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Analysis of Lecturer Publication Performance Using Predictive Analytics and Reinforcement Learning
(Case Study of a Public University in West Java)

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Abstract:
Lecturers are valuable and essential assets who serve as the cornerstone of higher education institutions in carrying out the Tridharma Perguruan Tinggi functions: education, research, and community service. They also play a vital role in supporting the implementation of the university's strategic plans. Evaluating lecturers' publication performance is a crucial aspect of assessing how well they fulfill their responsibilities. Research and publication are mandatory duties in the field of research and development, and the resulting publications contribute to scientific knowledge as well as to society and national progress.

XYZ University is one of the public universities in Indonesia that implements the Tridharma Perguruan Tinggi. By leveraging information technology and data-driven approaches in managing lecturer performance, the university can conduct more accurate and systematic evaluations.

This study aims to explore the application of predictive analytics by forecasting lecturers' performance for the upcoming year based on data from the past five years. The goal is to provide an overview of publication productivity. The results of this study are expected to offer valuable insights to enhance the quality of lecturers' publication performance, while also supporting the university's efforts to improve academic quality and institutional reputation.

The ANOVA analysis results show that some demographic factors, such as academic rank and department or study program, do not have a significant impact on publication scores. However, there is a significant interaction between academic rank and department, indicating that the effect of position on publication scores may vary depending on the department in which the lecturer is based. These findings offer important insights for educational institutions in designing more tailored career development policies according to each department's needs.

The use of larger and more heterogeneous data in predictive analytics models such as training history, teaching load, education level, and involvement in research or publication can help develop a people analytics model in the context of human resource management. This can generate more relevant and useful insights for decision-makers in educational institutions.

Reinforcement Learning (RL), particularly Q-Learning, is used to recommend appropriate interventions for lecturers based on predicted performance outcomes. Through this approach, the system can identify the most effective actions to support the improvement of future publication performance. Institutions are advised to adopt a differentiated approach in evaluating lecturer performance by considering department-specific characteristics and providing more tailored support according to each department's needs.

Keywords: Lecturer performance, predictive analytics, Reinforcement Learning.

1. Introduction
Competition in the field of education, both domestically and internationally, encourages universities to develop excellence (Indiyati, 2018). Globalization and the demand for high-quality human resources have

become major challenges for universities. Suboptimal performance of human resources can hinder effective management and the achievement of institutional goals (Indiyati et al., 2016). In the current knowledge-driven economy, research is acknowledged as a fundamental pillar of higher education systems (Vuong et al., 2018). Both the volume and quality of research heavily influence global university rankings. Consequently, enhancing lecturers' research productivity plays a crucial role in improving teaching quality as well as boosting the international reputation and standing of universities (Vuong et al., 2018). Judging from their role, lecturers have an important role, namely as the spearhead of higher education in the sustainability and competitive advantage of higher education in the future, so that every policy issued by higher education must be able to support improving lecturer performance.

Research on human resource management (HRM) in higher education, particularly talent management, is still very limited. According to the review by (THUNNISSEN & GALLARDO GALLARDO, 2017)only a few publications discuss public sector organizations, and even fewer focus specifically on higher education institutions.

In recent decades, the internet has transformed the way scientific publishing is conducted, making it more efficient and facilitating the development of global bibliographic databases. The role of bibliometrics, which involves the quantitative analysis of publications, citations, and related data to assess the quality and impact of research, has increased dramatically since then (Pişirgen et al., 2025). The rapid development of information and communication technology has resulted in a significant increase in the amount of data regarding lecturer performance that can then be collected and analyzed.

The research conducted(Nasril et al., 2021) shows that by predicting performance, decision-making related to employee development and management strategies can be considered and planned more objectively and effectively, with top priority given to individuals with high potential.

The article "Is HR the Most Analytics-Driven Function?" by (Davenport, 2019) in Harvard Business, Review states that the Human Resources (HR) function now heavily relies on data and analytics. In fact, HR is more advanced in utilizing technologies such as predictive models and artificial intelligence. With the use of this data, management can make more accurate and effective decisions in human resource management.

Predictive analytics is a branch of data analytics that focuses on using statistical methods, forecasting modeling, machine learning, and data mining to analyze recent historical data with the aim of predicting events or conditions that are yet unknown in the future (Jamarani et al., 2024).

To further strengthen the quality of strategic recommendations, this study also introduces Reinforcement Learning (RL) a branch of machine learning where an agent learns to make decisions by interacting with an environment. Reinforcement Learning (RL) is a part of artificial intelligence that allows systems to learn from experience. The system, called an agent, tries different actions and observes the results. If the action is good, the agent gets a reward; if not, the agent learns to avoid it. The agent keeps trying and learning to choose the best actions in the future (Arulkumaran et al., 2017)

The research problem in this study is: How can a model predict the achievement of lecturers' publication performance and support appropriate intervention decisions using predictive analysis and Reinforcement Learning to assist university management?

2. Literature Review

2.1. HR Management

Human resource management is a series of processes aimed at optimizing the potential within individuals with the support of organizational management.(Hasibuan, 2016, p. 10) explain that Human resource management is a combination of knowledge and skills in managing the interaction and contribution of the workforce effectively and efficiently to achieve the goals of the company, employees, and society. According to (Indiyati et al., 2016) Human resources are a vital component of intellectual capital, serving to enhance organizational performance and provide competitive advantage.

Every person in an organization must be well managed because they are valuable assets for the organization. (Indiyati et al., 2021) stated the existence of human resources in an organization is a very valuable asset and a source of competitive advantage for the organization. Werdhiastutie et al. (2020) stated that human resource development should focus more on improving productivity and efficiency.

2.2. Performance Management

Performance management is related to the actions taken to ensure the achievement of targets. (Wardhana et al., 2022) explained that Performance management is a process to ensure that organizational goals are achieved effectively, and this process can be applied to the entire organization, departments, individuals, or specific tasks related to task execution. Performance is an individual's achievement within an organization, demonstrated through the processes and efforts made to attain the organization's goals(Soegoto et al., 2017).

(Indiyati et al., 2021) stated each employee plays a crucial role in the organization because their performance influences the success of each organizational function, which in turn impacts the overall performance achievement of the organization or company. Performance management helps organizations or companies clarify the roles of each employee and develop competencies that support organizational success(Nasril et al., 2021).

2.2.1 Lecturer Publication Performance

Lecturer publication performance is the work of lecturers in producing and sharing research, which is assessed based on the achievement of targets and the impact of the research. (Putri & Hertina, 2019) defines that the success of an organization depends on the performance of its employees, In the context of higher education, the success of an institution largely depends on how lecturers fulfill their duties and responsibilities.

In Indonesia, scientific publication is a mandatory obligation for lecturers as part of their academic duties, which is legally regulated in Article 46 paragraph (2) of Law Number 12 of 2012. This article emphasizes the role of lecturers in developing knowledge through research activities and the publication of their research results. According to Retnowati et al. (2018), lecturer publication performance is the ability of lecturers to produce scientific works that meet quality and quantity standards.

2.3 Predictive analytics

Predictive analysis research aims to determine/estimate the probability of an individual achieving his/her performance in the following year. Predictive Analytics is the process of analyzing past data using statistics and machine learning to predict future events or trends, thereby helping to make more accurate decisions (Panda & Agrawal, 2024). According to the research by (Sin & Muthu, 2015) the data used in the prediction process can provide insights into the behavior and performance of the subjects, which is useful for supporting decision-making. Predictive analytics is an analytical approach used to estimate the likelihood of future events based on historical data (Utomo et al., 2021).

With the emergence of big data systems on the internet concerning lecture publications, predictive analytics has become more feasible to perform. Big data is the process of managing extremely large volumes of data using advanced methods, the potential of big data is optimally utilized in predictive analytics to anticipate future events or trends (Jamarani et al., 2024).

2.4 Reinforcement learning

In this study, Reinforcement Learning is used to provide appropriate intervention recommendations based on the predicted performance of lecturers. According to (Arulkumaran et al., 2017) Reinforcement Learning is a part of artificial intelligence, where an agent (a system or program) learns through interaction with its environment. The agent tries different actions and observes the outcomes in the form of rewards or punishments. From this experience, the agent can learn to choose the best actions in the future.

According to (Naeem et al., 2020) humans learn from experience to interact better with their environment. Similarly, artificial agents in Reinforcement Learning try to mimic this learning behavior. By understanding key concepts such as states, actions, environment, and rewards, the agent aims to find the best policy for each situation in order to maximize long-term outcomes. Based on the study (Andreanus & Kurniawan, 2018), agents in Reinforcement Learning learn by interacting with and observing their environment

3. Research Methods

The study adopts the concepts of big data and predictive analytics. Big data refers to very large and diverse datasets that require special techniques for processing and Predictive analytics uses historical data and machine learning algorithms to forecast future events or trends (Jamarani et al., 2024).

This study uses a data analysis approach that includes several stages, from data collection to Recomendation. The data were collected from publication platforms such as Sinta, Google Scholar, and PDDIKTI, originating from a state university in West Java, Indonesia. These stages are illustrated in Figure 1.

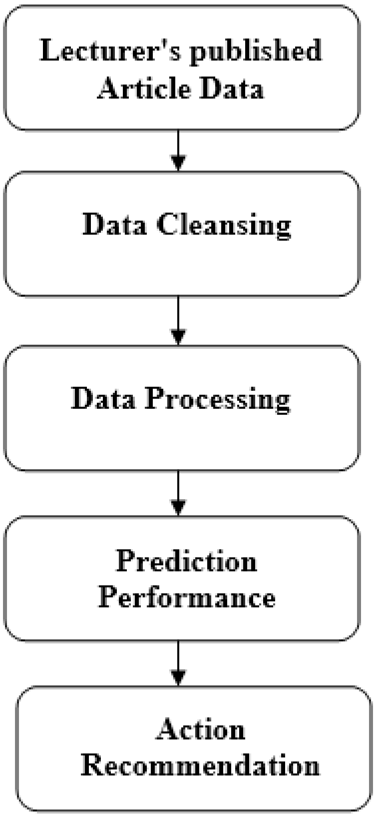


Figure 1. Research Stages
Source: Processed data by researchers (2025)

1. Data Collection: At this stage, data is collected for all required attributes. The data retrieval process is carried out using web scraping tools, with sources from publication platforms such as Sinta, Google Scholar, and PDDIKTI. Although the data used is secondary, the data collection process still adheres to ethical standards and applicable regulations. Therefore, the researcher first requested permission from the authorized party responsible for publications at XYZ University before using the data in this study.
2. Data Cleansing: The next step in this study is to select and sort the data obtained from the previous process. This stage ensures that the data to be used is appropriate, and that there are no duplicate data or data that cannot be read by the system.
3. Data Processing: This stage involves processing the data through transformation, feature weighting, and grouping into quantile classes. By assigning appropriate weights to the most relevant features, the model can better focus on factors that significantly influence lecturers' publication performance. The outcome of this step is a refined dataset that is ready for the prediction phase.
4. Prediction Performance: This stage involves data analysis and the development of a predictive model aimed at estimating lecturers' publication performance for the following year based on historical data. The prediction results provide an initial overview of each lecturer’s potential performance and serve as

input for the Reinforcement Learning (RL) method to determine the most appropriate intervention or treatment recommendations.

5. Action Recommendation: This stage focuses on determining the most appropriate intervention for each lecturer based on the predicted performance results. By using the Reinforcement Learning (RL) method, particularly the Q-Learning algorithm, the system learns from past outcomes to identify the most effective actions such as training, incentives, or no intervention that have the potential to improve future publication performance.

4. Results and Discussion

4.1 Data Distribution

Based on data accessed from the official SINTA page of XYZ University, over the past five years (2020–2024), several indicators of lecturers' publication and research performance can be analyzed. The following is the initial data obtained.

Tabel 1. Initial data

No	Data Type	Total
1	Number of publications indexed in Sinta 1	56
2	Number of publications indexed in Sinta 2	428
3	Number of publications indexed in Sinta 3	681
4	Number of publications indexed in Sinta 4	1.158
5	Number of publications indexed in Sinta 5	603
6	Number of publications indexed in Sinta 6	50
7	Number of Scopus-indexed publications in Q1	139
8	Number of Scopus-indexed publications in Q2	107
9	Number of Scopus-indexed publications in Q3	303
10	Number of Scopus-indexed publications in Q4	312
11	Number of Scopus publications in non-Q journals	94
12	Number of research grants	714
13	Number of lecturers	4.616

Source: Processed from SINTA data of XYZ University (2025)

Based on the data table 1, the researcher will use data from active lecturers in 2024, totaling 426 individuals. The following is the dataset obtained to carry out the prediction process of lecturer publication performance in 2025:

The data attributes used in this study are the result of a Data Cleansing process applied to the selected sample and are summarized based on their characteristics.

Table 2. Data Attribute

ID	Lecturer Serial Number
Author	Lecturer Name
GENDER	Gender
PROFILE-DEPT	Academic Department
Title	Educational Qualification
Department	Academic Rank

Scopus H-Index_scored	Lecturer’s H-Index value based on the Scopus database in 2024
Google Scholar H-Index	Lecturer’s H-Index value based on the Sinta database in 2024
Total Sinta_scored	Total publication score of the lecturer in Sinta-accredited journals from 2020 to 2024.
Total Scopus_scored	Total publication score of the lecturer in Scopus-indexed journals from 2020 to 2024
Total Jurnal_scored	Number of journals published by the lecturer annually from 2020 to 2024
Total Grant	Research grants received by the lecturer annually from 2020 to 2024
Performance class	Performance class over a five-year period from 2020 to 2024, consisting of five performance class attributes

Source: Data Processed (2025)

4.2 Results

4.2.1 ANOVA (Analysis of Variance)

Conducting a significance test in this context aims to assess whether the independent variables, in this case demographic data, have a statistically significant effect on the dependent variable, namely the lecturers' publication performance**.**

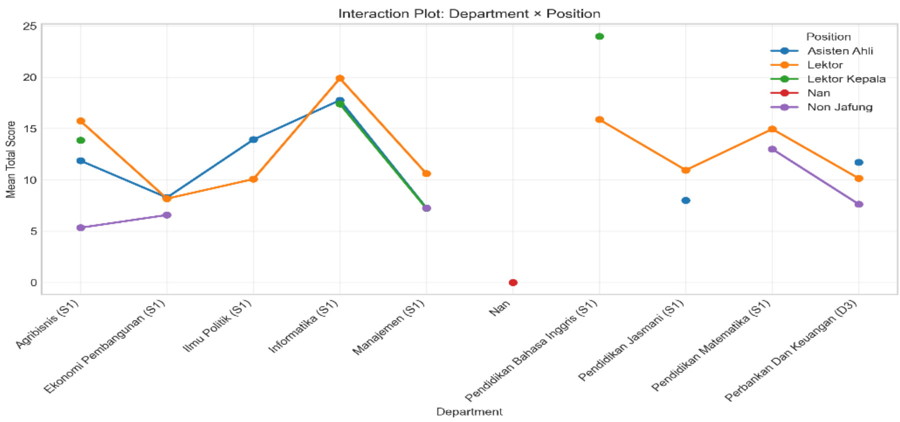
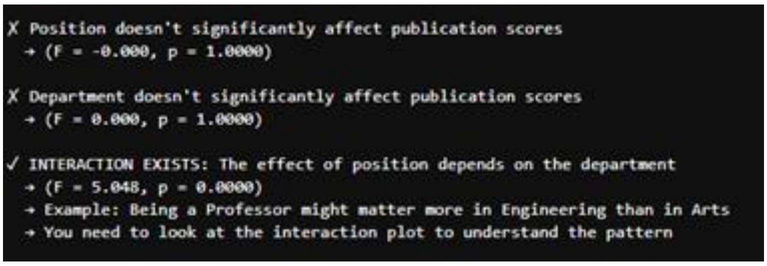


Figure 2. Interaction Plot

Source: Processed data by researchers (2025)

1) **The main results of ANOVA (Analysis of Variance) are as follows**

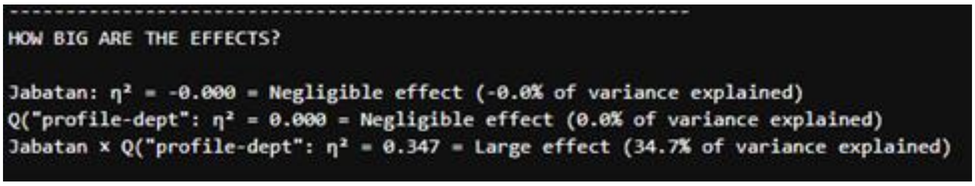


```
X Position doesn't significantly affect publication scores
  → (F = -0.000, p = 1.0000)

X Department doesn't significantly affect publication scores
  → (F = 0.000, p = 1.0000)

✓ INTERACTION EXISTS: The effect of position depends on the department
  → (F = 5.048, p = 0.0000)
  → Example: Being a Professor might matter more in Engineering than in Arts
  → You need to look at the interaction plot to understand the pattern
```

Figure 3. Anovatest
Source: Processed data by researchers (2025)

a) **Academic position does not have a significant effect on publication scores:** The F-statistic for Position is 0.000, and the p-value is 1.0000, which is very high. This indicates that one's academic position (e.g., Professor or Assistant Lecturer) does not significantly affect publication scores, as the p-value > 0.05.
b) **Department or study program does not have a significant effect on publication scores:** The F-statistic for Department is 0.000, with a p-value of 1.0000. This also shows that the department (e.g., Engineering, Arts) does not significantly influence publication scores. Again, the p-value > 0.05.
c) **There is an interaction effect between academic position and department:** The F-statistic for the interaction between academic position and department is 5.048, with a p-value < 0.05. This indicates a statistically significant interaction between position and department. The effect of academic position on publication scores varies depending on the department, meaning that certain positions (e.g., Professor) have different impacts across different departments.

2) Effect Size:



```
------------------------------------------------------------
HOW BIG ARE THE EFFECTS?

Jabatan: η² = -0.000 = Negligible effect (-0.0% of variance explained)
Q("profile-dept": η² = 0.000 = Negligible effect (0.0% of variance explained)
Jabatan × Q("profile-dept": η² = 0.347 = Large effect (34.7% of variance explained)
```

Figure 4. Effects
Source: Processed data by researchers (2025)

a) A very small η^2 value, such as 0.000, indicates that position (academic rank) does not have a significant effect on the variance in publication scores.
b) The η^2 value for the department (profile-dept) is also very small, at 0.000, meaning that the department has no significant effect on publication scores.
c) Position × Department indicates the interaction between academic rank and department. An η^2 value of 0.347 suggests an effect, meaning that the interaction between position and department accounts for approximately 34.7% of the variance in publication scores.

4.2.2 Forming a prediction model

In this study, the researcher tested four prediction models: Random Forest, Extreme Gradient Boosting, K-Nearest Neighbor, and Multilayer Perceptron. Each model was trained using historical data from 2020 to 2023 to predict lecturers' performance class for the year 2024, represented as Rank-N (from 1 to 5). The predictions from the four models were then evaluated using two main metrics: accuracy and log loss, based on validation data from 2024. The evaluation results are as follows:

Tabel 3. Prediction model

Model	accuracy	Log Loss
Random Forest	0.736	0.605
XGBoost	0.702	0.733
MLP	0.699	0.707
KNN	0.651	2.022

Source: Processed data by researchers (2025)

Based on the evaluation results, Random Forest demonstrated the best performance with an accuracy of 73.6% and the lowest log loss (0.605). Therefore, it was selected as the primary model for predicting lecturer performance in 2025 (q2025_pred). The predictions generated by the Random Forest model serve as the foundation for designing an intervention recommendation system using Reinforcement Learning.

4.2.3 Forming a Random Forest prediction model

The prediction model was built using the Random Forest algorithm based on predefined variables. Publication performance data from 2020 to 2023 was used as training data, and 2024 data was used for testing. This process included selecting relevant features, splitting the data, and evaluating the model's accuracy using regression metrics such as MAE, RMSE, and R^2. Here are the results:

```
📊 Random Forest Evaluation (2024):
MAE: 0.2943961187214612
RMSE: 0.410472229219964
R²: 0.8540227409388873
```

Figure 5. Model evaluation
Source: Processed data by researchers (2025)

The Random Forest model demonstrated very good predictive performance in projecting lecturers' publication performance, with an R^2 value of 85.4%, indicating that most of the variance in the target data can be explained by the model. The MAE value of 0.29 and RMSE value of 0.41 show that the average prediction error is relatively low, making the model sufficiently accurate and stable for use in performance prediction contexts.

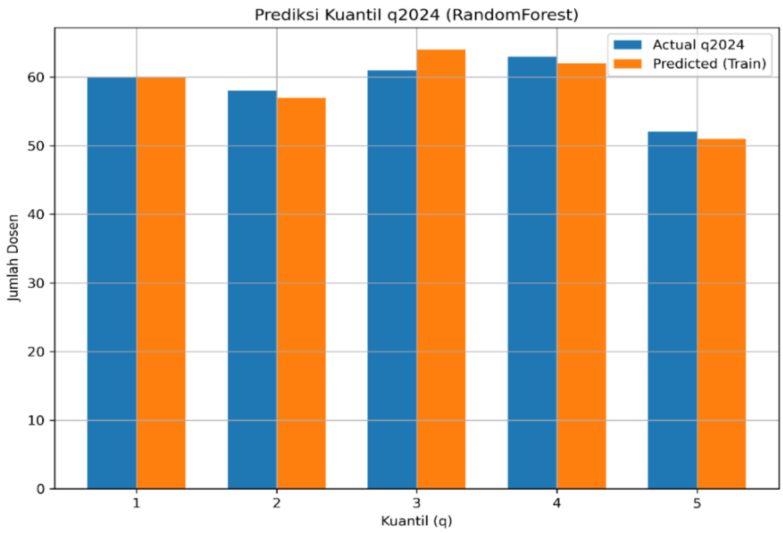


Figure 6. RF Chart
Source: Processed data by researchers (2025)

4.2.3.1 Building a Performance Prediction Model for 2025

The next step is to build the 2025 performance prediction model using the previously trained Random Forest (RF). Each decision tree in the RF model generates a prediction for 2025 performance, and all predictions are then combined and averaged to produce a continuous estimated value for the 2025 performance.
Example of Predicted Class Performance Results for the Year 2025.

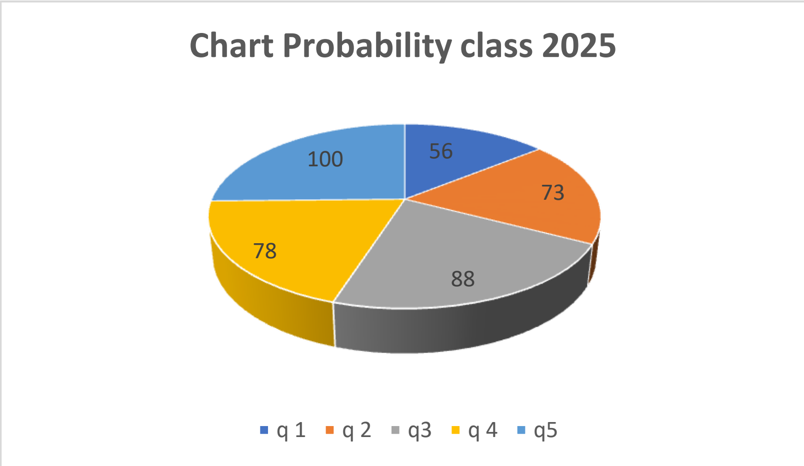


Figure 7. RF Chart Probability class
Source: Processed data by researchers (2025)

Figure 7 above illustrates the number of lecturers predicted to fall into each quantile class (q1–q5) for publication performance in 2025. The quantile scale ranges from q1 (best performance) to q5 (lowest performance), indicating that the lower the q-value, the better the expected performance.Based on these results, changes in predicted performance classes can also be observed, indicating whether a lecturer's performance is expected to remain stable, decline, or improve.

Tabel 4. Example result Predicted Performance Probability for 2025

Lecturer Number	actual_q2024	predicted_q2025	prob_q2025_class1	prob_q2025_class2	prob_q2025_class3	prob_q2025_class4	prob_q2025_class5	Performance_Change
1	2	2	0	0.432	0.298	0.26	0.01	Same
2	4	4	0	0.006	0.11	0.5	0.384	Same
3	5	5	0	0.002	0.004	0.1	0.894	Same
4	1	4	0	0.008	0.21	0.55	0.232	Declined
5	4	3	0.008	0.34	0.464	0.17	0.018	Improve
6	2	2	0.004	0.324	0.288	0.34	0.044	Same

Source: Processed data by researchers (2025)

The prediction results indicate the potential changes in lecturer grades: improvement, decline, or remain unchanged. The q-value represents performance level on a scale of 1 to 5, where a lower q indicates better performance. Lecturers with potential improvement are predicted to perform better, while those expected to remain stable are predicted to have no change in performance in 2025. The results are as follows:

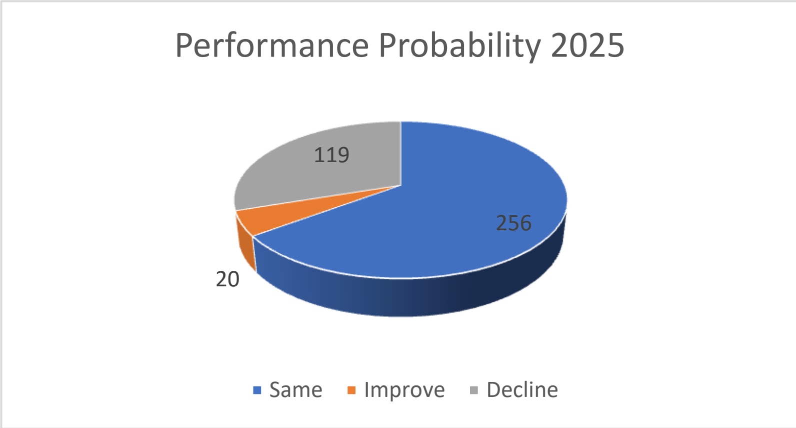
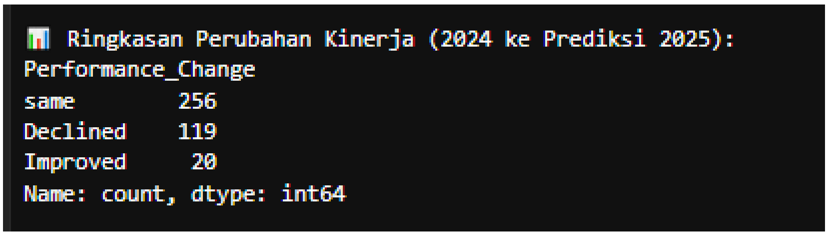


Figure 8. RF Chart Probability
Source: Processed data by researchers (2025)

The prediction results indicate potential changes in lecturer grades: decline, improvement, or stability. The q-value is used to measure performance on a scale of 1 to 5, where a lower value indicates better performance. These predictions reflect the likelihood of improvement, decline, or stability in lecturer performance in 2025. The results are as follows:



```
📊 Ringkasan Perubahan Kinerja (2024 ke Prediksi 2025):
Performance_Change
same        256
Declined    119
Improved     20
Name: count, dtype: int64
```

Figure 9. Performance Status
Source: Processed data by researchers (2025)

The prediction results show changes in lecturer performance grades from 2024 to 2025. A total of 256 lecturers are predicted to remain the same, 20 to improve, and 119 to decline. This indicates that most lecturers are expected to remain stable, a small number may improve, and a significant portion are predicted to experience a decline in performance.

4.2.4 Determining Treatment Grades Using Reinforcement Learning

After predicting lecturer performance for 2025 using the Random Forest model, the researcher applied a Reinforcement Learning (RL) approach, specifically the Q-Learning algorithm, to determine the appropriate intervention or treatment. The predicted quantile (q) value represents the lecturer's performance level, where a lower q indicates better performance.

Q-Learning is used to evaluate various action options such as training, providing incentives, no incentives, or no intervention based on the lecturer's performance history. This method allows the system to learn from past experiences and choose the action with the highest potential to improve future performance. The following are the results obtained:

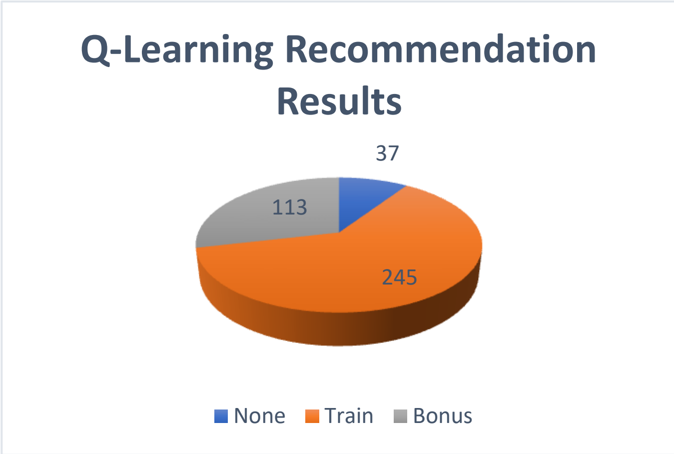


Figure 10. Q-learning Recommendation
Source: Processed data by researchers (2025)

The Q-Learning system produced a fairly balanced distribution of intervention recommendations, with a tendency toward active strategies. From the 395 lecturers analyzed:

- 113 lecturers were recommended to receive a bonus as an incentive for good performance.
- 245 lecturers were recommended to undergo training, as they were assessed to have potential for improvement.
- 37 lecturers received no intervention (None); this does not always indicate stable performance but may reflect the system's assessment that intervention would not be effective.

The implementation of the Reinforcement Learning (RL) algorithm, specifically the Q-Learning model, has been carried out to provide intervention recommendations for lecturers based on their historical performance patterns from 2020 to the predicted quantile in 2025. Each lecturer is represented in the form of a sequence of annual quantile values, referred to as a state. Based on the learning process conducted through simulation, the RL model generates recommendations in the form of four types of actions: None, Train and Bonus.

Table 5. Sample Q-Learning Intervention Recommendations

Lecturer Number	q2020	q2021	q2022	q2023	q2024	predicted_q2025_RF	Group	recommended_action_id	recommended_action
1	3	4	5	5	2	2	(3, 4, 5, 5, 2, 2)	1	Train
2	1	2	1	4	4	4	(1, 2, 1, 4, 4, 4)	2	Bonus
3	5	5	5	5	5	5	(5, 5, 5, 5, 5, 5)	0	None
4	2	1	2	1	1	1	(2, 1, 2, 1, 1, 1)	1	Train
5	4	3	2	4	4	4	(4, 3, 2, 4, 4, 4)	1	Train
6	1	1	2	4	2	2	(1, 1, 2, 4, 2, 2)	1	Train

Source: Processed data by researchers (2025)

Based on the Q-Learning recommendation results, the performance pattern of the lecturer:

- (3, 4, 5, 5, 2, 2) → Train, Performance initially declined but then improved, so training is recommended to maintain the improvement.

- (1, 2, 1, 4, 4, 4) → Bonus, stabilized at quantile 4, which may be considered acceptable in certain contexts, thus a bonus is given as an incentive.
- (5, 5, 5, 5, 5, 5) → None, consistently poor performance; no intervention is recommended as it is considered ineffective.
- (2, 1, 2, 1, 1, 1) → Train, good and stable performance; training is recommended to maintain consistency.
- (4, 3, 2, 4, 4, 4) → Train, performance showed improvement but then stagnated; training is recommended to boost performance again.
- (1, 1, 2, 4, 2, 2) → Train, fluctuating performance with signs of recovery; training is recommended to strengthen the positive trend

Overall, these results show that Q-Learning provides adaptive, data-driven intervention recommendations tailored to each lecturer's performance trends.

5. Conclusions and Recommendations

5.1 Conclusions

Lecturer performance management is essential to ensure they work effectively in supporting institutional goals. Good performance not only maintains educational quality but also enhances the university's reputation. Regular monitoring allows for systematic evaluation of individual and team performance.

The use of information technology through predictive models helps HR management analyze and map potential issues in lecturers' publication performance. This approach provides an objective early overview before decisions are made, unlike methods that rely solely on intuition or personal experience.

ANOVA analysis shows that demographic factors such as academic rank and department do not have a significant direct effect on publication scores. However, there is an interaction between the two, meaning the influence of academic rank may vary depending on the department.

The application of predictive analytics in performance management is done by analyzing past publication data. This system provides insight into performance potential and helps design development programs such as writing training or research support to boost productivity. This data-driven approach enables more targeted and effective decision-making.

Predictions indicate that approximately 65% of lecturers are expected to maintain their performance in 2025, around 30% are at risk of performance decline, and only 5% are predicted to improve. These insights can help institutions identify lecturers who may require targeted support such as training, mentoring, or incentives and assist in more effective resource allocation, budget planning, and development policy formulation.

To support intervention decisions, the Q-Learning method was implemented to analyze lecturers' historical performance data and generate personalized action recommendations. The results show that out of 395 lecturers analyzed, 113 were recommended to receive a bonus as recognition for strong or improving performance, 245 were advised to undergo training due to their potential for development, and 37 received a no intervention recommendation. This indicates that Q-Learning generally favors active strategies for lecturers with growth potential, while the "no intervention" category reflects cases where additional support may not lead to meaningful improvement based on past performance trends.

5.2 Recommendations

Reinforcement Learning (RL) can be enhanced by grouping lecturers based on performance profiles and assigning different policies to each group to make the system more personalized and responsive.

Universities can utilize RL as a decision-support system for managing lecturer performance, using historical data such as publication quantiles, research involvement, and academic achievements. RL helps recommend interventions such as training, incentives, or workload adjustments.

analytics can also be used to forecast lecturer performance in the following year, providing valuable input for more accurate and data-driven managerial decision making.

6. References

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