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Optimizing Human Resource Selection Through TOPSIS-Based Multi-Criteria Decision Making

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ABSTRACT

Human resource quality is a pivotal determinant of organizational success, yet recruitment often suffers from subjectivity and inefficiency. This study addresses challenges in applicant mapping and assessment bias by implementing a Decision Support System (DSS) using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The research utilizes four selection criteria based on standard Indonesian recruitment frameworks : General Intelligence Test (30%), National Insight Test (10%), fild ability test (20%), and Interview Performance (40%). Methodologically, the TOPSIS method was employed to rank candidates based on their geometric distance from the positive and negative ideal solutions. Results demonstrate that the TOPSIS-based DSS achieved 90% alignment with historical corporate hiring decisions. Furthermore, the system improved decision-making effectiveness by 98.78%, accelerating the overall recruitment timeline by 30%. This study contributes to the field of HR technology by providing a scalable, objective framework for multi-criteria candidate evaluation. By integrating mathematical rigor into personnel selection, the proposed system minimizes human error and optimizes organizational efficiency in the Indonesian corporate context.

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1. Introduction

Companies require integrated tools to manage internal business processes, particularly Human Resources (HR) management. HR serves as the foundational “root” of an organization [1], where specific competencies and skills must align with corporate strategic needs [2][3]. As a primary determinant of profitability, institutional existence, and long-term development, employees are the “spearhead” of organizational success [4][5]. Consequently, the recruitment process is the vital first step in securing this success and must be conducted comprehensively by evaluatingapplicant competencies againts rigorous qualification standard [6][7].

However, the complexity of modern recruitment presents a significant risk of selection error [8]. This challenge is evident at Company X, a State Owned Enterprise (BUMN) in Surakarta, which consistently attracts thousands-sometimes millions-of applicants. This overwhelming volume makes it difficult for the organization to identify candidates who meet specific criteria[9]. Currently, the selection process involves four stages : administrative screening, the general intelligence test (TIU), the national insight test (TWK), the field ability test (TKB), and an interview (TW). Despite utilizing computer-based testing, the company faces persistent decision-making hurdles. Recruiter often suffer from fatigue, which can lead to subjectivity [10]. Furthermore, screening based solely on TIU, TWK, and TKB scores is suboptimal for capturing nuanced qualifications, and differing perspectives during interviews often lead to conflicting decisions. This can prolonged process, which can last months, result in substantial recruitment costs.

Advancements in technology offer an opportunity to automate and optimize these processes through Decision Support Systems (DSS). A DSS provides recommendations to help decision-makers identify the best alternatives. In the context of recruitment, the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method is highly effective [11]. TOPSIS measures the similarity between an applicant's profile and the company's ideal requirements. Research indicates that TOPSIS can validate multi-criteria weighting, thereby reducing ambiguity [12][13]. Furthermore, its adaptability to corporate managerial culture minimize bias and inconsistent weighting [14]. Recent findings also suggest that TOPSIS supports sustainable automation, maintaining optimal performance even when criteria are adjusted over time [15].

In the long term, recruitment efficiency directly influences corporate profitability. Prior research emphasizes that recruitment software must align with real-world conditions to be effective [16]. While some studies suggest using machine learning or the VOBN method [17], these approaches often require large datasets of prior hires to achieve high accuracy. Other approaches have utilized fuzzy logic to evaluate critical thinking and problem solving [18].

Building on these studies, this research focuses on the automation and optimization of the recruitment process specifically tailored to the conditions at Company X. Unlike previous models, this study utilizes multi-criteria and weights derived from an in-depth analysis by Company X's expert recruitment team. The TOPSIS method was selected for its ability to calculate the ideal geometric distance between an applicant's qualifications and the organization's requirements, effectively identifying the relative advantages and disadvantages of each candidate through a mathematically rigorous formula.

2. Research Method

This study was conducted using the Prototyping Model development cycle. To ensure the research objectives were met, a systematic series of stages was implemented to allow for iterative refinement based on organizational requirements. Figure 1 illustrates the sequential steps and phases integrated into this research framework.

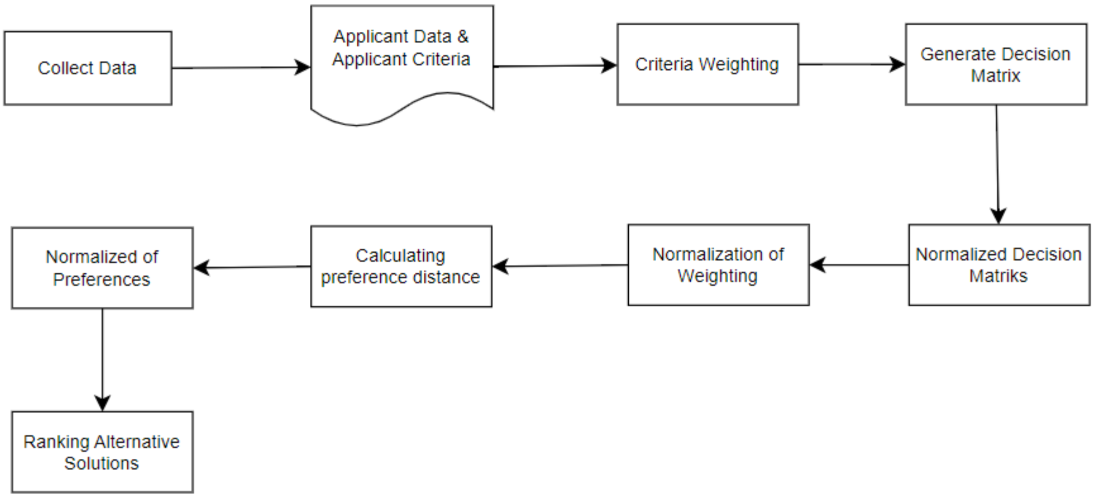

Figure 1. Research Development Cycle

2.1. *Data Collection*

This research requires a comprehensive dataset to serve as simulation data, reflecting the actual conditions of the candidate recruitment stages. To ensure validity, the researcher acquired empirical data from Company X. The dataset includes candidate scores across multiple selection phases, which were utilized to test the TOPSIS model's accuracy against the company's historical hiring outcomes [19].

2.2. *Applicant Data and Selection Criteria*

The subsequent phase involves processing applicant data for simulation using the TOPSIS method [20]. At this stage, candidates are evaluated based on four key performance indicators mandated by the company's recruitment standards : the general intelligence test (TIU), the national insight test (TWK), field ability test (TKB), and the interview (TW). To facilitate the DSS, these qualitative and quantitative inputs are transformed into a decision matrix, where each applicant represents an alternative, and the test results serve as the evaluation criteria.

2.3. Criteria Weighting

The third stage of this research marks the initial implementation of the TOPSIS method. In this phase, specific weights are assigned to the four predefined selection criteria. These weighting factors are determined based on the technical skill requirements and the strategic importance of the preferences established by Company X. By assigning numerical weights to each criterion, the system ensures that the most critical evaluation stages-such as interviews or field specific tests- have a proportional impact on the candidate's final ranking. This step is fundamental to transforming the company's qualitative priorities into a mathematically structured decision model [21].

2.4.Generate Decision Matrix

The decision matrix maps the evaluation of each existing alternative. From this matrix, a model is developed to evaluate these alternatives against predefined criteria and the specific values assigned to each alternative's [22]. The decision matrix X is an $m\,x\,n$ matrix where m represents the number of applicants (alternatives) and n denotes the selection criteria.

2.5.Normalize Decision Matrix

The next stage involves normalizing the constructed decision matrix. Normalization is conducted to standardize the values across all alternatives, ensuring they are commensurable. This process is essential because this evaluation scales for each criterion often differ significantly. By balancing these values, an accurate comparison between the decision matrices for each criterion can be achieved [23]. Equation 1 is employed to perform this normalization process :

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad (1)$$

Where element x_{ij} represents the score of the score of the i-th applicant relative to the j-th criterion. While R_{ij} is the resulting normalized value. This step ensures that all criteria are within a comparable range, typically between 0 and 1.

2.6. Normalization of Weighting

Once the decision matrix has been normalized, the subsequent stage is to calculate the weighted normalized matrix. This process involves multiplying the normalized values by assigned weight of each respective criterion. Weighted normalization is conducted to determine the extend to which the preferences of the alternative solutions (applicants) align with requirements of the decision makers (the company) based on the predefined priority levels [24]. Equation 2 is utilized to compute these weighted values :

$$Y_{ij} = W_j r_{ij} \qquad (2)$$

The weighted normalized value Y_{ij} is calculated by multiplying the normalized matrix element r_{ij} with the weight W_j corresponding to the j-th criterion. This step is critical as it scales the candidate's performance according to the organizational priority of each recruitment.

2.7. Calculating Preference Distance

Calculating the preference distances is essential for identifying the most ideal values required for selection. This process is conducted after the weighted normalization stage to ensure that the distance between an applicant's qualifications and the company's requirements is balanced and unbiased. There are two distinct types of preference calculations : the Positive Ideal Solution (A^+) and the Negative Ideal Solution (A^-). To derive the positive ideal solution matrix, Equation 3 is utilized [25] :

$$A^+ = y1^+, y2^+, y3^+, \dots, yn^+ \qquad (3)$$

The positive ideal solution matrix represents the best possible multi-criteria outcome. Consequently, the superior alternative is the one with the shortest geometric distance and the minimal variance from the results of the positive-ideal solution matrix. Conversely, the negative ideal solution matrix is determined using equation 4 [25] :

$$A^- = y1^-, y2^-, y3^-, \dots, yn^- \qquad (4)$$

The negative ideal solution matrix represents the worst possible multi-criteria outcome. Therefore, the most favorable alternative is the one that maintains the maximum distance and the greatest deviation from the results obtained in the negative-ideal solution matrix. In this study, all criteria are tested as benefit criteria, meaning a ahigher score is preferable. Thus $A^+$is determined by the maximum value in the weighted normalized matrix for each criterion, while A^- is determined by the minimum value.

2.8. Normalized the Preference Distance

In the subsequent stage, the preference distances are calculated. This process is essential for quantifying the deviation between each alternative solution's value and the ideal benchmarks established in the previous step. Calculating these distances helps determine exactly how far each applicant's profile lies from the positive ideal solution and the negative ideal solution. To determine the distance between an alternative solution and the positive ideal solution matrix, Equation 5 is employed [23] :

$$Dj^{+} = \sqrt{\sum_{j=1}^{n}(y_{ij} - y_i^{+})^2} \quad (5)$$

Conversely, to calculate the distance between each alternative solution and the negative ideal solution matrix, Equation 6 is utilized [23] :

$$Dj^{-} = \sqrt{\sum_{j=1}^{n}(y_{ij} - y_i^{-})^2} \quad (6)$$

Subsequently, using the results of these preference distances for each alternative across all criteria, a calculation is performed to determine the relative closeness of each applicant. This result represents the preference gap between the positive and negative ideal matrices. Equation 7 is used to obtain the final preference value (v_i) for each alternative [23] :

$$Vi = \frac{D_i^{-}}{D_i^{-} + D_i^{+}} \quad (7)$$

2.9. Ranking Alternative Solution

Following the completion of the preference analysis, the final stage involves assessing the feasibility of each alternative solution (applicant) based on the organization's requirements. Once the final preference values are calculated, the alternatives are ranked in descending order, from the most significant to the least significant. A higher final value indicates that the applicant's competencies possess the highest degree of proximity to the company's ideal requirements. Conversely, the lowest values signify that the applicant's competencies do not align with the necessary qualifications. Equation 8 is utilized to determine the final score for each alternative [24]. The resulting sorted list serves as a prioritized recommendation for management, transforming multi-dimensional test score into a single, objective performance metric.

3. Result and Discussion

3.1. TOPSIS Implementation

Following the systematic research stages illustrated in Figure 1, sufficient empirical data was gathered for further analysis. Through the data acquisition process, test results were compiled consisting of applicant identities and their respective scores across each recruitment criterion established by the organization. Table 1 presents the specific criteria and their assigned weights, while Table 2 provides the raw applicant data and the scores achieved for each criterion.

Table 1. Recruitment Criteria

Criteria	Attribute	Weight
TIU	Benefit	0,30
TWK	Benefit	0,10
TKB	Benefit	0,20
TW	Benefit	0,40

As indicated in Table 1, the weighting distribution for the four criteria utilized in Company X's recruitment process is assigned as follows: TIU (30%), TWK (10%), TKB (20%), and TW (40%). The allocation of these weights reflects the organization's strategic priorities, where the interview (TW) holds the highest significance. This suggests that while technical and cognitive abilities (TIU and TKB) are essential baseline requirements, the company places a premium on the qualitative competencies and behavioral fit assessed during the final interview stage.

The cummulative weight of 50% for TIU and TKB ensures that candidates possess the necessary foundational intelligence and technical mastery, while the 40% weight for the interview acts as a decisive filter for organizational alignment. This balanced weighting scheme is designed to mitigate the risk of hiring candidates who are technically proficient but lack the soft skills required by the corporate culture of Company X.

Table 2. Applicant's Score

No	**Name**	**TIU**	**TWK**	**TKB**	**TW**
1	Abdul Wahid	110	75	180	300
2	Achmad Sofyan	90	90	170	280

3	Adha Nur	85	125	166	300
…					
…					
129	Yuliana Saraswati	150	100	166	296
130	Zaky Zain	105	100	180	376

Based on the acquired data, the decision matrix was constructed to map each applicant against the selection criteria. By applying Equation 1, the normalization factors for each criterion were determined as follows : TIU (1154.91), TWK (1068.2), TKB (2150.67), and TW (3657.43). These values serve as the denominators for vector normalization, ensuring that all scores are transformed into a dimensionless, comparable format. Table 4 presents the normalized decision matrix resulting from these calculations applied to the raw applicant data.

Table 4. Decision Matrix

No	Name	TIU^2	TWK^2	TKB^2	TW^2
1	Abdul Wahid	12100	5625	32400	90000
2	Achmad Sofyan	8100	8100	28900	78400
3	Adha Nur	7225	15625	27556	90000
…					
…					
130	Zaky Zain	11025	10000	32400	141376
		1333825	1141050	4625381	13376787
	Matriks Keputusan	1154,91	1068,2	2150,67	3657,429

Once the decision matrix was established, equation 2 was applieed to calculate the weighted normalized decision matrix. The results of this normalization represent the specific decision scores for each alternative solution across the defined criteria. The data processing results indicate that each alternative has a decision score between o and 1. When expressed as percentages, it is evident that the scores of each alternative across the various criteria influence the final decision within a 0% to 100% range. Table 5 illustrates the comprehensive results of the weighted normalized decision matrix.

Table 5. Normalized Decision Matrix

No	Name	TIU	TWK	TKB	TW
1	Abdul Wahid	0,095245235	0,070211609	0,083694853	0,082024832
2	Achmad Sofyan	0,07792792	0,084253931	0,079045139	0,07655651
3	Adha Nur	0,073598591	0,117019348	0,077185253	0,082024832
…					
…					
130	Zaky Zain	0,090915906	0,093615479	0,083694853	0,102804456

The subsequent stage involved applying the criteria weights to the normalized matrix. Table 6 presents the results of the weighted normalized decision matrix across all criteria. These calculations determine the specific impact of an applicant's score relative to the organization's desired preferences. For instance, the candidate Abdul Wahid achieved a weighted normalized score of 0.028573571. This indicates that the candidate's performance in that specific criterion contributes 2.857% toward meeting the company's minimum required qualifications. This granural level of analysis enables the recruitment team to identify which specific criteria drive a candidate's overall ranking, ensuring a transparent, data-driven selection process.

Table 6. Normalized Weight Score

No	Name	TIU	TWK	TKB	TW
1	Abdul Wahid	0,028573571	0,007021161	0,016738971	0,032809933

2	Achmad Sofyan	0,023378376	0,008425393	0,015809028	0,030622604
3	Adha Nur	0,022079577	0,011701935	0,015437051	0,032809933
…					
…					
130	Zaky Zain	0,027274772	0,009361548	0,016738971	0,041121782

By applying Equation 3 and 4 to the weighted normalized alternative values, the preference distance for each criterion and existing alternative solution were obtained. Table 7 presents the positive ideal solution matrix and the negative solution matrix for each respective criterion.

Table 7. Idela Solution Matrix

	TIU	**TWK**	**TKB**	**TW**
A+	0,022079577	0,006085006	0,015437051	0,02460745
A-	0,03896396	0,014042322	0,020923713	0,043199745

The positive ideal solution (A+) represents the maximum value for benefit criteria and the minimum value for cost criteria across all alternatives. Conversely, the negative ideal solution (A-) identifies the least desirable outcomes. These matrices serve as the benchmarks for calculating the relative closeness of each applicant to the ideal recruitment profile.

As indicate din Table 7, the positive ideal separation for the criteria as follows : TIU (2.2%), TWK (0.06%), TKB (0.15%), and TW (0.24%). Conversely, the negative ideal separation measures are TIU (0.389%), TWK (0.14%), TKB (0.209%), dan TW (0.43%). Based on the ideal solution matrices, the variance of each alternative solution can be observed through the ideal preference distances required by the company.

Table 8 illustrates the normalized preference distances for each criterion relative to the organization's ideal solution matrix. The calculation results reveal that the applicant with the highest alignment possesses the closest proximity to the positive ideal solution with a distance of 0.004030177. Meanwhile, the applicant with the greatest separation from the negative ideal solution exhibits a distance of 0.024107503. Furthermore, the final preference value (Vi) representing the relative closeness of the alternative solution, is calculated at 52.41065271. The final preference index for the top candidates was 52.41%, signifying a mid to hight level of competency relative to the ideal recruitment profile.

Table 8. Normalized Preference

No	**Name**	**Dj+**	**Dj-**	**Vi**
1	Abdul Wahid	0,010584142	0,016814195	0,386305999
2	Achmad Sofyan	0,006594296	0,021419729	0,23539266
3	Adha Nur	0,009941359	0,020702933	0,32441144
…				
…				
130	Zaky Zain	0,017667596	0,013430441	0,568125758
				52,41065271

Before determining the final ranking of applicants, the preference value (Vi) was calculated to obtain a comprehensive evaluation score for each candidate based on the recruitment criteria established by the organization. The preference value serves as the final decision-making indicator by integrating the performance of each applicant across all assessment criteria into a single numerical score. This score reflects the extent to which an applicant's qualifications, competencies, and overall profile correspond to the ideal requirements defined by the company.

The calculation of the V value enables decision-makers to objectively compare candidates and identify those who best meet organizational expectations. Candidates with higher V values demonstrate stronger alignment with the desired qualifications and are therefore considered more suitable for the position. Conversely, lower scores indicate a greater gap between the applicant's capabilities and the target competency profile. Table 9 presents the final preference values for all applicants, arranged in descending order. This ranking provides a clear and systematic basis for selecting the most qualified candidates and supports a more transparent and data-driven recruitment process.

Table 9. Final V Score

No	Name	V	V*1000
1	KIRANA ATSIILA	0,013192	13,19221
2	Liswanto	0,012542	12,54172
3	Miski Utami	0,01181	11,81048
4	Surya Putra	0,011694	11,69373
5	Sunarya	0,011411	11,41077
6	Friska Lutfiana	0,011403	11,40252
7	Yuliana Saraswati	0,011294	11,29411
8	Fareza Aulia	0,011118	11,11803
9	Putra Akbar	0,011028	11,02809
10	MAHARANI	0,010969	10,96888
11	Lismawati	0,010955	10,9553
12	Inni Rusydiana	0,010954	10,95449
13	Bagas Fajar	0,010912	10,9123
14	Affandi	0,010864	10,86394
15	Ni Nyoman	0,010846	10,8458
16	Zaky Zain	0,01084	10,83989
17	kartika Fernanda	0,010776	10,77566
18	Mawar Utami	0,010658	10,65763
19	Rizki Pratama	0,010642	10,64232
20	Nur Addinda	0,010548	10,54754
…			
127	Adib Fahmi	0,003486	3,485715
128	Atra Atlanta Putra	0,003077	3,076867

3.2. System Development

The developed system features two distinct user access levels : the HR division and the applicants. To ensure data security and personalized functionally, each user group is required to undergo a registration and authentication process via a login interface before accessing the recruitment platform's features.

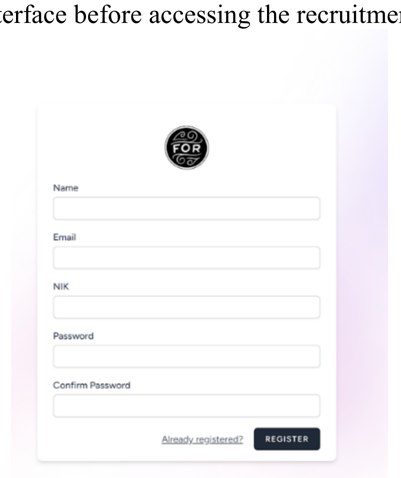

Figure 2. Registration Page

Figure 2 illustrates the registration interface of the recruitment system, which is accessible to both the HR division and applicants for account creation. During this process, users are required to provide essential personal information, including their full name, email address, national identification number, and a secure password to gain authorized access of the system. This registration stage ensures that each user identity is uniquely verified within the database, maintaining data integrity throughout the recruitment process.

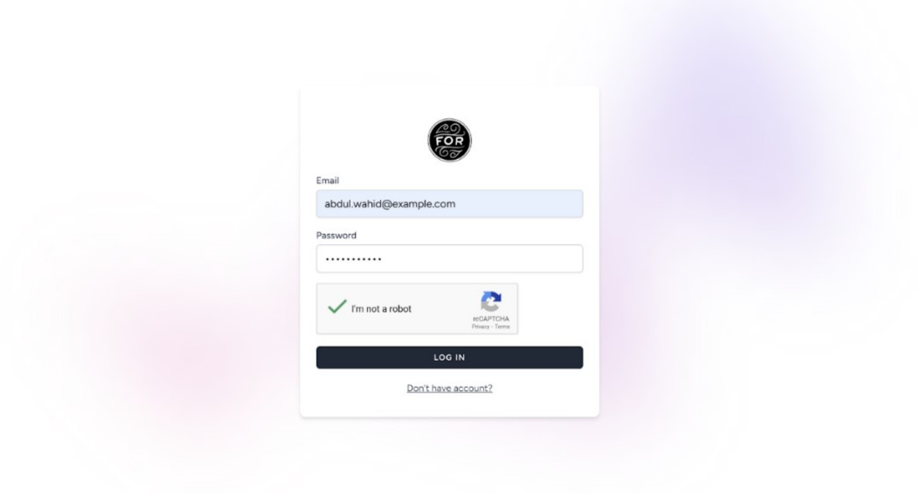

Figure 3. Login Page

Once an account has been created, users can authenticate themselves through the login interface as illustrated in Figure 3. Upon a successful login, the system's role-based access control mechanism automatically redirects the user to their respective dashboard, tailored specifically for either the HR administrator or the applicant, depending on their assigned previleges. The HR dashboard focuses on candidate evaluation and decision support analytics, whereas the applicant dashboard provides features for applicant tracking and profile updates.

3.2.1. Applicant Interface

Within the applicant dashboard, users are required to complete several mandatory documents essential for the recruitment process. Figure 4 illustrates the applicant profile page, which must be fully updated with accurate information before the system permits the uploading of formal job application documents. This profile completion stage serves as an initial data validation filter, ensuring that all candidate information is standardized before being processed by the TOPSIS method.

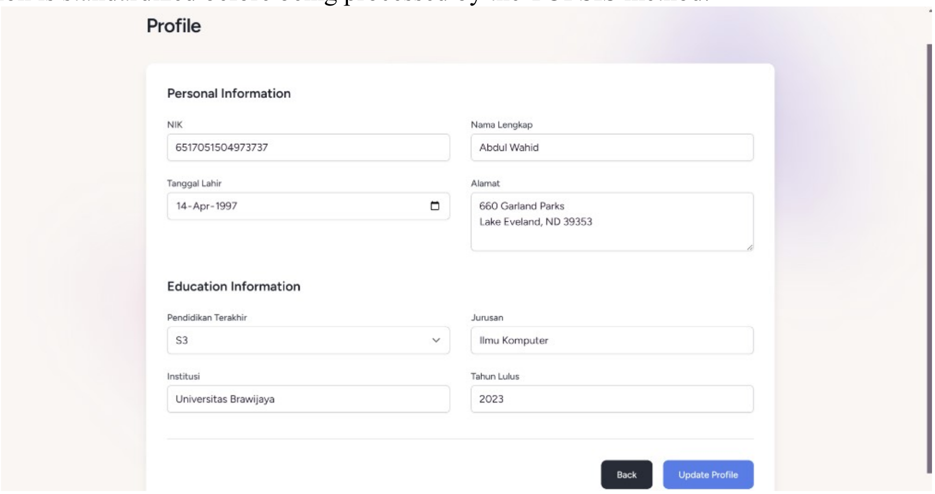

Figure 4. Profile Page

After completing the personal profile data, applicants are then permitted to proceed with the submission of the required recruitment documents. Figure 5 illustrates the document completeness interface, where users can upload and manage the files necessary for their application. This module ensures that all qualitative and quantitative are centralized, providing the necessary input for the HR division to begin the evaluation process.

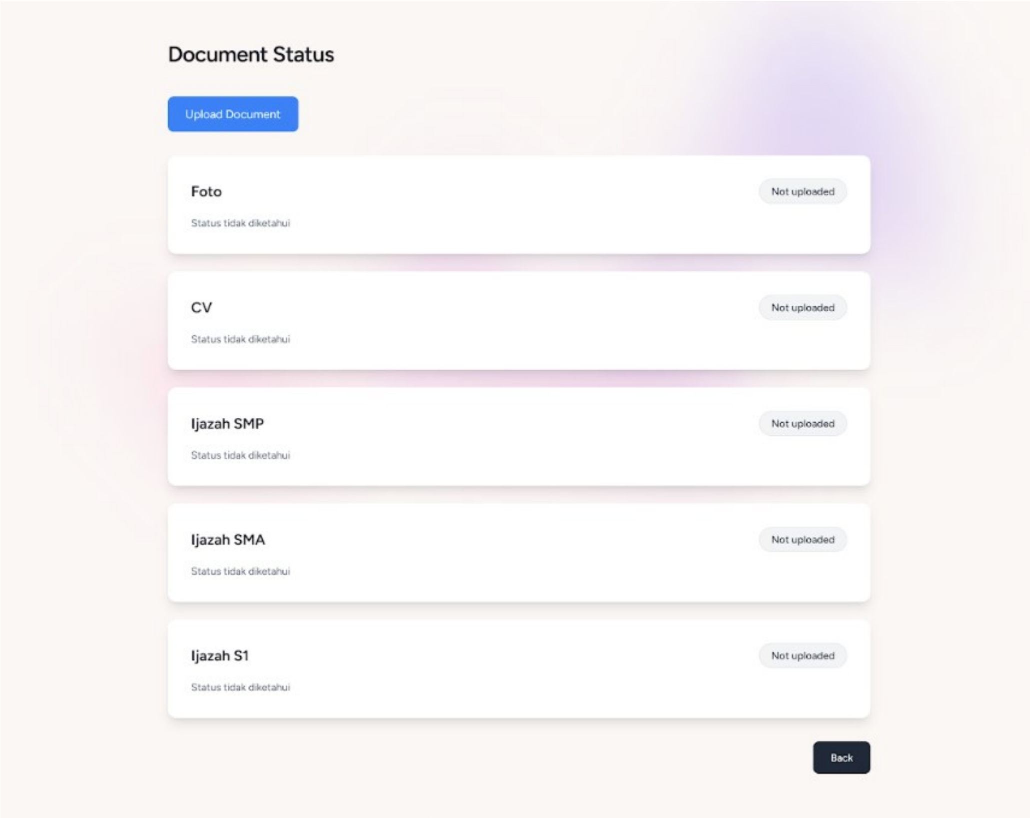

Figure 5. Applicant Management Profile

As shown in Figure 5, applicants are required to upload several mandatory documents, including a recent photograph, a CV, and their academic results. Figure 6 illustrates the specific file upload interface provided by the system, which is designed to facilitate the secure and organized submission of these credentials. The interface supports standard document formats to ensure data compatibility and to streamline the verification process by the HR department during the prescreening phase.

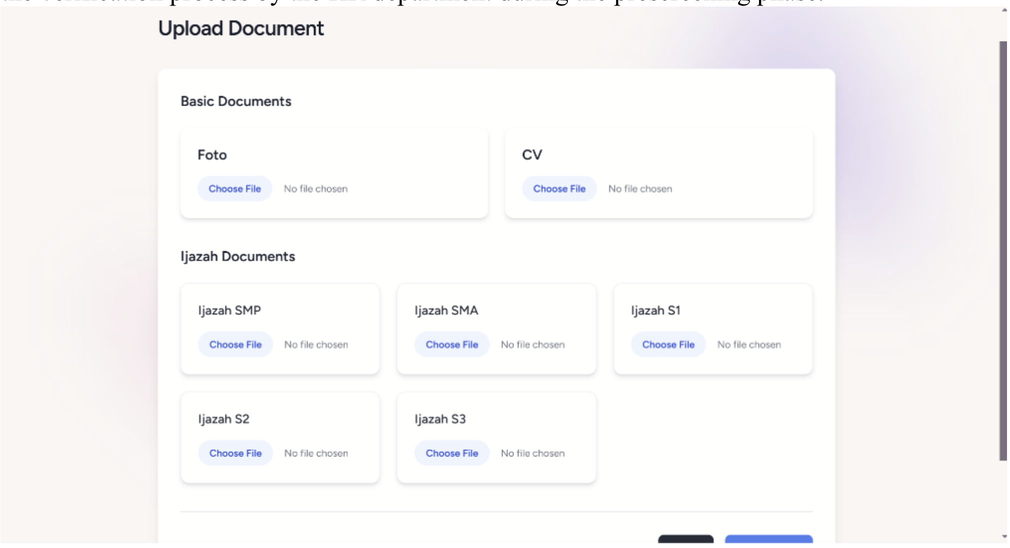

Figure 6. Applicant Document Upload

Upon the successful completion of all document submission, applicants enter the waiting phase for the administrative screening results. The HR division evaluates the submitted credentials, and the final status-wheter the applicant has passed or failed the administrative selection- is communicated automatically. Notifications are dispatched via registered email address and phone number provided in the system's database, ensuring a transparent and timely recruitment update. Candidates who successfully pass this administrative threshold will then proceed to the scoring stage, where their performance is evaluated using TOPSIS-based decision-making module.

3.2.2. HR Administrator Interface

The HR division is responsible for managing the recruitment and selection process for new employees. Through the HR administrative interface, the team can evaluates test scores and performance metrics for each candidate to assess their overall quality and suitability for the position. Figure 7 illustrates the HR dashboard, which provide a centralized view of applicant data and analytical tools.

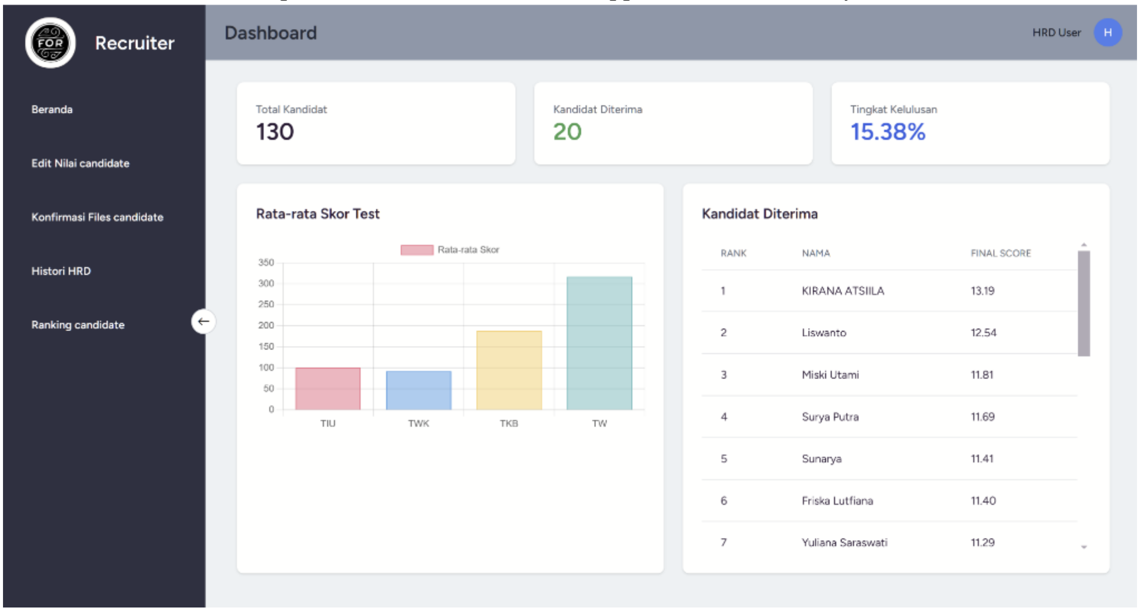

Figure 7. HR Dashboard

As illustrated in Figure 7, the HR team is granted specific administrative previleges, including the ability to update the scores, validate candidate documents, access the evaluation history across the entire HR department, and view the final selection rankings. Futhermore, HR personnel are required to complete their professional profiles before initiating the recruitment selection process. This requirement is implemented as a safeguard to ensure accountability and to prevent arbitrary evaluations. By enforcing profile completion, the system can meticulously track and record every modification made by the HR team, creating a transparent audit trail. Figure 8 displays the HR profile management page.

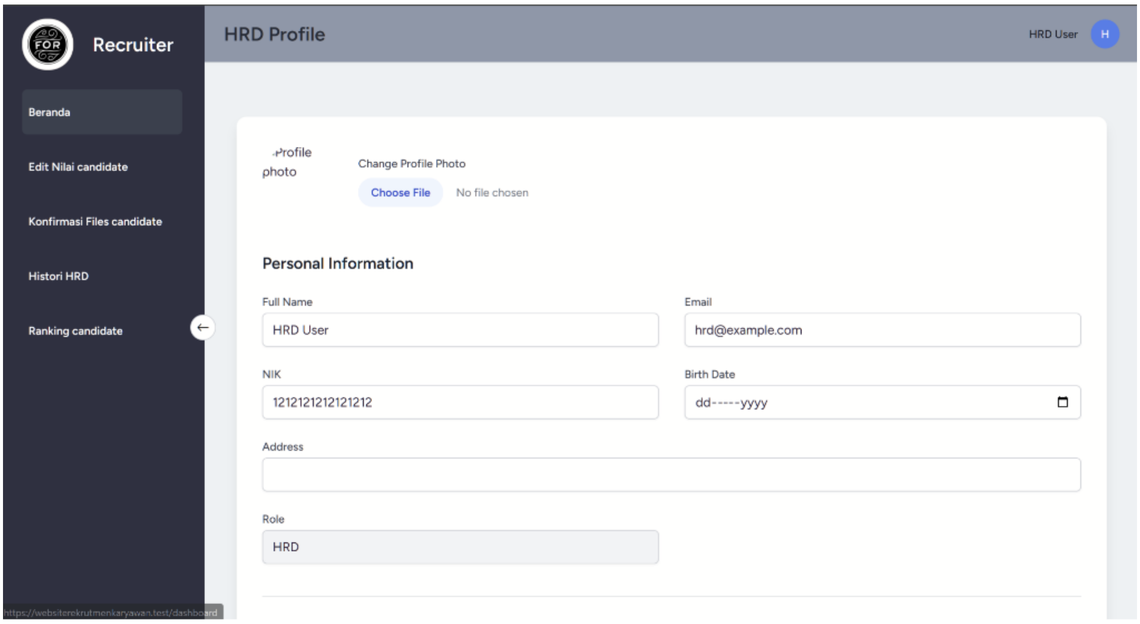

Figure 8. HR Profile Page

Once the HR profile is fully completed, the team can proceed to validate the documents uploaded by the applicants. This module allows HR personnel to verify the authenticity and eligibility of each submission. In cases where a document does not meet the predefined requirements, the HR team has the authority to reject the submission by providing specific feedback or an invalid status to the applicant. Figure 9 illustrates the document validation interface, which ensures a rigorous and transparent administrative screening phase.

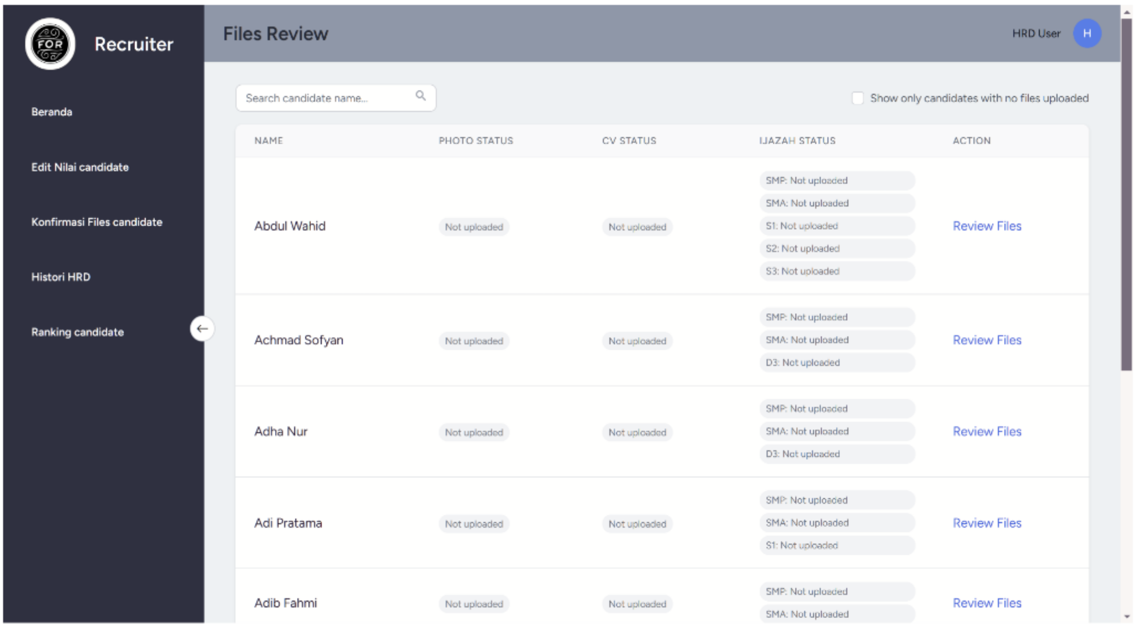

Figure 9. Validation Page

Following the validation of the applicant's documents, the system enables the entry of scores for each candidate based on their performance in the conducted tests. Figure 10 illustrates the candidate assessment interface, where HR personnel input the quantitative data required for the decision-making process. The scoring module is designed to standardize the evaluation process, ensuring that every applicant is assessed objectively against the established criteria before the TOPSIS algorithm performs the final ranking calculation.

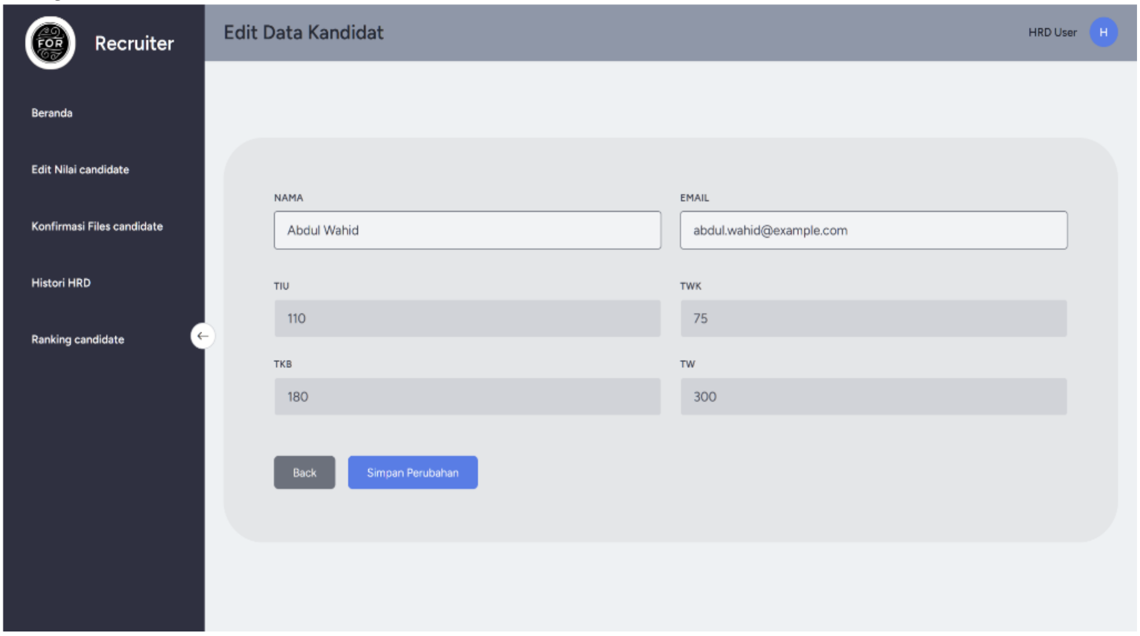

Figure 10. Update Score Page

After scoring was completed, the system will entry all candidates, the system generates a comprehensive overview of the scores. Figure 11 illustrates the consolidated scoring interface, which allows

HR personnel to review and compare the performance metrics of all applicants simultaneously before the final TOPSIS ranking is finalized.

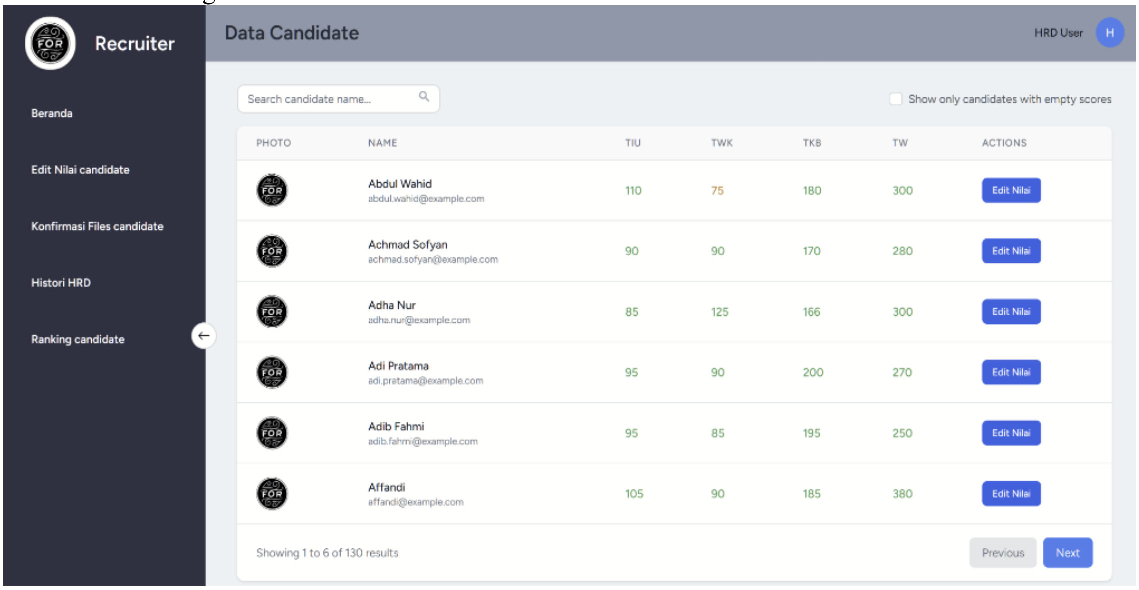

Figure 11. Applicant's Score Page

Subsequently, the recruitment system leveraging the TOPSIS method generates recommendations for the most qualified candidates by assigning an "Accepted" status. In accordance with the specific requirements of Company X, the system is configured to recommend only the top 20 applicants based on their final preference scores. Figure 12 illustrates the final ranking interface produced by the Decision Support System (DSS), providing a clear, data-driven hierarchy of the candidates.

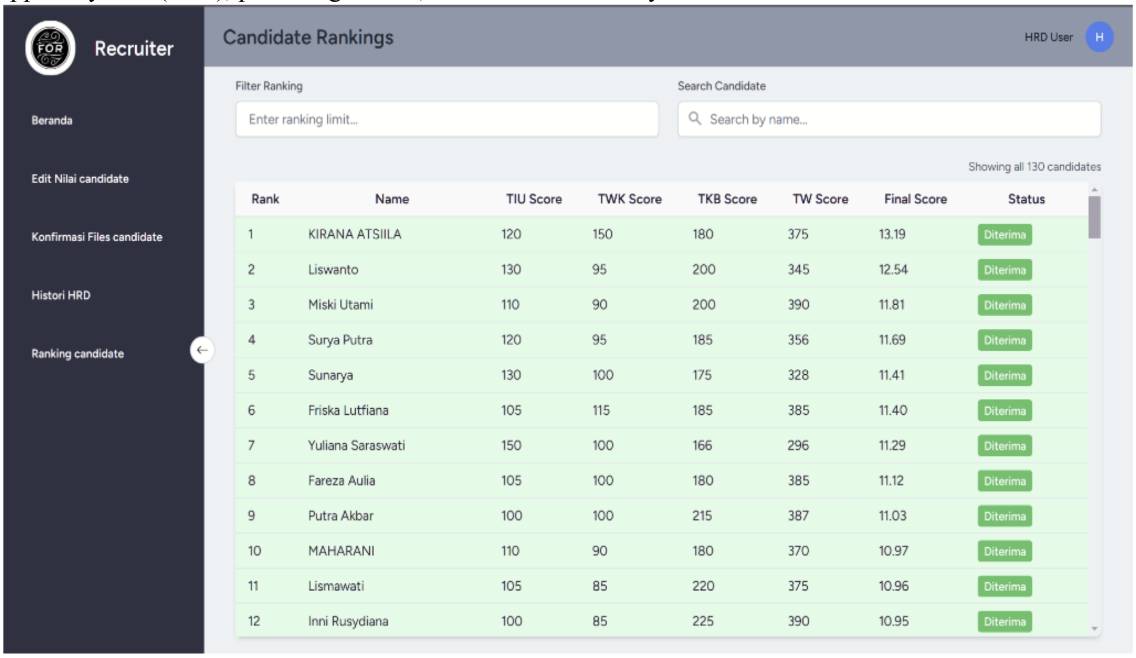

Figure 12. Applicant's Ranking Analytics

3.3. System Testing

The DSS utilizing the TOPSIS method was rigorously tested to evaluate its performance in meeting the recruitment requirements of Company X. The evaluation involved an accuracy calculation by comparing the system's output with factual selection results-specifically the manual recruitment decisions previously made by the HR team. This comparative analysis between the TOPSIS results and factual data was executed using automated scripts. Figure 13 illustrates the data input process for both the factual rangkings and the TOPSIS generated ranking within a Phyton programming environtment.

```
import pandas as pd

df = pd.read_excel('/content/Data Faktual.xlsx')
df
```

	No	Nama
0	1	KIRANA ATSIILA
1	2	Liswanto
2	3	Miski Utami
3	4	Surya Putra
4	5	Sunarya
...	...	...
125	126	Diastuti Putri
126	127	Adib Fahmi
127	128	Atra Atlanta Putra
128	129	Dwi Putra
129	130	Dua Dwiyanto

```
import pandas as pd
df2 = pd.read_excel('/content/Hasil Perangkingan TOPSIS.xlsx')
df2
```

	No	Nama
0	1	KIRANA ATSIILA
1	2	Liswanto
2	3	Miski Utami
3	4	Surya Putra
4	5	Sunarya
...	...	...
125	126	Diastuti Putri
126	127	Adib Fahmi
127	128	Atra Atlanta Putra
128	129	Dwi Putra
129	130	Dua Dwiyanto

130 rows × 2 columns

Figure 13. Factual Ranking (left) and TOPSIS Ranking (Right)

Subsequently, a programmatic verification was conducted to identify any discrepancies between the two ranking sets. Figure 14 illustrate the process of cross-checking the ordinal consistency between the factual requirement data and the results generated by the TOPSIS implementation. This verification process utilize the applicant's "Name" column as the primary unique identifier (ID) to ensure precise data mapping and to detect any shifts in the ranking order across the two datasets.

```
Name: Nama, Length: 130, dtype: bool

Number of differences in 'ID' column: 26
```

Figure 14. Discrepancies Testing

Analysis of the results shown in Figure 14 reveals that there are 26 discrepancies in the ranking order between the factual data and the rankings generated by the TOPSIS method. This comparison provides a clear metric for the accuracy of the recruitment process when transitioning from manual selection to a TOPSIS-based system. The accuracy testing concludes that the TOPSIS method achieves an 80% alignment rate with the factual recruitment rankings. Figure 15 presents the visualization of this accuracy metric.

```
Total number of entries in 'Nama' column: 130
Number of matching entries in 'Nama' column: 104

True Percentage of matching 'Nama' entries: 80.00%
```

Figure 15. Accuracy Testing

In addition to accuracy testing, a restricted pilot test was conducted to evaluate the effectiveness of the TOPSIS method in enhancing time efficiency within the recruitment decision-making process. This test involved a simplified recruitment simulation using 30 randomly selected scoring datasets form the research sample. Table 10 presents the results of this effectiveness evaluation, comparing the operational performance of the TOPSIS method against traditional manual procedures.

Table 10. Effectiveness Evaluation

Aspect	Without TOPSIS (minutes)	With TOPSIS (minutes)
Scoring time for TIU	9	1
Scoring time for TWK	9	1
Scoring time for TKB	9	1
Scoring time for TW	9	1
Multi-criteria weighting analysis	60	1
Decision Matrix Construction	60	1
Ranking results generation	10	1

Total time consumed	166	7
Effectiveness Rate	95.78%	

The results of the restricted effectiveness simulation for recruiting and ranking 30 applicants revealed a significant performance gap between manual processes and the proposed system. Conducting the recruitment process without the TOPSIS method required a total of 166 minutes. In constrast, the implementation of the TOPSIS method reduced the duration to a mere 7 minutes. Consequently, the integration of the TOPSIS method successfully optimized the recruitment decision-making process by drastically cutting the time required form 166 minutes to 7 minutes. This transition represents 95.78 % increase in effectiveness regarding process acceleration and operational efficiency.

A comprehensive simulation was also conducted to evaluate the effectiveness of the entire recruitment lifecycle. According to data provided by the recruitment team, the manual process for selecting 20 new employees from a pool of 130 applicants requires a total of 30 working days. This timeline consist of 5 days for TIU and TWK competency tests, 5 days for TKB, 10 days for interviews (TW) and an additional 10 days for manual evaluation and ranking.

By implementing the TOPSIS method, this duration is significantly reduced to 1 days when evaluation and ranking. Consequently the integration of this system accelerates the overall recruitment process by 30%. Figure 16 illustrates the comparative effectiveness of the recruitment process duration.

```
•••  Initial recruitment time: 30 days
     New recruitment time: 21 days
     Effectivity (reduction in time): 30.00%
```

Figure 16. Effectiviness of Recruitment Process

Based on evaluation results of the TOPSIS method within the employee recruitment framework, it is concluded that the system significantly enhances both the effectiveness and efficiency of the recruitment process. The achieved accuracy rate of 80% demonstrates that the recruitment team at Company X can reliably depend on the system's ranking recommendation.

Furthermore, in term of decision-making performance, the TOPSIS method exhibited superior optimization with an effectiveness value of 95.78%. this high performance ensures that the selection process minimizes subjective bias and differing perspectives, as the TOPSIS algorithm meticulously calculates the similarity between applicant qualifications and the specific requirements of the company. Additionally, the system successfully improved the overall recruitments lifecycle efficiency by 30%. These findings indicate that the implementation of TOPSIS not only accelerates the hiring process but also strategically minimizes the company's operational expenditures.

4. Conclusion

The results of this study demonstrate that the implementation of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method within a Decision Support System (DSS) significantly improves the employee recruitment process at Company X. The developed system was subjected to comprehensive unit testing and integration testing to ensure that all modules and functionalities operated correctly. The testing results confirmed that the system performed reliably, with all features functioning according to the specified requirements and successfully supporting the recruitment workflow.

The system is capable of generating a ranked list of applicants and recommending the top 20 candidates based on their overall performance across multiple evaluation criteria. This recommendation threshold can be adjusted according to the company's recruitment needs, particularly for trainee programs where the number of accepted candidates may vary. Following the selection process, candidates participate in a training period during which their work ethic, adaptability, and professional behavior are further assessed. The outcomes of this training phase also assist management in determining appropriate divisional placements that align with each candidate's competencies, personality traits, and professional qualifications.

Empirical evaluation indicates that the TOPSIS method serves as an effective and reliable decision-making tool for recruitment teams. The method achieved an accuracy rate of 80%, demonstrating its capability to produce recommendations that closely match actual recruitment decisions. Furthermore, the system increased decision-making effectiveness by 95.78%, enabling recruiters to make more objective and consistent selections while reducing subjective bias. The implementation of the DSS also improved recruitment process efficiency by 30%, reducing the time and effort required to evaluate large numbers of applicants.

Although the study produced promising results, there remains an opportunity for future improvement. Subsequent research could enhance the system by refining and expanding the evaluation criteria used in the decision-making process. A more detailed Multi-Criteria Decision Making (MCDM) framework could be incorporated to capture additional aspects of candidate assessment, thereby increasing the precision, transparency, and overall effectiveness of recruitment decisions.

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