

From Prediction to Strategy: Machine Learning and SWOT-TOWS Analysis for Structuring Lecturer Academic Workload Using Lecturer-Semester Data

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ABSTRACT

Extended undergraduate study duration beyond the normative eight semesters is a significant concern in higher education management and may be associated with lecturers' academic workloads. This study analyzes teaching and supervisory workload patterns, compares machine learning regression models for predicting students' average ongoing study duration, and formulates workload management strategies using SWOT-TOWS analysis. Using the CRISP-DM approach and secondary data from Universitas Padjadjaran's Integrated Academic Information System (n = 10,079 lecturer-semester observations), four algorithms—Linear Regression, Random Forest, Gradient Boosted Trees, and XGBoost—were evaluated using a 90:10 hold-out scheme. XGBoost performed best on three of five metrics (RMSE = 1.224; correlation = 0.658; R^2 = 0.433). Supervisory workload was the most influential predictor. The findings informed four strategies: predictive workload monitoring, discipline-sensitive supervision thresholds, gradual model implementation, and adaptive workload allocation guidelines. The study contributes a lecturer-centered predictive perspective and provides an analytical basis for academic workload management.

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1. INTRODUCTION

Student study duration is one of the indicators that routinely receives attention from higher education administrators, both as part of academic quality evaluation and as a component of accreditation instruments. In undergraduate programs, the normative duration of study is generally set at eight semesters. However, in practice, a

considerable number of students approach or even exceed this threshold. This condition cannot be separated from various contributing factors, one of which is lecturers' capacity to optimally perform their teaching and thesis supervision roles. Lecturers in higher education generally undertake multidimensional academic workloads encompassing teaching, supervision,

research, and institutional service, all of which are performed within the same period [1], [2]. When lecturers face high teaching and supervisory workloads, their capacity to provide feedback, guidance, and support to supervised students may become constrained [3]. This condition can be explained through the Job Demands–Resources (JD-R) Model [4], which suggests that when job demands exceed available resources—in this case, lecturers' time and energy—their capacity to perform supervisory roles optimally becomes limited. Consequently, this condition may be associated with slower progress in supervised students' thesis completion, as identified in studies examining supervisors' strategies for providing feedback under time constraints [5]–[7], as well as at the institutional level, where excessive supervisory workloads have been identified as one of the factors contributing to delays in study completion [8].

From a regulatory perspective, lecturers in Indonesia are positioned as professional educators and scholars responsible for implementing the *Tridharma Perguruan Tinggi*, encompassing education, research, and community service [9], [10]. Lecturer adequacy, human resource planning, and the evaluation of study completion are also included among the criteria for external quality assessment through the Higher Education Accreditation Instrument 4.0 (BAN-PT Regulation No. 27 of 2024). These provisions are further aligned with the internal quality assurance system stipulated in the Regulation of the Minister of Higher Education, Science, and Technology No. 39 of 2025 concerning Higher Education Quality Assurance. Therefore, data-driven efforts to manage lecturers' academic workloads are not only managerially relevant but also consistent with Indonesia's higher education quality assurance and regulatory framework ([11]).

Research on predicting student academic outcomes and studies examining lecturers' academic workloads have largely developed as separate streams of inquiry. The first stream, machine learning-based academic prediction research, consistently positions students as the unit of analysis,

using predictors such as grade point averages, academic records, attendance, and learning management system activities [12]–[14]. The second stream, research on lecturers' academic workloads and supervision, has predominantly employed qualitative approaches or perception-based surveys to explain lecturers' experiences, challenges, and supervisory strategies [15], [16], without integrating historical teaching and supervision data into machine learning-based predictive models. This gap provides the foundation for the present study: research remains limited in positioning the academic service context at the lecturer level, rather than individual student characteristics, as the basis for predictive analysis.

This study addresses this gap by integrating lecturers' teaching workloads, supervisory workloads, the academic conditions of supervised students, and their average ongoing study duration into a single predictive analytical framework. The study uses lecturers observed at the semester level, rather than individual students, as the unit of analysis. This choice is important because decisions regarding the allocation of courses, classes, and supervised students are practically made at the lecturer level and recur each semester. Consequently, predictive information generated at the same level of analysis can be more directly utilized by decision-makers at the study program and faculty levels. From a strategic perspective, this study is positioned at the functional strategy level within the Hierarchy of Strategy framework [17], referring to strategies within functional academic areas that support the broader strategic objectives of study programs, faculties, and universities.

Based on this rationale, this study aims to: (1) analyze the characteristics and distribution patterns of teaching workloads, supervisory workloads, the academic conditions of supervised students, and their average ongoing study duration; (2) develop, compare, and evaluate several machine learning regression models to identify the best-performing model for predicting the average ongoing study duration of supervised students; and (3)

formulate strategies for managing lecturers' teaching and supervisory workloads based on descriptive findings and predictive model results using SWOT analysis and the TOWS Matrix. The predictive analysis in this study is not intended to establish a causal relationship between lecturers' academic workloads and the study duration of supervised students. Rather, it seeks to assess the ability of lecturers' academic workload data to predict the average ongoing study duration of supervised students and subsequently translate these findings into an analytical foundation for developing strategies to manage lecturers' academic workloads in higher education.

2. METHODS

This study employed a quantitative approach within a business analytics framework encompassing descriptive and predictive analyses [18], following the stages of the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework: business understanding, data understanding, data preparation, modeling, evaluation, and deployment [19]. The unit of analysis was the lecturer-semester, whereby each observation represented the academic conditions of an individual lecturer during a particular academic semester. The study utilized secondary quantitative data obtained from the Integrated Academic Information System (*Sistem Informasi Akademik Terpadu* [SIAT]) of Universitas Padjadjaran. The data

covered the period from the second semester of the 2020/2021 academic year to the first semester of the 2025/2026 academic year and included undergraduate students from the 2018 to 2022 cohorts. Following preprocessing procedures—including restructuring the data from wide to long format and integrating data from multiple sources at the lecturer-semester level—and the data preparation stage in RapidMiner (Altair AI Studio), the dataset was filtered to include only lecturers with active supervised students (*Jumlah_Mhs_Bimbingan* > 0) and identifiable academic unit categories. Missing values were addressed, relevant attributes were selected, and categorical attributes were transformed. The final dataset comprised 10,079 lecturer-semester observations derived from 1,661 unique lecturers.

The target variable was *Rata_Lama_Studi*, defined as the average ongoing study duration, measured in semesters, of all active students supervised by a lecturer during a particular semester. It was calculated from the students' first semester of enrollment until the semester in which the data were recorded. Using average ongoing study duration rather than the final time to graduation allowed all supervised students—including those who had and had not yet graduated at the time of data collection—to be included in the analysis while avoiding the censored-data problem commonly encountered in time-to-completion research. The predictor variables used in this study are presented in Table 1.

Table 1. Operationalization of Research Variables

Attribute	Operational Definition	Data Type	Role in the Model
Number of Courses Taught	Number of courses taught by a lecturer in one semester	Integer	Predictor – teaching workload
Credit Hours Taught	Total number of credit hours taught by a lecturer in one semester	Integer	Predictor – teaching workload
Total Classes	Total number of classes taught by a lecturer in one semester	Integer	Predictor – teaching workload
Average Students per Class	Average number of students enrolled in classes taught by a lecturer	Real	Predictor – teaching workload
Total Students Taught	Total number of students taught by a lecturer in one semester	Integer	Predictor – teaching workload
Number of Supervised Students	Number of students receiving final-project supervision from a lecturer in a particular semester	Integer	Predictor – supervisory workload

Average Student GPA	Average cumulative grade point average (GPA) of supervised students during the supervision period	Real	Predictor – students' academic condition
Home Study Program	Lecturer's home study program	Polynomial (dummy coding)	Predictor – academic unit context
Average Ongoing Study Duration	Average ongoing study duration (in semesters) of a lecturer's actively supervised students	Real	Target/label

Source: Summarized From The Operationalization of The Research Variables, 2026.

As an attribute representing the academic unit context, this study used lecturers' home study programs rather than faculty affiliation because study programs provide a more granular contextual representation and are consistent with the novelty of this research. This approach also avoids perfect multicollinearity resulting from the nested relationship between faculties and study programs. The home study program variable was transformed into numerical form through dummy coding, generating additional binary attributes representing each of the 125 study program categories. Four machine learning regression algorithms were compared in this study: Linear Regression, Random Forest Regression, Gradient Boosted Trees Regression, and XGBoost Regression. Default hyperparameters were used, except for mandatory technical adjustments required to enable the algorithms to operate in regression tasks. All four algorithms were trained using the same training dataset (90%) and tested using the same testing dataset (10%) through a hold-out validation scheme with a fixed local random seed. Model performance was evaluated using five regression metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Relative Error, Correlation, and Squared Correlation (R^2) [19].

The results of the descriptive and predictive analyses were subsequently used as the basis for strategy formulation through SWOT analysis and the TOWS Matrix. Internal factors, consisting of strengths and

weaknesses, and external factors, consisting of opportunities and threats, were identified based on the descriptive findings, predictive modeling results—including feature importance—and relevant literature. These factors were subsequently combined through the TOWS Matrix to generate four strategic alternatives: SO, ST, WO, and WT strategies. The predictive analysis in this study is associative rather than causal, consistent with a predictive research design based on historical data rather than experimental evidence.

3. RESULTS AND DISCUSSION

3.1 Characteristics and Distribution Patterns of Lecturers' Academic Workloads

Descriptive statistics for the eight research attributes are presented in Table 2. On average, a lecturer taught approximately eight courses, totaling 24 credit hours per semester. The relatively large standard deviations across all teaching workload attributes indicate that teaching workloads varied substantially among lecturers. Regarding supervisory workload, the Number of Supervised Students attribute showed an average of 4.80 students per lecturer per semester (median = 4.00; range = 1–42). Most lecturers supervised between one and eight students, although some carried supervisory workloads substantially above the average.

Table 2. Descriptive Statistics of Lecturers' Academic Workloads and Supervised Students' Academic Conditions ($n = 10,079$)

Attribute	Mean	Median	Standard Deviation	Minimum	Maximum
Number of Courses Taught	8.25	7.00	5.43	0	65
Credit Hours Taught	24.12	21.00	17.49	0	290.85

Total Classes	8.30	7.00	5.50	0	65
Average Students per Class	30.65	27.00	29.44	0	635.82
Total Students Taught	254.27	196.00	417.21	0	8,438
Number of Supervised Students	4.80	4.00	4.14	1	42
Average Student GPA	3.53	3.55	0.19	2.49	4.00
Average Ongoing Study Duration	9.68	9.50	1.57	6	16

Source: Research Data Processing Using Rapidminer, 2026.

The average ongoing study duration of supervised students was 9.68 semesters (median = 9.50; range = 6–16 semesters), indicating that, on average, the students included in this dataset had approached or exceeded the normative eight-semester duration of undergraduate study. Distribution patterns across faculties showed that academic fields with higher average supervisory workloads, such as law and fisheries and marine sciences, tended to exhibit longer average ongoing study durations. In contrast, medical sciences, which employ a block-based curriculum with a structure different from that of other faculties, demonstrated both the lowest average supervisory workload and the shortest average ongoing study duration. This pattern is consistent with previous findings suggesting that supervisors with heavy workloads may face limitations in providing timely feedback to their supervised students [5], [20], [21]. Importantly, all relationships described in this section are descriptive and associative rather than causal, given that the present study is based on a predictive design

using historical data rather than an experimental design.

3.2 Comparison of Machine Learning Regression Model Performance

The performance comparison of the four regression models on the testing dataset is presented in Table 3. XGBoost outperformed the other models on three of the five evaluation metrics, achieving the lowest RMSE (1.224), the highest Correlation (0.658), and the highest Squared Correlation ($R^2 = 0.433$). However, Linear Regression achieved slightly lower MAE (0.907) and Relative Error (9.28%) than XGBoost, indicating close competition between the two models at the study-program level of granularity. Based on RMSE and Squared Correlation (R^2), two metrics commonly emphasized in regression model selection because RMSE is sensitive to large prediction errors while R^2 reflects the proportion of variance explained by the model, XGBoost was selected as the best-performing model and served as the primary basis for subsequent interpretation.

Table 3. Performance Comparison of Four Machine Learning Regression Models

Evaluation Metric	Linear Regression	Random Forest	Gradient Boosted Trees	XGBoost
RMSE	1.233	1.442	1.484	1.224
MAE	0.907	1.125	1.159	0.919
Relative Error	9.28%	11.79%	12.22%	9.58%
Correlation	0.645	0.545	0.504	0.658
Squared Correlation (R^2)	0.415	0.297	0.254	0.433

Source: Research data processing using RapidMiner, 2026. Bold values indicate the best performance for the respective metric.

The XGBoost Squared Correlation (R^2) value of 0.433 indicates that the model explained approximately 43.3% of the variation in the average ongoing study duration of supervised students based on the lecturers' teaching workload, supervisory workload, supervised students' academic

conditions, and lecturers' academic contexts included in the model. The remaining approximately 56.7% may be attributable to factors beyond the scope of this study, such as student motivation, personal circumstances, or other individual characteristics not recorded in institutional academic data. This

level of explanatory performance is comparable to that reported in related studies predicting academic outcomes using institutional data rather than psychological survey data or more granular individual-level student academic data [13]. Study duration is influenced by multiple interacting factors and therefore cannot be fully explained solely by lecturers' workload data.

3.3 Feature Importance Analysis and Interpretation of Predictive Attributes

To identify the attributes that contributed most substantially to the predictive capability of the models, feature importance values were extracted from all four models, as presented in Table 4 for the

eight substantive numerical attributes. The Number of Supervised Students, representing lecturers' supervisory workload, received the highest importance value among all attributes in the best-performing model, XGBoost, at 6,143.90. This value was substantially higher than that of the second-highest numerical attribute, Average Students per Class (1,771.83), as well as the highest-weighted categorical attribute, namely the Medicine study program category (809.77). These findings indicate that lecturers' supervisory workload remained the most relevant predictor in the best-performing model, directly supporting the relevance of the present research topic.

Table 4. Feature Importance of Numerical Predictive Attributes Across the Four Models

Attribute	XGBoost	Gradient Boosted Trees	Random Forest	Linear Regression (Coefficient)
Number of Supervised Students	6,143.90	3,792.93	0.085	-0.020
Total Students Taught	812.94	23,906.30	0.125	-0.00001
Total Classes	1,287.43	2,344.41	0.088	0.029
Average Students per Class	1,771.83	4,556.85	0.123	0.001
Semester	342.64	14,699.23	0.119	-0.001
Number of Courses Taught	279.01	112.09	0.085	-0.021
Credit Hours Taught	7.17	1,701.75	0.092	-0.005
Average Student GPA	0 (not used)	93,199.34	0.180	-3.442

Source: Research data processing, 2026. Importance scales differ across models (XGBoost and Gradient Boosted Trees: total gain/split; Random Forest: normalized importance ranging from 0 to 1; Linear Regression: signed regression coefficients). Therefore, comparisons should be made based on relative rankings within each model rather than absolute values across models

A notable contrast was also observed for the Average Student GPA attribute across algorithms. It received the highest importance among the numerical attributes in both Random Forest (0.180) and Gradient Boosted Trees (93,199.34), and had the coefficient with the largest magnitude in Linear Regression (-3.442), yet received zero importance in XGBoost and was not used by the model. This contrast may be explained by the mechanism of boosting algorithms. XGBoost constructs trees sequentially; therefore, when information contained in Average Student GPA overlaps with attributes that have

already been used for splitting, such as the Number of Supervised Students, its marginal contribution to error reduction may approach zero. Nevertheless, the attribute may still exhibit a strong individual association, as indicated by the Random Forest and Linear Regression results. The negative coefficient in Linear Regression further suggests that supervised students with higher average GPAs tend to be associated with shorter ongoing study durations.

Lecturers' supervisory workload, identified as the strongest predictor of the average ongoing study duration of

supervised students, is consistent with the mechanism described by the Job Demands–Resources Model [4]. When lecturers' job demands exceed their available work resources, their capacity to perform supervisory responsibilities optimally may become constrained, which may subsequently be associated with longer student study durations. This finding is also consistent with qualitative studies reporting that supervisors with heavy workloads tend to provide delayed and less comprehensive feedback [5], [20], [21], as well as studies examining supervisors' strategies for providing feedback under time constraints [6], [7]. It should again be emphasized that all interpretations of predictive attributes in this section are predictive and associative rather than causal, as the study is based on a predictive design using historical rather than experimental data

3.4 Formulating Strategies for Managing Lecturers' Academic Workloads through SWOT and the TOWS Matrix

Referring to the Hierarchy of Strategy framework [17], the strategic recommendations in this section are positioned at the functional strategy level, specifically within the academic functional area related to lecturer workload management, rather than at the overall corporate or business strategy level of the university. Internal factors, consisting of strengths and weaknesses, and external factors, consisting of opportunities and threats, were identified based on the descriptive and predictive analyses presented in the previous sections, as summarized in Table 5.

Table 5. Identification of Internal and External Factors (SWOT) for Lecturers' Academic Workload Management

Category	Factors
Strengths	S1. The availability of structured academic data on lecturers and supervised students at the lecturer-semester level. S2. The availability of a predictive model (XGBoost) with the best performance (RMSE = 1.224; $R^2 = 0.433$) for predicting the average ongoing study duration of supervised students at the study-program level. S3. The consistent identification of the Number of Supervised Students as the strongest predictor, providing a clear and measurable intervention point.
Weaknesses	W1. Substantial variation in supervisory workloads among lecturers (1–42 supervised students per semester), indicating uneven workload allocation. W2. The R^2 value of the best-performing model (0.433) indicates that approximately 56.7% of the variation in study duration cannot be explained by lecturers' academic workload data alone. W3. The absence of formal mechanisms or guidelines governing data-driven allocation of lecturers' supervisory workloads.
Opportunities	O1. The development of business analytics and educational data mining enables the continuous utilization of historical academic data (Gaftandzhieva et al., 2023). O2. The availability of data-processing infrastructure that can be periodically replicated by academic units. O3. Increasing demands for accountability and transparency in the management of lecturers' workloads [1].
Threats	T1. Potential resistance from lecturers and academic units to changes in supervisory workload allocation mechanisms. T2. Variations in study program and disciplinary characteristics require workload management approaches that cannot be uniformly applied across all units. T3. Dependence on the quality and completeness of academic data recorded in source information systems.

Source: Developed from the descriptive and predictive findings of this study, 2026.

Based on these internal and external factors, four strategic alternatives were

formulated through the TOWS Matrix, as presented in Table 6.

Table 6. TOWS Matrix for Strategies to Manage Lecturers' Teaching and Supervisory Workloads

Combination	Strategic Formulation
SO Strategy	Develop a predictive model-based monitoring system for lecturers' supervisory workloads (leveraging S1, S2, S3, and O1, O2), updated every semester, enabling study program and faculty leaders to identify lecturers with potentially high-risk supervisory workloads at an early stage.
ST Strategy	Establish threshold policies for the number of supervised students that consider disciplinary and faculty characteristics (leveraging S1 and S2 to address T2), ensuring that policies are not applied uniformly but are adapted to the context of each academic unit.
WO Strategy	Develop a socialization mechanism and conduct gradual pilot implementation of predictive model utilization across selected study programs (leveraging O1, O2, and O3 to address W1 and W3) before broader implementation.
WT Strategy	Develop adaptive guidelines for allocating lecturers' supervisory workloads and involve relevant academic units in their formulation (addressing W3 while anticipating T1 and T3), thereby improving institutional acceptance of the policy.

Source: Developed From The SWOT Analysis of This Study, 2026.

Among the four strategic alternatives, the SO and WT strategies are most directly connected to the operational utilization of predictive model results through the development of a model-based monitoring system and the establishment of adaptive workload allocation guidelines. Consistent with the view that data-driven decision-making tools can assist higher education leaders in making more informed decisions [22], these four strategies are intended to ensure that predictive findings do not remain merely academic outcomes but can instead be translated into initial inputs for study programs and faculties in managing lecturers' teaching and supervisory workloads more proportionally and systematically based on data. Nevertheless, SWOT analysis and the TOWS Matrix remain subject to limitations because they depend on the accuracy of internal and external factor identification. Therefore, the resulting strategies should be interpreted as preliminary strategic recommendations that require further consideration by decision-makers according to institutional policies, resources, and conditions rather than as final decisions.

4. CONCLUSION

Based on the results of the analysis, three main conclusions can be drawn. First, the characteristics and distribution patterns of

lecturers' academic workloads at Universitas Padjadjaran demonstrate substantial variation, with an average supervisory workload of 4.80 students per lecturer per semester and an average ongoing study duration of supervised students of 9.68 semesters. Faculties with higher average supervisory workloads tended to exhibit longer average ongoing study durations, whereas medical sciences demonstrated a different pattern due to the structure of its block-based curriculum.

Second, among the four regression algorithms compared, XGBoost demonstrated the best performance on three of the five evaluation metrics (RMSE = 1.224; Correlation = 0.658; R^2 = 0.433). Lecturers' supervisory workload, represented by the Number of Supervised Students, was identified as the attribute with the highest predictive importance, substantially exceeding the importance of other attributes.

Third, based on the descriptive and predictive findings, four strategic alternatives for managing lecturers' teaching and supervisory workloads were formulated through SWOT analysis and the TOWS Matrix: the SO strategy involving the development of a predictive model-based monitoring system; the ST strategy involving discipline-sensitive supervisory workload threshold policies; the WO strategy involving

the gradual piloting of predictive model utilization; and the WT strategy involving the development of adaptive guidelines for allocating supervisory workloads.

From a managerial perspective, leaders at the study program, faculty, and university levels are encouraged to consider the equitable distribution of lecturers' supervisory workloads as an explicit academic policy instrument, given that supervisory workload was identified as the strongest predictor of the average ongoing study duration of supervised students. Institutionally, integrating lecturers' and students' academic data within a unified information system at the lecturer-semester level would support the sustainable implementation of the SO and WT strategies.

This study has several limitations that provide opportunities for future research. The R^2 value of the best-performing model (0.433)

indicates that substantial variation in study duration remains unexplained by lecturers' academic workload data alone. Future research may therefore consider incorporating more individual or process-related variables, such as final-project topic characteristics or the frequency of supervisory meetings, provided that such data are available and comply with research ethics. Future studies may also optimize the hyperparameters of all four algorithms, as the present study deliberately employed default hyperparameters. In addition, this study specifically limited its scope to strategy formulation through SWOT analysis and the TOWS Matrix. Translating the SO and WT strategies into more detailed Standard Operating Procedures (SOPs) for allocating lecturers' supervisory workloads represents a relevant agenda for future research and policy development.

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