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Constraint Clustering for Promotion Application: Central Java Case Study

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Abstract: Organizations utilize Talent Management to enhance competitiveness, improve employee quality, develop potential, and retain talent. Talent management also plays a crucial role in the career development of lecturers. Promotions in the academic ranks and positions of lecturers in Indonesia are essential to consider, as they significantly impact the quality of lecturers, the accreditation value of higher education, and the global rankings of universities. In this study, a questionnaire was administered to 406 respondents. The results revealed six clusters correlated with the challenges of applying for functional lecturer positions. Based on the cluster analysis, Cluster 0 (20%) exhibited minimal obstacles, Cluster 1 (27%) faced highly challenging obstacles, Cluster 2 (13%) experienced neutral obstacles, Cluster 3 (15%) encountered manageable obstacles, Cluster 4 (18%) dealt with easily surmountable constraints, and Cluster 5 (7%) experienced significant hurdles. Future research could explore implementing a new talent management model, particularly for lecturers who need help applying for functional positions.

Keywords: Talent Management; Competitiveness; Employee Quality; Career Development; Lecturer Positions.

1. Introduction

Talent Management is a structured approach that encompasses the entire lifecycle of individuals within an organization. It involves systematically attracting, identifying, developing, engaging, retaining, and strategically deploying individuals with unique skills, knowledge, and abilities that contribute to the organization's success [1]. By implementing effective Talent Management practices, companies can ensure the acquisition and retention of exceptional talent, enhancing their competitive advantage and enabling them to achieve sustainable strategic success. This holistic process focuses on finding and nurturing talented individuals and creating an environment where they are motivated, engaged, and given opportunities to thrive and grow. Ultimately, Talent Management is a strategic driver for organizations to build a capable and high-performing workforce, leading to increased productivity, innovation, and overall success.

Maintaining a qualified workforce is paramount, and Talent Management plays a critical role in achieving this objective [2]. By implementing effective Talent Management strategies, organizations can attract, develop, and retain individuals who possess the necessary skills, knowledge, and expertise to meet the evolving demands of the job market. This ensures the organization has a pool of qualified and competent employees who can contribute to its success and competitiveness. Additionally, Talent Management helps to create a positive work environment that fosters employee engagement, motivation, and satisfaction, further enhancing the organization's ability to retain top talent and build a sustainable workforce capable of driving future growth and innovation.

Talent management is not limited to corporate settings; it also applies to the career development of lecturers in academic institutions. The Human Resource Management department is crucial in organizing various activities to nurture and develop lecturer talent [3]. These activities encompass sourcing and attracting highly qualified individuals, conducting outreach efforts to identify potential talent, ensuring the maintenance and engagement of current lecturers, and implementing effective selection processes. By strategically managing lecturer talent, educational institutions can cultivate a skilled and knowledgeable faculty that positively impacts students' learning experience. This comprehensive approach to talent management in academia contributes to the professional growth and career advancement of lecturers while enhancing the overall quality and reputation of the institution.

Lecturers play a crucial role in academia as they are professional educators and dedicated scholars. Their primary responsibility extends beyond delivering lectures and facilitating learning; they are actively involved in generating, developing, and disseminating knowledge. Through research, lecturers contribute to expanding the boundaries of knowledge in their respective fields, conducting studies, publishing scholarly articles, and participating in academic conferences [4]. Additionally, they engage in community service by sharing their expertise with the broader community, collaborating with industry professionals, offering consultations, and participating in outreach programs. This multifaceted role of lecturers underscores their importance in fostering intellectual growth, promoting critical thinking, and driving innovation within the educational landscape. In Central Java, Indonesia, the projected number of lecturers in 2022 is 13,994. Permanent and non-permanent lecturers can hold functional positions such as Professor, Associate Professor, Assistant Professor, and Lecturer based on their expertise, experience, and academic qualifications.

In the context of education in Central Java, Indonesia, both groups of lecturers have equal opportunities to advance their careers based on their expertise and academic interests. Permanent lecturers have long-term job security and can attain functional positions based on their achievements, research contributions, and academic excellence. Meanwhile, non-permanent lecturers can also achieve the same functional positions based on their academic qualifications, teaching experience, and contributions to the educational institution. In practice, granting functional positions usually involves a rigorous evaluation and selection process by the relevant educational authorities or institutions. These functional positions are determined based on academic qualifications, teaching experience, research achievements, and academic contributions made by the lecturers. With equal opportunities for both groups of lecturers to hold functional positions, Central Java can harness a diverse range of talents and knowledge to enhance the quality of education and research in the region. This diversity will enrich students' learning experience and foster a dynamic and innovative academic environment.

The challenges faced in advancing the ranks of lecturers are multifaceted and extend beyond their level of preparedness in pursuing scientific advancements. Limited availability of information about promotion criteria is one significant factor contributing to delays in lecturer promotions to higher positions. Clear and transparent guidelines outlining the requirements, expectations, and evaluation process for promotion are crucial in providing lecturers with a roadmap for career advancement. When the requirements are precise and not widely known, it can create uncertainty and hinder lecturers' ability to effectively plan and work towards meeting the requirements for promotion. Enhancing communication and providing comprehensive information regarding promotion criteria can alleviate these challenges and enable lecturers to navigate their career paths better, fostering a more equitable and supportive environment for professional growth within the academic community. Research conducted by [5] and [6], particularly in Indonesia, indicates that a few academics progress in their careers due to insufficient knowledge about promotion criteria. Their approach to promoting their abilities could be more strategic, as they primarily focus on improving their teaching and learning functions, neglecting the importance of community service as one of the promotion criteria.

2. Research Method

2.1 Data Collection and Variable Selection

This study focused on analyzing lecturer data from LLDIKTI Region VI in Central Java, Indonesia. The data set consisted of information obtained through a sampling technique involving 410 lecturers. The study examined 14 variables as the basis for analysis. These variables encompassed a range of questions that served as attributes for this research. These questions were carefully designed to explore various aspects related to the lecturers' backgrounds, qualifications, teaching methodologies, research involvement, community service activities, and professional development. By investigating these attributes, the study aimed to gain a comprehensive understanding of the lecturer population in Central Java and draw meaningful insights to inform future improvements in the educational landscape.

Q1: How long does it work?
Q2: Current functional position?
Q3: How long have you been in a functional position?
Q4: Reasons for promotion
Q5: Number of credits per semester
Q6: Number of national/ international journals
Q7: Number of national/ international proceedings
Q8: Number of books with ISBNs
Q9: Implementation of research in textbooks
Q10: Number of HaKI
Q11: Amount of community service
Q12: Number of community service publications
Q13: Being a member of a committee at a university
Q14: Being a member of a committee in a government institution

2.2 Correlation analysis between variables

Correlation analysis is a statistical technique utilized to assess the relationship between variables in a study. It helps researchers understand the extent to which changes in one variable correspond to changes in another. Positive correlation indicates that the variables move together in the same direction, while negative correlation suggests they move in opposite directions. A correlation coefficient close to +1 or -1 signifies a strong relationship, while a coefficient close to 0 indicates a weak or negligible relationship. Correlation analysis provides valuable insights into the interdependency of variables, aiding researchers in drawing meaningful conclusions and informing decision-making processes. The researcher utilized RapidMiner Studio, a powerful data mining and predictive analytics software, to analyze the data. The focus of the study was to examine the variables related to lecturers' backgrounds, qualifications, teaching methodologies, research involvement, community service activities, and professional development, specifically regarding their desire for promotion. By utilizing RapidMiner Studio, the researcher was able to explore and extract insights from the dataset, uncovering patterns and relationships between the variables. This analysis provided valuable information regarding the lecturers' aspirations for career advancement and shed light on factors that contribute to their desire for promotion. RapidMiner Studio facilitated a comprehensive examination of the data, empowering the researchers to understand the lecturers' perspectives and inform future strategies for supporting their career growth and advancement opportunities.

Table 1. Correlation between the dependent variable and the independent variable

No	Variable	Desire for Promotion	No	Variable	Desire for Promotion
1	Q3	0.131	8	Q5	-0.019
2	Q2	0.128	9	Q14	-0.023

3	Q4	0.088	10	Q9	-0.023
4	Q1	0.174	11	Q7	-0.024
5	Q8	0.027	12	Q12	-0.042
6	Q10	-0.002	13	Q13	-0.064
7	Q6	-0.013	14	Q11	-0.141

Table 1 presents the correlation between the dependent variable, the desire for promotion, and several independent variables denoted as Q1, Q2, Q3, and so on. The table displays the correlation coefficients for each independent variable about the desire for promotion. The correlation coefficient measures the strength and direction of the linear relationship between two variables. A positive correlation coefficient indicates a positive relationship, meaning that as one variable increases, the other also tends to increase. On the other hand, a negative correlation coefficient signifies a negative relationship where an increase in one variable is associated with a decrease in the other. In Table 1, the desire for promotion is the dependent variable, while the independent variables are represented by Q1, Q2, Q3, and so forth. The correlation coefficients for each independent variable are provided in the table. For instance, Q3 has a correlation coefficient of 0.131, which indicates a weak positive relationship with the desire for promotion. This means that as the score on Q3 increases, there is a slight tendency for the desire for promotion also to increase.

Similarly, Q2 has a correlation coefficient of 0.128, suggesting a similar weak positive relationship.

In contrast, some variables display negative correlation coefficients. For example, Q11 has a correlation coefficient of -0.141, indicating a moderately strong negative relationship with the desire for promotion. This means that as the score on Q11 decreases, the desire for promotion increases. It is important to note that correlation coefficients close to 0 suggest a weak or negligible relationship between the variables. These coefficients, such as Q8 with a correlation of 0.027 or Q10 with a correlation of -0.002, indicate that these variables have little impact on the desire for promotion. By examining the correlation coefficients in Table 1, researchers can gain insights into the variables that exhibit a stronger association with the desire for promotion. This information can inform further analysis and help identify critical factors that contribute to lecturers' aspirations for career advancement within the academic realm.

Table 1 presents the variables influencing a lecturer's desire for promotion in descending order based on their correlation coefficients. The most influential variable is the length of time in a functional position, indicating that lecturers who have been in a functional position for longer tend to have a stronger desire for promotion. Following that, the current functional position and reasons for promotion also positively correlate with the desire for promotion, suggesting that a higher functional position and clear reasons for seeking promotion contribute to a greater aspiration for advancement. Other factors such as the length of work, number of books, number of HaKI (Intellectual Property Rights) publications, number of journals, number of credits per semester, being a member of a government agency committee, implementation of research in textbooks, number of national/international productions, number of public service publications, being a member of a committee in college, and the amount of community service all show varying degrees of positive correlation with the desire for promotion. These findings provide valuable insights for educational institutions and policymakers to understand the factors driving lecturers' career advancement ambitions. By recognizing and supporting these influential variables, institutions can implement targeted strategies, such as providing opportunities for professional development, encouraging research and publication activities, and fostering a supportive environment for community engagement. Such measures can create a conducive atmosphere for lecturers to achieve their career aspirations while promoting excellence and innovation in the academic landscape.

2.3 Clustering Methods

Talent management analysis can be effectively conducted through the utilization of clustering models. Clustering is a powerful technique in data mining that aims to categorize or group data points based on their similarity to each other. This process involves mapping individual data points into specific clusters, allowing for the identification of patterns, trends, and relationships within the dataset. By applying clustering analysis to talent management, organizations can gain valuable insights into their workforce and identify distinct groups of individuals with similar characteristics, skills, or potential. This helps in understanding the diverse talent pool within the organization and tailoring talent management strategies accordingly. Through clustering, organizations can identify common traits or attributes among employees, such as educational background, experience level, job performance, or career aspirations. This information can assist in creating targeted development programs, succession planning, and talent acquisition strategies. It allows organizations to use resources effectively, provide relevant training opportunities, and foster career growth pathways aligning with employees' strengths and aspirations.

Clustering models can help organizations identify high-potential employees, detect talent gaps, and support decision-making in talent deployment and workforce planning. Organizations can identify emerging skill trends or areas where additional talent may be required by analyzing clusters, enabling proactive talent acquisition and development strategies. Moreover, clustering analysis provides a data-driven approach to talent management, allowing organizations to move beyond subjective perceptions and biases. Organizations can make informed decisions and develop evidence-based talent management practices by leveraging objective data and analytics. Clustering is a valuable technique in talent management analysis where data points with similar characteristics are grouped within the same cluster, while data points with distinct traits are placed in different clusters. One commonly used model for clustering analysis is the K-Means algorithm. This method is employed to discover cluster structures within a dataset, characterized by the most significant similarity within the same cluster and the most prominent differences between different groups. The K-Means algorithm operates by iteratively assigning data points to clusters and adjusting the cluster centroids to minimize the sum of squared distances between data points and their assigned centroids. Through this process, the algorithm seeks to identify natural groupings within the data based on their intrinsic similarities. By applying the K-Means algorithm to talent management data, organizations can uncover meaningful patterns and groupings among employees. This allows them to identify distinct clusters of individuals who exhibit similar characteristics, skills, or performance levels. Such insights enable organizations to tailor talent management strategies, including recruitment, training, and career development initiatives, to cater to each cluster's unique needs and potential. Moreover, the K-Means algorithm assists in identifying any outliers or anomalies within the talent pool. These outliers may represent exceptional performers or individuals who possess rare skills. Organizations can devise targeted approaches to nurture and leverage their talents by identifying and understanding these outstanding cases.

Clustering techniques, such as the K-Means algorithm, provide organizations with a data-driven approach to talent management. By categorizing employees into clusters based on their similarities, organizations can optimize talent allocation, enhance workforce planning, and implement tailored strategies to support employee development and organizational success. From a statistical point of view, clustering methods are generally divided into probability model-based approaches and non-parametric approaches [22]. They are grouping data using K-Means. The clustering parameters used are 3 clusters. The results of the clustering processing are as follows.

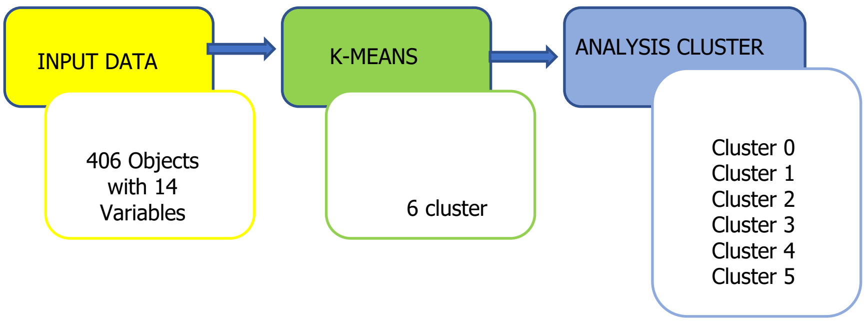

Figure 1. Clustering Using K-Means

3. Result and Discussion

3.1 Results

Data mining is an essential process that involves uncovering valuable insights, trends, and hidden patterns within extensive datasets stored in databases, data warehouses, or other data repositories. It utilizes various techniques, algorithms, and statistical methods to extract meaningful information from raw data. The primary goal of data mining is to transform vast amounts of complex and unstructured data into actionable knowledge. Analyzing the data, patterns, relationships, and trends that may not be apparent at first glance can be identified, providing organizations with valuable insights to support decision-making, enhance operations, and drive strategic initiatives. Data mining involves multiple steps, including cleaning, preprocessing, transformation, and modelling. These steps help to prepare the data and make it suitable for analysis. Once the data is appropriately prepared, advanced algorithms are applied to uncover patterns and relationships among the variables.

The insights derived from data mining can have significant applications across various domains. It can be used in business to understand customer behaviour, identify market trends, optimize marketing strategies, detect fraud, and improve operational efficiency. Data mining can contribute to medical research, disease detection, patient diagnosis, and treatment optimization in healthcare. It also has applications in fields such as finance, telecommunications, manufacturing, and transportation. Data mining plays a crucial role in converting raw data into valuable information, enabling organizations to gain a competitive edge, make informed decisions, and discover new opportunities. By leveraging the power of data mining, businesses and researchers can unlock the hidden insights within their data, leading to improved processes, enhanced outcomes, and innovation.

The purpose of data mining about upgrading to a functional position is to uncover valuable insights and patterns within a dataset that can inform and support career advancement. Data mining techniques can be utilized to analyze various factors, variables, and criteria contributing to the promotion to a higher functional position. By applying data mining, organizations can identify patterns and trends related to the qualifications, experience, performance, and achievements of individuals who have successfully upgraded to higher functional positions. This analysis can provide valuable insights into the specific attributes, skills, and experiences associated with career advancement. Through data mining, organizations can identify the key factors that significantly contribute to the likelihood of promotion to a higher functional position. This may include variables such as years of experience, educational qualifications, research productivity, teaching effectiveness, leadership qualities, and other relevant factors. By leveraging data mining techniques, organizations can develop models and algorithms to predict the likelihood of success in upgrading to a higher functional position. These predictive models can consider a range of variables and criteria to provide insights and recommendations to individuals seeking career advancement. This can help individuals assess their strengths and areas for improvement, allowing them to strategically focus on enhancing the skills and qualifications most relevant to their desired functional position.

Furthermore, data mining can aid in identifying potential barriers or challenges that individuals may encounter in their journey towards upgrading to a higher functional position. By analyzing historical promotion data and examining patterns, organizations can gain insights into common obstacles and develop strategies to address them, such as targeted training programs or mentorship initiatives.

Table 2. Rapid Miner Configuration

Number Questions	Responden	Minimum	Maximum	Mean	Number Questions	Responden	Minimum	Maximum	Mean
Q1	406	1	4	6.655	Q8	406	1	2	1.022
Q2	406	1	3	1.874	Q9	406	1	2	1.007
Q3	406	1	3	1.310	Q10	406	1	2	1.076
Q4	406	1	4	2.581	Q11	406	1	4	1.409
Q5	406	1	4	2.648	Q12	406	1	2	1.126
Q6	406	1	4	1.246	Q12	406	1	4	1.517
Q7	406	1	2	1.143	Q14	406	1	4	1.148

The data displayed in the table provides insights into the respondents' ratings for each question. For Q1, the ratings range from 1 to 4, with a mean value 6.665. This indicates that, on average, the respondents gave higher ratings, suggesting a relatively positive perception or response to the item assessed by Q1. Moving on to Q2, the ratings range from 1 to 3, with a mean value of 1.874. This suggests that, on average, the respondents provided relatively low ratings, indicating a less favourable or more mixed response.

Similarly, for Q3, the ratings range from 1 to 3, with a mean value of 1.310, indicating moderate ratings on average. Q4 shows ratings ranging from 1 to 4, with a mean value of 2.581, suggesting relatively higher ratings on average. Q5 follows a similar pattern, with ratings from 1 to 4 and a mean value of 2.648, indicating moderate ratings on average. Q6 has ratings ranging from 1 to 4, with a mean value of 1.246, suggesting relatively low ratings on average. For Q7, the ratings range from 1 to 2, with a mean value of 1.143, indicating that most respondents selected the first option. Q8 also has ratings from 1 to 2, with a mean value of 1.022, suggesting a similar trend of the majority choosing the first option. Lastly, Q9 shows ratings ranging from 1 to 2, with a mean value of 1.007, suggesting that most respondents selected the first option for this question. These ratings provide initial insights into the respondents' perceptions or opinions regarding each question, forming a basis for further analysis and interpretation of the survey results.

The Davies-Bouldin value is a metric commonly used to evaluate the quality of clustering algorithms. It measures the average similarity between clusters while also considering their separation. A lower Davies Bouldin value indicates better-defined and more distinct clusters. Researchers can identify the number that yields the most favourable results by evaluating the Davies-Bouldin value for different clusters. This approach allows for determining the ideal clustering configuration that maximizes cluster separation while minimizing overlap.

Analyzing the performance of different operators for each number of clusters provides valuable insights into the stability and robustness of the clustering solution. By comparing the results, researchers can identify trends and patterns in how the clusters are formed and assess the suitability of different cluster numbers for the specific problem. The final decision on the best number of clusters is based on selecting the operator with the lowest Davies Bouldin value. This choice indicates the most effective and accurate clustering solution for the dataset, where the clusters are well-separated and distinct from each other. Using this approach, researchers can obtain a reliable and optimized clustering outcome. The selected number of clusters ensures that the dataset is divided into meaningful and well-separated groups, allowing for practical analysis and interpretation of the underlying patterns and relationships within the data.

Table 3. Results of K-Means Performance Analysis

Clustering	Davies Boudien
2	1.649
3	1.638
4	1.599
5	1.511
6	1.444

Five performance models were evaluated in the previous computations to determine the best choice. Each model produced different Davies Bouldin values. The analysis revealed that the smallest Davies Bouldin value was obtained with 6 clusters, yielding a value of 1.444. Therefore, the decision is made to use 6 clusters for this case. This stage showcases several cluster models generated by computational analysis. The models include Cluster 0 with 81 items, Cluster 1 with 109 items, Cluster 2 with 51 items, Cluster 3 with 63 items, Cluster 4 with 72 items, and Cluster 5 with 30 items. In total, there are 6 cluster models. Each model classifies the 406 items based on the clustering process.

Table 4. Cluster Models

Cluster	Member of Item
0	81 Item
1	109 Item
2	51 Item
3	63 Item
4	72 Item
5	30 Item

The determination of the number of respondents facing difficulties in applying for functional positions was based on the analysis of the questionnaire results from 406 respondents. The constraints for functional position submissions were determined based on centroid values. Table 4 displays the centroid values, with higher values indicating very easy, easy, neutral, easy, very easy, and very easy constraints. The cluster analysis revealed that 63 respondents (15%) faced very easy constraints, 81 respondents (20%) faced very easy constraints, 72 respondents (18%) faced easy constraints, 51 respondents (13%) faced neutral constraints, 30 respondents (7%) faced difficult constraints, and 109 respondents (27%) faced very difficult constraints.

Table 5. Utilization of Clusters for Functional Position Submission Constraints

Cluster	Centroid (Mean Value)	Submission Constrain	Member of Item
0	1.318	Very Easy	81
1	1.729	Very Difficult	109
2	1.378	Neutral	51
3	694	Easier	63
4	1.357	Easy	72
5	1.522	Difficult	30

3.2 Discussion

The findings from the cluster analysis provide valuable insights into the challenges lecturers face in Indonesia when applying for functional positions. The six distinct clusters identified in this study represent varying obstacles, ranging from minimal to highly significant challenges. This differentiation is critical for understanding the diverse experiences of lecturers and the specific factors that may hinder their career progression. Cluster 1, which includes 27% of the respondents, highlights a group facing particularly challenging obstacles. This cluster may represent lecturers who are either less familiar with the promotion criteria, lack adequate support or resources, or face systemic barriers within their institutions. Identifying such a group suggests a need for targeted interventions, such as more transparent communication of promotion criteria, enhanced mentoring programs, or additional resources to assist lecturers in meeting the requirements for functional positions. In contrast, Cluster 0, comprising 20% of the respondents, indicates lecturers who face minimal obstacles in their application process. This cluster could represent well-prepared lecturers with extensive experience or a strong track record in research and community service. This cluster suggests that while some lecturers navigate the promotion process relatively quickly, others encounter significant barriers that must be addressed to ensure equity in career advancement opportunities.

Moreover, Clusters 2 and 3, which represent neutral and manageable obstacles, respectively, point to a middle ground where lecturers face neither negligible nor insurmountable challenges. These groups might benefit from moderate interventions, such as professional development workshops or peer support networks, to help them overcome obstacles. Cluster 4, with 18% of the respondents, demonstrates that some lecturers experience quickly surmountable constraints. This suggests that these lecturers could successfully navigate the promotion process with minimal adjustments or support. However, Cluster 5, which accounts for 7% of respondents facing significant hurdles, underscores the need for a comprehensive review of the promotion system to identify and mitigate the factors contributing to these substantial barriers. The clustering results suggest that while many lecturers experience the promotion process as straightforward, many face various difficulty levels. These findings have important implications for policy and practice within academic institutions. To foster an equitable environment, institutions should consider developing a more tailored approach to talent management and career development, ensuring that all lecturers have the support and resources they need to advance in their careers. Future research could build on these findings by exploring the underlying causes of the challenges identified in each cluster. Additionally, investigating the effectiveness of specific interventions designed to address these challenges would provide further insights into how to support lecturers in their career progression.

4. Related Work

Gallardo-Gallardo *et al*. (2020) emphasize the critical role of adapting talent management strategies to the unique requirements of organizations, highlighting that the success of these strategies depends on their alignment with specific organizational needs [7]. Hongal and Kinange (2020) provide empirical evidence that effective talent management directly enhances organizational performance, establishing a clear link between well-managed talent and improved productivity [2]. Selvanathan *et al*. (2019) explore the application of talent management in academic settings, showing that lecturers perceive effective talent management practices as essential for improving teaching and research outcomes in higher education institutions [3]. Muluk and Amelia (2019) discuss strategies for accelerating the promotion of lecturers, noting the importance of clear criteria and support mechanisms in facilitating career progression [5]. Similarly, Setyowati *et al*. (2018) emphasize the significance of functional positions in advancing lecturers' careers, although their work needs to delve into the specific challenges encountered during the promotion process [6]. The current study extends these discussions by using K-means clustering to identify and categorize the particular obstacles lecturers face when applying for functional positions, thereby offering a quantitative analysis that complements the qualitative insights provided by previous research. Sinaga and Yang (2020) describe the application of K-means clustering in data analysis, which forms the methodological backbone of the current study's approach to identifying patterns in the challenges faced by lecturers [22]. This quantitative method allows for a more precise categorization of difficulties, distinguishing this research from prior studies primarily focused on qualitative assessments.

Kaleem (2019) explores how talent management impacts employee performance in the public sector, emphasizing the need for alignment with organizational goals to enhance outcomes. This is similar to the current study's focus on the strategic importance of talent management, though it specifically addresses the academic sector [8]. Crane and Hartwell (2019) discuss global talent management and its interaction with human and social capital, highlighting its role in organizational success. The current study parallels this by examining talent management within academia, but it narrows the focus to lecturers in Indonesia using a quantitative approach [9]. Shahi *et al*. (2020) examine the behavioral factors influencing talent management, highlighting the complexity of managing talent effectively. The current study builds on this by categorizing challenges lecturers face in academic promotions, offering a quantitative analysis that complements previous qualitative insights [11]. Similarly, Rasool *et al*. (2019) focus on HR practices that drive sustainable performance through innovation. The current study aligns with this by exploring tailored talent management strategies to support lecturers' career progression [12]. While prior studies have explored talent management and its impact across various sectors, the current study distinguishes itself by applying a quantitative clustering method to identify specific challenges in academic promotions. This approach provides detailed insights into barriers to career advancement in academia and suggests targeted strategies for improvement.

Moreover, the current study builds on the findings of Mahyuni *et al*. (2020), who investigate strategies for accelerating academic rank advancements in Indonesian universities but without the detailed clustering approach used here [18]. By applying a more nuanced data analysis technique, this research provides deeper insights into the specific barriers that impede lecturers' career progression. While previous studies have explored the importance of talent management and the factors influencing academic career advancement, this research distinguishes itself by applying a quantitative clustering method to uncover lecturers' specific challenges. This approach complements the existing body of knowledge and provides a more detailed understanding of the obstacles to career advancement in the academic sector.

5. Conclusion

There are 6 clusters identified in this study. The analysis reveals that the duration of a lecturer's tenure in a functional position significantly influences their desire to be promoted, indicating a strong correlation between the dependent and independent variables. Examining the clusters representing the constraints faced during the submission of functional positions, the findings are as follows: cluster 0 (20%) represents very easy constraints, cluster 1 (27%) represents very difficult constraints, cluster 2 (13%) represents neutral constraints, cluster 3 (15%) represents very easy obstacles, cluster 4 (18%) represents easy constraints, and cluster 5 (7%) represents complex constraints. These clustering results shed light on the various obstacles encountered by lecturers during the submission of functional positions, with a notable number of respondents facing complex and very difficult challenges. Developing a new talent management model specifically tailored to address the issues lecturers face in submitting functional positions is recommended for future research. This model can contribute to improving the overall talent management process and support the career development of lecturers.

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