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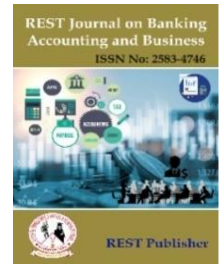

Analyzing Employee Selection Criteria Using Weighted DEMATEL Approach

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***Abstract**: Employee selection is a critical process in human resource management that significantly impacts organizational success. This brief examines the various methods, tools, and challenges involved in selecting the right candidates for specific job roles. The employee selection process involves multiple stages, such as job analysis, screening, testing, interviewing, and final decision-making, all of which aim to identify individuals with the skills, experience, and personality that align with the organization's needs. Mythology: alternative: security requirements, cost requirements, strategic requirements, technical requirement. result: According to the results Strengthen of AS security requirements, M mining act/law to enforce the involvement of mining professionals ranked highest, technical requirements, according to the DEMATEL Method approach, Wheat has the highest value for risk management.*

***Keywords:** Employee Celestine, recruitment, screening, interviewing, assessment, BIT, performance, retention, completions, technology.*

1. INTRODUCTION

The personnel selection process is often complex and prone to subjectivity, especially when the decisions rely heavily on human judgment. In this context, the use of multi-criteria decision-making (MCDM) methods, in particular the Simple Additive Weighting (SAW) technique, has proven to be very useful. The results of this study demonstrate that the use of SAW can significantly improve the objectivity and consistency of the selection process by measuring and ranking candidates based on several predefined criteria. This method allows for a systematic assessment of applicants, where each candidate is scored and compared based on weighted factors such as qualifications, experience, technical skills, and personal attributes [1]. A sensitivity analysis was conducted on the results obtained from two MCDM (Multi-Criteria Decision Making) methods to examine the impact of uncertainty within human resource management (HRM) operations and processes. This approach introduces a new way to address the variability and unpredictability associated with evaluation criteria and employee performance evaluation. By analyzing how changes in weights or decision parameters affect the final ranking or selection results, sensitivity analysis improves the robustness and reliability of a decision-making model [2]. In addition, employee turnover not only has direct financial costs, but also has significant indirect effects that affect overall organizational performance. When employees leave, it often leads to a decrease in morale among the remaining employees, who may feel overburdened or uncertain about job security. This decline in morale can translate into poor customer experiences, as service quality declines due to low motivation or staff shortages. Furthermore, turnover disrupts established professional networks and team dynamics, weakening collaboration and knowledge sharing [4]. Organizations also lose valuable skills and organizational knowledge, which are difficult and time-consuming to replace. As a result, the process of hiring and training new employees requires significant time, effort, and capital, and further straining resources. These cumulative effects make turnover a costly and strategic concern that requires proactive management [5]. Failures in international assignments can have serious implications for both employees and organizations, often resulting in employees being reluctant to accept future global positions. Such denials disrupt human resource planning as organizations struggle to allocate the right talent to international assignments, potentially delaying important projects or operations overseas. Furthermore, these setbacks hinder the adoption and implementation of global strategies, as the lack of experienced employees in international markets weakens the organization's ability to adapt and compete globally [6]. In addition, failure in international assignments can lead to a loss of control and coordination across international branches, which can impact communication, operational consistency, and overall organizational cohesion. The consequences extend beyond financial costs, affecting morale, reputation, and the organization's long-term global leadership development efforts [7]. Based on the above evidence, a multi-criterion decision-making (MCDM) approach combined with a machine learning-based T-Pareto policy scheme has been selected to effectively address the issue of employee attrition. This integrated approach leverages the strengths of MCDM in systematically assessing multiple factors that influence employee turnover – such as job satisfaction, compensation, work environment, and career development – while the machine learning component enhances the model by identifying hidden patterns and predicting attrition potential with greater accuracy. The T-Pareto principle helps filter out less significant criteria, allowing decision makers to focus on the most important factors contributing to employee attrition. This hybrid model not only improves the accuracy of attrition prediction but also supports strategic interventions by HR managers to retain high-potential employees. Ultimately, the approach ensures data-driven and efficient resource allocation, helping organizations proactively manage turnover and maintain a stable, committed workforce [8]. Current studies conducted by researchers in the field of HR analytics primarily focus on attrition prediction, aiming to understand the underlying causes and risk factors that lead to attrition. These studies use various statistical methods and machine learning algorithms to analyze historical employee data, including factors such as job satisfaction, performance ratings, tenure, salary, and workplace engagement. The aim is to develop predictive models that can accurately identify employees who are likely to leave, which helps organizations take proactive retention measures [9]. While these studies have provided valuable insights into attrition behavior, many have focused primarily on prediction rather than integrating decision-making frameworks for strategic intervention. As a result, there is growing interest in combining predictive analytics with decision support systems such as multi-criteria decision making (MCDM), which not only predict attrition but also guide HR managers in prioritizing the factors and actions that have the most meaningful impact. This evolution reflects a shift from reactive to strategic and preventive HR management, where attrition is addressed through informed, data-driven planning [10]. A small gap, created by a larger value, indicates a greater alignment between an employee's qualifications and the job requirements, thereby increasing the likelihood of the employee being considered for the position. In decision-making models, particularly in MCDM or optimization frameworks, such gaps often represent the difference between ideal and actual performance or fitness. When this gap is small, it indicates that the candidate closely meets or exceeds the desired criteria. As a result, the likelihood of selection or promotion increases because the individual is seen as a strong fit for the role with minimal need for training or adjustment. This concept is particularly useful in recruitment, promotion, and internal mobility decisions, where organizations aim to effectively match the right talent to the right roles. Therefore, reducing the gap becomes a strategic goal in talent management, ensuring that both organizational performance and employee satisfaction are optimized [11]. Employee turnover is a critical issue that affects organizations of all sizes, from startups to large corporations. When many employees leave an organization, it can lead to a variety of negative consequences, including decreased productivity, loss of organizational knowledge, and disruption of team dynamics. High turnover rates can damage employee morale and increase the workload of remaining employees, which can further reduce turnover. For smaller organizations, the impact can be even more severe, as each employee often makes a critical, multifaceted contribution. In larger organizations, while the impact may be distributed, the cost of recruiting, hiring, and training still imposes a significant financial burden. Furthermore, customer relationships can suffer due to a lack of continuity in service and communication. It is essential to proactively address employee turnover through effective HR strategies, predictive modeling, and retention programs to maintain employee retention, ensure business continuity, and support long-term organizational growth [12]. If a company has insight into which employees are likely to resign, it can take proactive steps to mitigate the impact of a potential layoff. By identifying employees at risk through predictive analytics or employee behavior monitoring, the company can implement targeted retention strategies, such as providing career development opportunities, addressing workplace concerns, or adjusting compensation packages. This foresight allows the company to plan for succession, reallocate workloads, initiate timely recruitment if necessary, and ensure minimal disruption to operations. Furthermore, understanding the reasons behind potential layoffs helps HR teams refine policies and improve employee engagement across the organization. Ultimately, having this predictive capability helps the company make strategic changes, reduce the costs associated with unplanned layoffs, and develop a more stable, satisfied workforce [13]. Employee churn presents a serious challenge for organizations, as it directly impacts productivity, morale, and long-term sustainability. Addressing this issue requires complex decision-making, involving the analysis of multiple factors such as job satisfaction, career progression, compensation, and workplace culture. Since an organization's workforce is its most valuable asset, the loss of skilled employees can lead to significant setbacks, including increased recruitment costs, disruption of operations, and loss of institutional knowledge [14]. Retaining talent is not just an HR responsibility but a strategic priority that influences the organization's ability to innovate, compete, and grow.

Therefore, organizations must adopt a data-driven, proactive approach to understand the root causes of turnover and implement effective retention strategies. Investing in employee well-being, engagement, and development is essential to maintaining a committed and high-performing workforce [15]. A well-implemented and professional performance appraisal process plays a key role in improving employee loyalty and motivation. When employees receive fair, transparent, and constructive feedback, they feel valued and recognized for their contributions, which increases their commitment to the organization. This sense of appreciation not only improves individual performance but also fosters a positive work environment where employees are more likely to remain engaged and aligned with organizational objectives [16]. In addition, performance appraisals provide a platform for setting clear goals, identifying areas for growth, and aligning individual ambitions with organizational expectations. As a result, when appraisals are conducted effectively, they become a powerful tool for driving productivity, developing talent, and ultimately ensure that organizational goals are successfully achieved [17]. In many organizations, especially those with hierarchical structures, responsibility for quality is often delegated to middle and lower-level managers and ultimately to shop floor employees. While this delegation can empower operational employees and promote accountability at the execution level, it can lead to a disconnect between strategic objectives and day-to-day practices if not properly aligned [18]. When top management is not actively involved in quality oversight, it can create gaps in communication, lack of motivation, and inadequate resource allocation. To truly achieve and maintain high standards of quality, there must be shared responsibility and clear direction from leadership, as well as effective training and support for lower levels. Quality must be integrated into every layer of the organization, supported by a culture of continuous improvement. Only when all employees, from executives to frontline workers, are engaged and aligned with quality goals can an organization expect to achieve consistent performance and long-term success [19]. Employee selection is a key factor in determining the success and sustainability of an organization, especially in the fast-paced and highly competitive information technology (IT) industry. As technological advancements and market demands evolve rapidly, organizations need to hire individuals who not only possess the necessary technical skills, but also demonstrate adaptability, innovation, and problem-solving abilities. A well-structured selection process ensures that the most suitable candidates are identified who align with the organization’s culture, strategic goals, and future growth plans. Hiring the right talent can lead to improved productivity, improved project outcomes, and stronger competitiveness in the industry. Conversely, poor selection decisions can result in increased turnover, project delays, and wasted resources. Therefore, implementing effective and data-driven employee selection strategies is essential to building a skilled and resilient workforce that can thrive in a dynamic IT landscape [20].

2. MATERAL AND METHOD

The Decision Modeling and Evaluation Laboratory (DEMATEL) method is widely and successfully used in various research fields to analyze and solve complex decision-making problems. Its primary strength lies in its ability to transform complex and interdependent systems into clear, structured models by identifying and visualizing the cause-effect relationships between factors. By distinguishing between influential (cause) and dependent (effect) elements, DEMATEL provides a deeper understanding of how elements within a system interact, which is particularly useful in areas such as supply chain management, healthcare, environmental planning, strategic decision-making, and human resource management [1].Based on the seven core competencies previously identified, this research further used the DEMATEL (Decision Making Testing and Evaluation Laboratory) methodology to analyze and map the complex interactions between these competencies. While each competency has its own unique importance, their combined influence often creates interdependent effects that cannot be fully understood individually. DEMATEL is well-suited for this task because it helps identify cause-and-effect dynamics, distinguishing which competencies act as key drivers and which are more influential or dependent. With this approach, the research moves beyond simple rankings or scores to provide a structured visualization of the flow of influence among competencies. In doing so, it allows decision-makers and stakeholders to focus on improving the most influential competencies, which will drive improvements across the entire organization [2]. The final product of the DEMATEL process, called an impact-relationship map, serves as a powerful visual tool that reflects how individuals mentally construct and perceive the relationships between various factors in a system. This map illustrates the direction and strength of influence between components, revealing which factors are causes (drivers) and which are effects (consequences). In essence, it reflects how a respondent conceptualizes and organizes their understanding of actions, outcomes, and priorities in the real world. By externalizing these mental models, the impact-relationship map provides clarity about how outcomes are formed, and which components have the greatest influence in shaping outcomes. This visual framework is valuable not only for academic analysis but also for practical decision-making, helping stakeholders strategically target influential areas for intervention or improvement [3]. In this section, it is demonstrated that DEMATEL can be considered a specific case of the Fuzzy Decision-Making (FDM) method when the threshold function used in the model is linear. Both FDM and

DEMATEL are analytical techniques designed to evaluate and visualize complex interactions between multiple factors in a system. However, while FDM typically incorporates fuzzy logic to manage uncertainty and imprecision in expert assessments, DEMATEL [4]. When the threshold function is assumed to be linear in FDM, the process of filtering and defining the significance of the relationships mirrors the approach used in DEMATEL. This balance highlights the conceptual relationship between the two methods and underscores the ability of DEMATEL to be interpreted as a simplified or deterministic variant of FDM under specific conditions. Understanding this relationship provides researchers and decision makers with greater flexibility in choosing the appropriate method depending on the complexity of the problem and the level of uncertainty present in the data. This strengthens the methodological rigor behind DEMATEL by framing it within a broader family of fuzzy and systems-based decision-making approaches [5]. The DEMATEL analysis technique was used to systematically explore the causal relationships between the identified perspectives and criteria. This method helped transform subjective expert judgments into a structured model that highlighted how different elements influenced each other. By accounting for direct and indirect effects, DEMATEL effectively distinguished between causal factors that drive changes within the system and outcome factors that are more responsive or dependent on others. This analysis was essential in identifying which perspectives and criteria were of the most strategic importance and where interventions would have the greatest impact [6]. Using expert input ensured that the assessment was grounded in practical knowledge and real-world experience, improving the reliability and relevance of the findings. The resulting data provided a clear map of influence and interdependence, guiding decision-makers in prioritizing actions based on systematic understanding rather than isolated judgment. The results of these analyses, including aggregate relationship ranks, impact scores, and rankings, are presented in the following section to provide detailed insights into the structure and dynamics of the studied system [7]. This paper proposes an integrated approach that combines Rough Set Theory, Modified DEMATEL, and Interpretive Structural Modeling (ISM) to analyze the importance of each barrier and the interactions between them in detail. Rough Set Theory is initially used to handle uncertainty and reduce redundant data, allowing the identification of the most important barriers based on expert assessments. Following this, the Modified DEMATEL method is used to explore the cause-and-effect relationships between the selected barriers, highlighting which one’s act as key drivers and are most dependent on the system [8]. Finally, the ISM technique is used to structure these relationships hierarchically, providing a visual model depicting the flow of influence and dependency between barriers. This layering and systematic integration allows for both quantitative analysis and structural interpretation, ensuring that decision makers gain a clear, prioritized understanding of where to focus their efforts. This approach is particularly useful for addressing complex, real-world challenges where multiple barriers interact, such as strategic planning, policy implementation, or organizational change. By combining the strengths of each method, this paper presents a robust framework to support informed, data-driven decision-making [9]. In the present study, the DEMATEL method has been applied to analyze the complex interrelationships among various barriers to establishing waste processing units in India. By evaluating the cause-effect dynamics among the identified barriers, DEMATEL provides insights into which factors act as key drivers, and which are more dependent. Additionally, the study incorporates the Interpretive Structural Modeling (ISM) method to structure the barriers into a hierarchical model based on their level of influence and dependence. The results obtained from both methods—DEMATEL and ISM—have been systematically compared to identify the most prominent and critical barriers that hinder the effective setup of waste processing infrastructure [10].

Alternative:

1. Security Requirements → Data Security Requirements

- An alternative to security requirements is data security requirements, which focus on protecting sensitive information.
- It emphasizes compliance with privacy laws (e.g., GDPR), secure data storage, and access control.
- This includes cybersecurity protocols, encryption, and user authentication mechanisms.
- It ensures organizational resilience against cyber threats and data breaches.
- Prioritizing data security builds trust and maintains operational integrity.

2. Cost Requirements → Budget Performance Requirements

- Budget performance requirements highlight optimizing costs without compromising quality.
- This includes resource allocation, cost-benefit analysis, and financial planning.
- It promotes streamlined processes and eliminates unnecessary spending.
- The focus is on achieving objectives within financial limits.

- This approach supports sustainable decision-making and operational balance.

3. Strategic Requirements → Organizational Alignment Requirements

- Organizational alignment requirements refer to ensuring that decisions are aligned with long-term goals.
- They focus on mission coherence, stakeholder expectations, and future scalability.
- Such requirements guide the selection of options that reinforce the business vision.
- This includes adaptability to market trends and competitive positioning.
- This ensures that each action contributes to broader strategic outcomes.

4. Technical Requirements → System Capability Requirements

- System capability requirements emphasize the required operational and technical performance.
- They include software compatibility, infrastructure readiness, and integration feasibility.
- Such requirements ensure that technical solutions meet operational demands.
- They also account for scalability, reliability, and support availability.
- Meeting system capability requirements is critical for efficient implementation and maintenance.

3. ANALYSIS AND DISCUSSION

TABLE 1. DATA SEAT

DATA SEAT					
	security requirements	cost requirements	strategic requirements	technical requirements	Sum
security requirements	0.734	1.734	1.28	1.1	4.848
cost requirements	0.791	0.913	1.028	0.983	3.715
strategic requirements	0.762	1.145	0.802	0.937	3.646
technical requirements	0.585	0.927	0.82	0.598	2.93

The data presented in Table 1, titled "Data Seat," highlights the relative importance and interrelationships of four key criteria: security requirements, cost requirements, strategic requirements, and technical requirements. Each cell in the table represents a relative weight or score between a pair of criteria, reflecting how much one criterion influences or outweighs the other. The order-wise sum of these scores provides a total weight for each requirement, indicating its overall importance in the decision-making process. According to the table, security requirements receive the highest score with a total score of 4.848, indicating that in a given context, security is the most prioritized factor of all the criteria. This may be particularly relevant in situations involving sensitive data or high-risk environments where data security is of paramount importance.

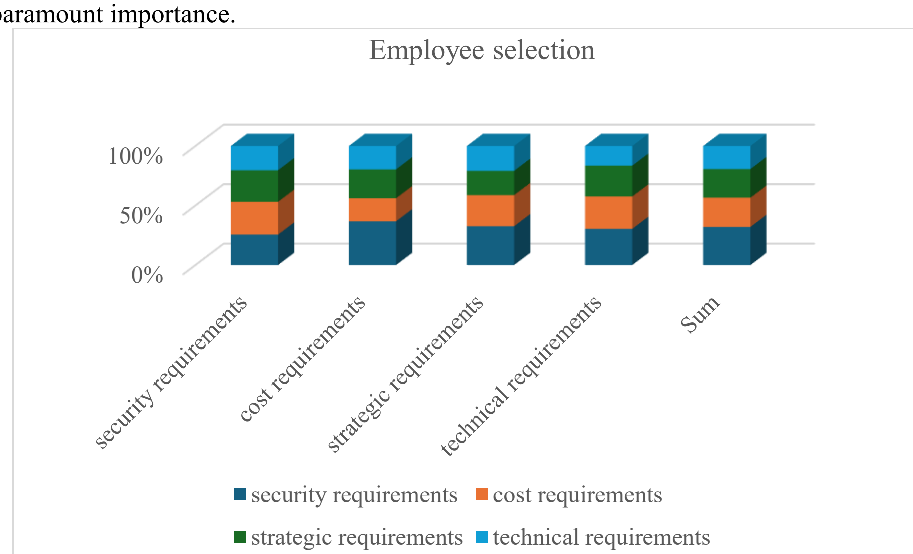

FIGURE 1. Employee selection

Figure 1 presents a 100% stacked column chart illustrating the weighted contribution of various requirements, security, cost, strategy, and technology—in the context of employee selection. Each column represents a criterion that is rated relative to the others, with the final column showing the total sum of all ratings. The height of each colored segment within the columns reflects the relative importance or influence of a requirement relative to the others. The chart visually reinforces that security requirements consistently occupy a significant portion of all columns, indicating that they are a high priority consideration in the selection process. Cost requirements and strategic requirements follow closely, indicating their strong influence on hiring decisions, which are tied to budgetary constraints and long-term organizational alignment. Technology requirements, as they exist, appear to contribute less across comparisons, meaning they may be viewed as more role-based or adaptive

TABLE 2. Normalization of direct relation matrix

Normalization of direct relation matrix				
	security requirements	cost requirements	strategic requirements	technical requirements
security requirements	0.122333333	0.289	0.213333333	0.18333333
cost requirements	0.131833333	0.152166667	0.171333333	0.16383333
strategic requirements	0.127	0.190833333	0.133666667	0.15616667
technical requirements	0.0975	0.1545	0.136666667	0.09966667

Table 2 provides a normalized direct relationship matrix that provides a standardized view of the influence or relationship between various criteria within the personnel selection process, including security requirements, cost requirements, strategic requirements, and technical requirements. Normalization is used to adjust the values to a common scale, which allows for easy comparison and ensures that no single criterion disproportionately influences the analysis due to differences in size. In the matrix, each row represents the influence exerted by one requirement on the others, while each column shows how much that requirement is influenced by the others. The safety requirements row has relatively high value (e.g., 0.289 under cost requirements), indicating a strong influence on other factors, especially cost and strategic requirements.

TABLE 3

	security requirements	cost requirements	strategic requirements	technical requirements
security requirements	0	0.166666667	0.333333333	0.16666667
cost requirements	0	0	0.333333333	0.16666667
strategic requirements	0	0.166666667	0	0.16666667
technical requirements	0	0.333333333	0.166666667	0

Table 3 presents a normalized pairwise influence matrix derived from the previous normalization step, where the diagonal elements are set to zero to exclude self-influence. This table illustrates how each requirement safety, cost, strategic, and technical influences the others in the context of employee selection. The values in the matrix indicate the strength of the relative influence that one criterion has over the other, with higher values indicating stronger influence. From the table, we observe that safety requirements influence both cost and strategic requirements with a relatively high value of 0.3333, indicating that safety plays a significant role in shaping budgetary and strategic decisions in the hiring process. On the other hand, cost requirements exert an equal influence on strategic requirements (0.3333) and a smaller influence on technical requirements (0.1667), highlighting the importance of financial constraints in aligning resources with strategic goals. Interestingly, technical requirements show a strong influence on cost requirements (0.3333), indicating that technical expectations can drive or constrain budget planning.

TABLE 4. I

	security requirements	cost requirements	strategic requirements	technical requirements
security requirements	1	0	0	0
cost requirements	0	1	0	0
strategic requirements	0	0	1	0
technical requirements	0	0	0	1

Table 4 illustrates an identity matrix labeled "I", which is a fundamental element in linear algebra and decision-making models. In this matrix, each diagonal element is 1, indicating complete self-influence of each criterion, while all off-diagonal elements are 0, indicating no influence from one criterion to another. The four criteria – safety requirements, cost requirements, strategic requirements and technical requirements – are represented as independent factors that each have full control over themselves and no mutual influence in this particular matrix. In the context of personnel selection, this identity matrix plays a key role in modeling and analyzing the complex interactions between decision-making factors. It is particularly used in methods such as DEMATEL (Decision Making Testing and Evaluation Laboratory) and total influence matrix calculations. Essentially, Table 4 is not used for interpretation in isolation, but rather as a mathematical tool to support further calculations. This ensures that each factor starts with an unbiased, unique impact, enabling a more accurate and meaningful assessment of interdependence in the structured decision-making model.

TABLE 5. Y

	security requirements	cost requirements	strategic requirements	technical requirements
security requirements	0	0.166666667	0.33333333	0.166666667
cost requirements	0.5	0	0.33333333	0.166666667
strategic requirements	0.5	0.166666667	0	0.166666667
technical requirements	0.333333333	0.333333333	0.16666667	0

Table 5 presents matrix Y, which represents the total indirect influence of the four main criteria safety requirements, cost requirements, strategic requirements, and technical requirements used in the employee selection process. Unlike the direct influence matrices, this matrix captures how one criterion indirectly influences another through inter-relationships. These values are often the result of multiplying the normalized direct relationship matrix with higher-order terms and reflect the deep interdependence in a system. From the matrix, we can observe that safety requirements receive significant indirect influence from other factors. For example, it receives an influence of 0.5 from cost and strategic requirements, indicating that although safety may not directly dominate the other criteria, it is significantly shaped by decisions involving cost and strategic alignment. Cost requirements also show influence from technical requirements (0.333) and strategic requirements (0.166), suggesting interrelated decision paths. Strategic requirements are similarly influenced by cost and technology factors, while technology requirements appear to be more of a receiver than an influencer, receiving input from all three other factors but exerting no direct influence in return. This matrix, essential in DEMATEL-based analyses, helps identify cause-and-effect relationships and guides balanced, data-informed decisions in prioritizing criteria for optimal staffing strategies.

TABLE 6. I-Y

	security requirements	cost requirements	strategic requirements	technical requirements
security requirements	1	-0.166666667	-0.3333333	-0.166666667
cost requirements	-0.5	1	-0.3333333	-0.166666667
strategic requirements	-0.5	-0.166666667	1	-0.166666667
technical requirements	-0.33333333	-0.333333333	-0.1666667	1

Table 6 presents the matrix I – Y, which is obtained by subtracting the total indirect influence matrix (Y) from the identity matrix (I). This operation is necessary in advanced decision-making methods such as DEMATEL and Analytical Network Process (ANP) to prepare for calculating the total relationship matrix or to obtain the final weights of the interrelated criteria. The resulting matrix expresses the adjusted self-dependence of each criterion after accounting for the indirect influence of other factors. In this matrix, the diagonal values are 1, which means the full self-influence of each requirement before adjustment. However, the values outside the diagonal are negative, indicating the indirect influence exerted by other criteria. For example, security requirements are negatively affected by cost (−0.166), strategic (−0.333), and technical (−0.166) requirements. Similarly, cost requirements face the influence of security (−0.5), strategic (−0.333), and technical (−0.166), which shows its vulnerability to other factors.

TABLE 7. (I-Y) ^-1

	security requirements	cost requirements	strategic requirements	technical requirements
security requirements	2.133595285	0.754420432	1.07269155	0.660117878
cost requirements	1.886051081	1.827111984	1.37917485	0.848722986
strategic requirements	1.650294695	0.848722986	1.956778	0.742632613
technical requirements	1.614931238	1.001964637	1.14341847	1.626719057

Table 7 provides an inverse representation of the $(I - Y)^{-1}$ matrix, a key component of the DEMATEL method used to model and analyze complex interdependent systems. This matrix expresses the total influence (direct and indirect) that each criterion exerts on or receives from others in the context of personnel selection. The values indicate how a change in one criterion spreads through the system and affects the others. In this table, each row represents a criterion that acts as a source of influence, while each column represents the target of the influence. For example, the value of 2.133 under "Security Requirements" in the first row and column indicates that security has the highest total influence on it. Meanwhile, its values of 0.754 for cost, 1.072 for strategy, and 0.660 for technology requirements show how it affects other factors throughout the system.

TABLE 8. Total Relation matrix (T)

Total Relation matrix (T)					
	security requirements	cost requirements	strategic requirements	technical requirements	
security requirements	2.133595285	0.754420432	1.07269155	0.660117878	**42.2947**
cost requirements	1.886051081	1.827111984	1.37917485	0.848722986	**37.67387**
strategic requirements	1.650294695	0.848722986	1.956778	0.742632613	**31.73281**
technical requirements	1.614931238	1.001964637	1.14341847	1.626719057	**26.53438**
	7.284872299	**4.432220039**	**5.55206287**	**3.878192534**	

Table 8 shows the total relationship matrix (T), which is a detailed representation of the direct and indirect influences on four key criteria in the employee selection process: safety requirements, cost requirements, strategic requirements, and technical requirements. Derived from the inverse matrix$(I-Y)$ −1(I−Y) −1, this matrix measures how each criterion influences and is influenced by others throughout the organization, thus helping decision makers understand complex interdependencies. Each row shows how much influence one criterion exerts on all the others, while each column indicates how much one criterion is influenced by the others. For example, the safety requirements row shows the highest total influence on other factors, with values such as 1.072 for strategy and 0.754 for cost. The diagonal elements reflect the influence of a criterion, with values above 1 indicating reinforcement through feedback loops. The final column (row sums) represents “given influence,” where security needs rank highest (42.29), followed by cost (37.67), strategic (31.73), and technical (26.53).

TABLE 9. RI And CI

	Ri	Ci
security requirements	**42.29469548**	7.284872299
cost requirements	**37.67387033**	4.432220039
strategic requirements	**31.73280943**	5.552062868
technical requirements	**26.53438114**	3.878192534

Table 9 presents the influential degree (R_I) and dependence degree (C_I) for each criterion involved in the employee selection process: security requirements, cost requirements, strategic requirements, and technical requirements. These values are derived from the Total Relation Matrix (T) and provide deep insights into the role and behavior of each factor within the decision-making system. The R_I (row sum) reflects how much a criterion influences other criteria, while C_I (column sum) represents how much it is influenced by others. A high R_I value indicates a criterion has strong influence, while a high C_I suggests it is highly dependent. From the table, security requirements exhibit the highest influence (42.29) and also the highest dependence (7.28), showing that while it significantly drives other criteria, it is also sensitive to external inputs—reflecting its central role in the selection process. Cost requirements follow in influence but with lower dependence, indicating a more stable and influential role. Strategic and technical requirements show decreasing influence and varying dependence, suggesting supporting roles.

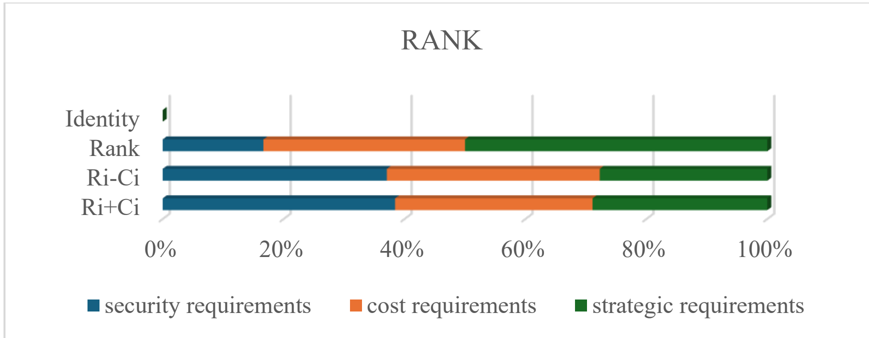

FIGURE 2. Rank

Figure 2 displays the ranking of personnel selection criteria - security requirements, cost requirements, and strategic requirements based on their influence and bias values, calculated using the DEMATEL method. The bar chart presents three criteria: R_I + C_I (importance), R_I − C_I (net influence), and the final ranking derived from these indices. The R_I + C_I indicates the total importance (influence and bias) of each criterion in the decision-making system. Strategic requirements dominate this bar, indicating high overall interactions within the network. Security requirements follow closely, with cost requirements also playing a significant but slightly smaller role. The R_I _I bar shows the net influence, or how much one factor influences others. Here, security requirements take the lead, confirming their role as the primary driver in the employee selection system

TABLE 10. T Matrix

	Ri +Ci	Ri-Ci	**Rank**	**Identity**
security requirements	49.579568	35.009823	1	cause
cost requirements	42.106090	33.241650	2	cause
strategic requirements	37.284872	26.180747	3	effect
technical requirements	30.412574	22.656189	4	effect

Table 10 presents the final analysis of the Total Relation (T) Matrix using the DEMATEL method, providing critical insights into the influence and dependence of each criterion in the employee selection process. The values R_i + C_i represent the total involvement of each factor—how much it influences and is influenced by others—while R_i − C_i indicates the net influence, distinguishing between cause-and-effect relationships. From the table, security requirements hold the highest values in both R_i + C_i (49.57) and R_i − C_i (35.01), earning it Rank 1 and classifying it as a "cause" factor, meaning it strongly influences other criteria while being minimally influenced itself. Cost requirements, with a total score of 42.10 and net influence of 33.24, also act as a cause, placed at Rank 2. In contrast, strategic requirements and technical requirements have lower net influence values and are thus categorized as "effect" factors, being more dependent on other criteria. These ranking highlights that security and cost requirements are the primary drivers in the employee selection model, while strategic and technical requirements are outcomes shaped by those drivers. Understanding this hierarchy helps decision-makers prioritize key influencing factors for more effective selection strategies.

4. CONCLUSION

Employee selection is a critical process that significantly impacts an organization's overall performance, sustainability, and competitive advantage, especially in dynamic industries like information technology. A well-designed selection process helps organizations identify candidates who not only possess the necessary technical skills but also align with the organization's culture, strategic objectives, and long-term vision. As the job market becomes increasingly competitive, traditional selection methods may fail to address the challenges of hiring the right talent. Integrating structured, data-driven approaches, such as multi-criteria decision-making (MCDM) methods, including DEMATEL, SAW, and others, can greatly improve objectivity and consistency in evaluating applicants. These tools allow HR professionals to evaluate candidates on multiple dimensions, reducing subjectivity and ensuring fair, transparent decision-making. Furthermore, predictive and analytical techniques help identify the most influential factors that influence hiring decisions, such as safety, cost, strategic, and technological requirements. By prioritizing these key elements, organizations can build a strong, high-performing workforce. Ultimately, effective employee selection not only reduces turnover rates and recruitment costs, but also contributes to higher employee satisfaction, organizational performance, and long-term success. Therefore, investing in smart, systematic selection processes is crucial for modern organizations that want to thrive in today's competitive business environment.

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