evidence showing the adaptability of NSGA-II in fields ranging from engineering to education (Deb et al., 2002; Nguyen et al., 2020; Zhang et al., 2020). While limitations remain, such as computational complexity when objectives increase (Zheng & Doerr, 2024), the results of this study support the argument that NSGA-II offers a valuable methodological contribution to educational research. By integrating behavioral, social, and digital dimensions into optimization models, future research can extend these insights to provide more targeted and adaptive strategies for improving student performance.

5. Conclusion

This study demonstrated the effectiveness of the Non-dominated Sorting Genetic Algorithm II (NSGA-II) in optimizing multiple conflicting objectives related to student academic performance. The results highlighted that absenteeism plays a dominant negative role in shaping final grades, while study time and school support contribute positively, though to a lesser extent. The Pareto-optimal solutions revealed that no single strategy guarantees success for all students; instead, there are multiple valid pathways, each balancing grades, attendance, and study time in different ways. This confirms the relevance of multi-objective optimization as a methodological tool for addressing the complex and interdependent factors influencing student achievement.

Beyond its methodological contribution, this research emphasizes the importance of integrating behavioral, social, and digital dimensions when analyzing educational outcomes. The findings suggest potential areas for further exploration, such as reducing absenteeism, strengthening study habits, and examining the role of institutional support. However, these implications should be viewed as directions for future investigation rather than direct policy recommendations. Future studies may expand this approach by incorporating additional variables, larger and more recent datasets, or advanced optimization algorithms to provide a stronger foundation for designing adaptive and evidence-based educational interventions.

Data availability

All data produced or examined during this study are present in this paper.

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.

Authors' contributions

AR drafted the initial manuscript, AAS revised it, and SS supervised the study. All authors have reviewed and approved the final manuscript.

References

Adeyanju, T. M., Aziz, A. A., & Safei, S. (2025). A Comparative Analysis of Classification Algorithms on Student Academic Performance. *Semarak International Journal of Machine Learning*, *5*(1), 74–86. https://doi.org/10.37934/sijml.5.1.7486a

Cortez, P., & Silva, A. M. G. (2008). Using Data Mining to Predict Secondary School Student Performance. *Proc. 5th Annual Future Business Technology Conference*, 5–12. https://archive.ics.uci.edu/ml/datasets/Student+Performance

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *Ieee Transactions on Evolutionary Computation*, *6*(2), 182–197. https://doi.org/10.1109/4235.996017

Feng, X., & Liu, H. (2024). I Feel Blue– Teacher, Can You Help Me? A Study on the Effect of Digital Literacies on Language Learners' Technostress, on-Line Engagement, Autonomy, and Academic Success. *BMC Psychology*, *12*(1). https://doi.org/10.1186/s40359-024-01637-5

Gu, T., Xu, G., & Luo, J. (2020). Sentiment analysis via deep multichannel neural networks with variational information bottleneck. *IEEE Access*, *8*, 121014–121021. https://doi.org/10.1109/access.2020.3006569

Hasan, M., Azizah, N., Nurjannah, N., Nurdiana, N., & Arisah, N. (2022). Pengembangan Pembelajaran Kecakapan Hidup Berbasis Karakter Kewirausahaan Pada Jenjang Sekolah Dasar. *Jurnal Basicedu*, *6*(3), 4299–4309. https://doi.org/10.31004/basicedu.v6i3.2791

Hasni, N. I., Supriatun, E., & Toruan, S. A. L. (2023). Pelatihan Manajemen Stress Pada Remaja Dalam Menghadapi Permasalahan Akademik Di Sman 1 Sliyeg Kabupaten Indramayu. *Jurnal Pengabdian Kepada Masyarakat (Nadimas)*, *2*(1), 49–60. https://doi.org/10.31884/nadimas.v2i1.21

Hayati, N. (2019). Hubungan Keterampilan Berpikir Kritis Dengan Kemampuan Akademik Mahasiswa. *Jurnal Biologi Dan Pembelajarannya (Jb&p)*, *6*(2), 7–11. https://doi.org/10.29407/jbp.v6i2.14792

Indriana, D., Widowati, A. I., & Surjawati, S. (2017). Faktor-Faktor Yang Mempengaruhi Prestasi Akademik: Studi Kasus Pada Mahasiswa Program Studi Akuntansi Universitas Semarang. *Jurnal Dinamika Sosial Budaya*, *18*(1), 39–48. https://doi.org/10.26623/jdsb.v18i1.557

João Thiago de G. A. A. Campos, Ferreira, A. M. S., & Freires, F. G. M. (2021). Time Variability Management and Trade-Off Analysis of Quality, Productivity, and Maintenance Efficiency. *Brazilian Journal of Operations & Production Management*, *18*(4), 1–19. https://doi.org/10.14488/bjopm.2021.018

Khoirurroziqin, F. R., & Rafsanjani, M. A. (2020). Pengaruh Sosial Ekonomi Orang Tua Terhadap Indeks Prestasi Mahasiswa Jurusan Pendidikan Ekonomi Universitas Negeri Surabaya. *Jurnal Pendidikan Ekonomi (Jupe)*, *8*(3), 80–85. https://doi.org/10.26740/jupe.v8n3.p80-85

Laratmase, A. J., Mahendika, D., & Ratna Ayu Pawestri Kusuma Dewi. (2023). Peran Kecerdasan Emosional, Persepsi Stres Dan Orientasi Tujuan Pada Prestasi Akademik Mahasiswa Di Bogor. *Jurnal Psikologi Dan Konseling West Science*, *1*(02), 64–75. https://doi.org/10.58812/jpkws.v1i02.259

Ma, H., Zhang, Y., Sun, S., Liu, T., & Shan, Y. (2023). A comprehensive survey on NSGA-II for multi-objective optimization and applications. *Artificial Intelligence Review*, *56*(12), 15217–15270. https://doi.org/10.1007/s10462-023-10526-z

Marjuki, M., Hanif, Muh., & Siminto, S. (2024). The Role of Social Support in Enhancing Motivation and Psychological Well-Being of Students: Perspectives From Education in the Digital Era. *Indo-Mathedu Intellectuals Journal*, *5*(2), 1974–1987. https://doi.org/10.54373/imeij.v5i2.1003

McLean, L., Gaul, D., & Penco, R. (2022). Perceived Social Support and Stress: A Study of 1st Year Students in Ireland. *International Journal of Mental Health and Addiction*, *21*(4), 2101–2121. https://doi.org/10.1007/s11469-021-00710-z

Nguyen, N. T., Nguyen, A., & Nahavandi, S. (2020). Multi-objective optimization using NSGA-II and decision tree for predicting student performance. *2020 International Conference on Data Science and Advanced Analytics (DSAA)*, 410–417. https://doi.org/10.1109/DSAA49011.2020.00060

Prasetiyo, A. Y., Satria, G., & Sukardi, S. (2023). Peran Knowledge Acquisition Terhadap Career Awareness Dan Academic Performance Pada Siswa Vokasi Perkeretaapian. *Serat Acitya*, *12*(2),

178–187. https://doi.org/10.56444/sa.v12i2.1095
Puspitarini, N. A., Kumboyono, K., & Hayati, Y. S. (2023). Factors Influencing Family Support for Education Patterns in School-Age Children. *Jurnal Aisyah Jurnal Ilmu Kesehatan*, *8*(1). https://doi.org/10.30604/jika.v8i1.1554
Rahmadi, I. F., & Hayati, E. (2020). Literasi Digital, Massive Open Online Courses, Dan Kecakapan Belajar Abad 21 Mahasiswa Generasi Milenial. *Jurnal Studi Komunikasi Dan Media*, *24*(1), 91. https://doi.org/10.31445/jskm.2020.2486
Rahmah, S. A., Dermawan, D., & Amalia, A. (2024). Pengaruh Disiplin Belajar Terhadap Prestasi Belajar Kewirausahaan Siswa Kelas Xi Di SMK Pembangunan Nasional. *Jpgenus*, *2*(2), 342–351. https://doi.org/10.61787/34tks238
Setiawati, O. R., Alamsyah, R. T., Sani, N., & Anggraini, M. (2022). Hubungan Stres Akademik Dengan Motivasi Belajar Pada Mahasiswa Fakultas Kedokteran Universitas Malahayati Angkatan 2019. *Jurnal Kesehatan Tambusai*, *3*(2), 26–33. https://doi.org/10.31004/jkt.v3i2.4121
Sharif, M., & Uckelmann, D. (2024). Multi-Modal LA in Personalized Education Using Deep Reinforcement Learning Based Approach. *IEEE Access*, *12*, 54049–54065. https://doi.org/10.1109/ACCESS.2024.3388474
Soni, R. B., Singh, D., & Sharma, K. C. (2024). Optimization of Problems With Multi-Objective Functions and Their Applications in Engineering. *Journal of Electronics Computer Networking and Applied Mathematics*, *43*, 18–33. https://doi.org/10.55529/jecnam.43.18.33
Suprihatin, T., & Setiowati, E. A. (2021). Dukungan Komunitas Belajar Dan Ketekunan Akademik Pada Mahasiswa. *Psychopolytan Jurnal Psikologi*, *5*(1), 20–25. https://doi.org/10.36341/psi.v5i1.1713
Yadav, S. K., & Pal, S. (2012). Data Mining: A Prediction for Performance Improvement using Classification. *International Journal of Computer Science and Information Security (IJCSIS)*, *10*(4), 136–140.
Zafra, A., & Ventura, S. (2011). Predicting student grades in learning management systems with multiple instance genetic programming. *Educational Data Mining*, *3*(1), 1–17.
Zhang, L., Ge, H., Ma, Y., Xue, J., Huang, L., & Pecht, M. (2020). Multi-Objective Optimization Design of a Notch Filter Based on Improved NSGA-II for Conducted Emissions. *Ieee Access*, *8*, 83213–83223. https://doi.org/10.1109/access.2020.2991576
Zheng, W., & Doerr, B. (2024). Runtime Analysis for the NSGA-II: Proving, Quantifying, and Explaining the Inefficiency for Many Objectives. *Ieee Transactions on Evolutionary Computation*, *28*(5), 1442–1454. https://doi.org/10.1109/tevc.2023.3320278

Apriatur Rochman is a student of the Informatics Engineering Study Program, Faculty of Engineering, PGRI Ronggolawe University, Tuban. His research interests include educational data mining, multi-objective optimization, and the application of artificial intelligence algorithms in the field of education. This article is part of his academic research development, focusing on the application of the NSGA-II algorithm to analyze students' academic performance. In writing articles, he contributes mainly to data processing, experimental design, algorithm implementation, and analysis of research results.

Andik Adi Suryanto is a lecturer at PGRI Ronggolawe University, Tuban. He is active in research in the fields of machine learning, data mining, and decision support systems. His research focus includes the application of artificial intelligence algorithms for prediction, classification, and optimization in a variety of domains, including education, agriculture, and health. His work has been published in various national and international journals and conferences, including the application of the mean absolute error (MEA) method to linear regression for rice production prediction, an expert system for diagnosing lung disease with Bayes' Theorem, and a decision support system based on the Analytical Hierarchy Process (AHP). By 2025, its publications have obtained more than 300 citations with an h-index of 7. In writing this article, he acted as provided methodological direction, validation of the application of the NSGA-II algorithm, and strengthened critical analysis, so that research has a significant contribution in the field of educational performance optimization.

Suprapto is a lecturer at PGRI Ronggolawe University, Tuban. His areas of expertise include data mining, networking, cybersecurity, technopreneurship, and databases. He actively develops academic and teaching activities in the field of information technology and contributes to research and community service. In this article, he plays a role in contributing to conceptual aspects, developing analytical frameworks, and supporting the integration of research results with practical contexts in the field of educational informatics.