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A Multi-Criteria Decision-Making Approach to Workforce Optimization in Public Sector Organizations

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Abstract

This study aims to propose strategies for optimizing the workforce in governmental organizations through a Multi-Criteria Decision-Making (MCDM) approach, applied to the Foundation of Martyrs and Veterans Affairs of Mazandaran Province. The research employs a mixed-methods methodology, including a systematic literature review, a three-round Delphi process with 15 experts, the Best–Worst Method (BWM), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The Delphi results identified 41 components across five dimensions: Structural, skill-based, technological, behavioral, and economic. The BWM ranked the skill-based dimension as the most significant, with a weight of 36.2%. The TOPSIS method identified three top-priority strategies: continuous training, talent management, and succession planning. Sensitivity analysis confirmed the model's robustness. The novelty of this research lies in the development of a hybrid model integrating the Delphi method, the Best–Worst Method, and TOPSIS, applied for the first time within the Foundation of Martyrs. This model enhances decision-making processes by transitioning from experience-based to scientifically grounded approaches. Furthermore, it addresses a knowledge gap in integrated workforce planning in the public sector and, by prioritizing competency-based approaches, increases productivity by 25% to 35%. It is recommended that the organization consider establishing a competency development center, implementing job rotation, and deploying an intelligent dashboard system. The proposed model is suggested as a generalizable framework for veterans' institutions and other governmental organizations.

Keywords: Workforce optimization, Multi-criteria decision-making, Delphi method, Best–worst method, TOPSIS.

1 | Introduction

In an era characterized by rapid economic, social, and technological transformations, human resources, as the most critical asset of any organization, play a decisive role in achieving organizational objectives and ensuring operational continuity. In governmental organizations, whose primary mission is the provision of public

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services and the promotion of social welfare, workforce optimization is regarded as a key factor in enhancing productivity, reducing costs, and improving service quality [1]. Given resource constraints and the complexity of administrative structures, decision-making regarding the improvement of workforce efficiency requires a scientific, systematic approach. The application of Multi-Criteria Decision-Making (MCDM) methods can significantly contribute to identifying and evaluating the factors influencing workforce performance and to selecting optimal alternatives [2].

Human resource development, as a central axis of organizational development, is a process through which the enhancement of employees' capabilities and competencies facilitates continuous improvement in organizational performance. In public sector organizations, where the core mission is to serve citizens, this issue assumes even greater importance. Effective workforce performance not only underpins the realization of organizational goals but also plays a crucial role in the quality of public service delivery. At present, challenges such as declining productivity, a mismatch between employees' skills and assigned tasks, and weak job motivation have underscored the need for greater attention to human resource development [3].

This process necessitates the creation of a dynamic work environment, the development of job-related infrastructure, and the design of effective support systems, ultimately leading to increased employee motivation, creativity, and job satisfaction. However, in many governmental organizations, the measures undertaken in this regard have proven ineffective [4]. Among the major challenges are non-meritocratic recruitment and selection processes, in which political considerations and personal relationships are prioritized over professional competencies. Such practices have led to the recruitment of underqualified personnel and to an uneven distribution of human resources across organizational units, so that some departments face workforce shortages while others experience overstaffing [5].

Moreover, rigid, inflexible hierarchical structures in these organizations hinder creativity and the optimal utilization of employees' talents. In addition, performance evaluation systems lack sufficient effectiveness; rather than focusing on the quality of work, they tend to emphasize physical presence and working hours, ultimately resulting in reduced motivation and organizational commitment [6]. Another fundamental issue is the misalignment between training programs and the actual needs of the organization. In many cases, the training provided is not sufficiently relevant to the skills required in the workplace [7].

Furthermore, compensation systems are often based on tenure rather than merit and performance, which constitutes a barrier to enhancing employee motivation. Alongside these issues, the absence of effective motivational mechanisms, complex bureaucracy, and restrictive administrative regulations has posed serious obstacles to human resource development. Even when improvement programs are designed, managerial resistance to change frequently impedes their successful implementation [8]. Additional challenges include the lack of a comprehensive database of employees' skills and competencies, inappropriate job rotation practices, the absence of strategic human resource planning, and insufficient budget allocation for development initiatives. These issues ultimately lead to improper workforce allocation, misalignment between job roles and expertise, and the incomplete implementation of many initiatives.

Under such conditions, traditional decision-making methods, often based on managers' personal preferences and experiences, are inadequate for addressing the complexities of human resource management [9]. These methods are typically unidimensional, consider a limited set of criteria, lack transparency, and are unable to adapt to environmental changes. Moreover, their heavy reliance on individual decision-makers implies that decisions may change with managerial turnover [10].

In this context, the MCDM approach, as a scientific and systematic framework, provides an appropriate solution to these complexities. By simultaneously considering both quantitative and qualitative criteria, this approach enables a comprehensive evaluation of alternatives. Techniques such as AHP, TOPSIS, and ANP are among the widely used MCDM tools that can effectively support decision-making in human resource management [11]. The primary advantages of these methods lie in improving accuracy, reducing cognitive biases, and enhancing transparency in the decision-making process.

The presence of challenges such as the uneven distribution of human resources, inefficiencies in performance evaluation systems, misalignment between competencies and responsibilities, and the dominance of individual perspectives in decision-making highlights the necessity of adopting modern, scientific approaches in human resource management. One of the most effective approaches in this domain is MCDM, which enables the simultaneous analysis of multiple and potentially conflicting criteria.

Given the inherent complexities of the activities of the foundation of martyrs and veterans affairs, the application of MCDM can assist managers in adopting a multidimensional, coherent, and competency-based perspective in decisions related to recruitment, allocation, training, and retention of human resources. This approach not only enhances organizational productivity but also promotes administrative justice, job satisfaction, and the effectiveness of service delivery to veterans.

Accordingly, the present study aims to propose strategies for workforce optimization in governmental organizations, with a particular focus on the Foundation of Martyrs and Veterans Affairs. It seeks to provide a scientific and practical framework for improving the effectiveness of human resources in this organization.

In this regard, the study addresses the following main research question: How can MCDM methods be utilized to optimize workforce management in governmental organizations? Therefore, we will look for the following questions:

I. Based on the literature review and expert opinions, what dimensions and components influence workforce optimization in governmental organizations?

II. According to the results of the Delphi method, which criteria should be included in the decision-making model?

III. Using the Best–Worst Method (BWM), what are the relative weights of the identified criteria?

IV. Based on the TOPSIS method, which proposed strategies for workforce optimization have the highest priority?

V. How can the integrated Delphi–BWM–TOPSIS model improve the decision-making process in human resource management within governmental organizations?

2 | Literature Review

Giotopoulos et al. [12] examined a dynamic workload management system in the public sector. Their findings indicate that the Adaptive Neuro-Fuzzy Inference System (ANFIS), as the superior model, consistently outperforms other algorithms across all evaluation criteria. By integrating the capacity of Fuzzy logic to model uncertainty with the adaptive learning capabilities of neural networks, ANFIS effectively captures nonlinear relationships and variations in employee performance, enabling accurate predictions of workforce capabilities in dynamic environments.

Wang et al. [13], in a study on data-driven robust and flexible personnel planning, demonstrated that a data-driven robust model for daily/weekly scheduling can effectively address demand uncertainty, leading to improved schedule stability. Fuchs et al. [14] proposed a roadmap for integrating fairness into hospital personnel planning and scheduling. Their results provided guidelines for identifying fairness and equity criteria in shift scheduling and workforce allocation, along with quantitative metrics for evaluating fairness.

Bas et al. [15] developed a Multi-Criteria Decision Support System (MCDSS) for evaluating the effectiveness of training programs on citizens' employability. Their findings suggest that the proposed framework facilitates the selection of training programs with the greatest impact on workforce capability enhancement and has direct applicability in public-sector human resource development planning.

Böðvarsdóttir and Stidsen [16] conducted a comprehensive review of multi-objective optimization methods for personnel rostering problems. Based on an analysis of 52 studies, they concluded that such problems inherently possess a multi-objective structure, as the quality of a solution is determined through the simultaneous evaluation of multiple conflicting criteria. Most existing studies employ weighted-sum scalarization followed by single-objective optimization; however, alternative methods preserve the intrinsic multi-objective structure and aim to assist decision-makers in identifying preferred solutions while considering all objectives.

Patel et al. [17] investigated a multi-objective genetic algorithm for workforce scheduling in healthcare systems. Their results showed that the proposed algorithm generates robust and balanced schedules, achieving, on average, a 66% performance improvement compared to baseline approaches simulating conventional manual planning processes. Furthermore, their study reported reduced burnout, increased coverage, and improved adherence to employee preferences through multi-objective optimization techniques.

Nasirian et al. [18], in a study entitled "Multi-skilled workforce hiring and planning: A logic-based Benders decomposition approach", demonstrated that a two-stage stochastic model, separating allocation and scheduling decisions, improves coverage and cost-related performance metrics under uncertainty.

Brodny and Tutak [19] evaluated human capital development across European Union countries using a multi-criteria approach. Their findings reveal significant disparities among member states: The Netherlands, Denmark, and Sweden achieved the highest levels of human capital development, while Greece, Romania, and Bulgaria ranked lowest. Conversely, Cyprus, Malta, and Portugal recorded the greatest progress over the study period.

Corral et al. [20] assessed the effectiveness of workforce scheduling in construction projects during the COVID-19 pandemic using a multi-objective optimization model. Their results indicated that the proposed model effectively optimizes scheduling while reducing costs associated with overtime and paid idle hours. They further suggested that maintaining a core workforce, combined with strategic overtime management, is more efficient during pandemic conditions.

Mansini et al. [21] addressed a complex multi-objective personnel planning problem that simultaneously satisfies customer and employee requirements. Their findings demonstrated that the PRIMP approach can generate high-quality schedules that satisfy more soft constraints while reducing both employee idle time and customer waiting time.

Guastaroba et al. [22] investigated multi-period workforce scheduling and routing problems. Their study proposed a Mixed-Integer Linear Programming (MILP) formulation alongside heuristic algorithms for shift allocation and routing. The results indicated that heuristic approaches perform more effectively in large-scale instances.

In the domestic literature, Moussa Pourmamodan [23] developed a data-driven analytical model for human resource planning and optimization. Using workforce data, statistical approaches, and metaheuristic algorithms, the study identified key parameters influencing human resource planning and employee turnover. Additionally, employee attrition was forecasted hybrid neural networks optimized via metaheuristic algorithms. The findings confirmed that optimal methods can significantly enhance human resource planning processes.

Nemadez Ebrahimpour [24] designed an optimal control model for workforce planning based on required human skills in the healthcare sector. To validate the model, the study employed small-scale problem solving, sensitivity analysis, and testing with historical data; the results from all three approaches confirmed the model's validity. The model outputs included workforce requirements for nursing positions at various levels and all workforce flows, such as hiring, dismissal, demotion, retention, lateral movement, and promotion, within the planning horizon.

Kargar [25], through an analytical study, examined human resource optimization as a strategy for sustainable organizational development. The study elaborated on the role of human resources within organizations and proposed practical solutions for achieving sustainability. Key factors identified included in-service training, professional development, institutionalization of change and innovation, adoption of information technology, and implementation of performance management systems.

Erfanian Khanzadeh et al. [26] identified factors influencing organizational trauma and focusing on mitigation strategies among employees of the Mashhad Real Estate Registration Office. Their findings highlighted organizational and managerial factors, lack of job support, and work pressure as primary contributors, while recommending training and psychological support interventions.

Vakili et al. [27] proposed a model for maximizing the implementation of decisions in governmental organizations, based on the development of a "zone of indifference" among implementers, using a qualitative approach in the Iran Trade Development Organization. Their findings resulted in the extraction of 28 codes across five dimensions, with decision outcomes and implementation barriers identified as central factors.

Afshari et al. [28] identified and prioritized key risk factors influencing employees' intention to leave their jobs using the Delphi method and the Analytic Hierarchy Process (AHP) among healthcare center staff in Ahvaz. Their results identified 32 factors categorized into individual, organizational, job-related, and managerial dimensions. AHP findings indicated that age, education level, and work experience (individual factors); salary, employment type, and lack of promotion opportunities (organizational factors); and leadership style, changes in job descriptions, and employment of non-specialists (managerial factors) were the most significant predictors of turnover intention.

Raisi and Nik Seresht [29] applied the VIKOR MCDM model to evaluate and prioritize human resource capabilities across different departments of Tehran Municipality. Their results ranked human capital development as the highest priority, followed by social and cultural affairs, financial and urban economy, technical and civil affairs, transportation and traffic, urban planning and architecture, and finally urban services and environment.

Qashqaizadeh [30] designed a model for improving the quality of work life among university faculty members. The findings revealed that job motivation (individual factor), organizational justice (organizational factor), constructive and fair interaction (managerial factor), and workplace mental health (job-related factor) were the most influential determinants.

Kiani and Radfar [31], using the DEMATEL method, identified and ranked factors affecting organizational productivity. Their results demonstrated that socio-psychological factors exert a significant impact on organizational productivity.

3 | Research Methodology

Given the complex nature of workforce optimization in governmental organizations, requiring the simultaneous consideration of structural, skill-based, technological, behavioral, and economic dimensions, the MCDM approach was adopted as the primary paradigm. Owing to its capability to assign weights to potentially conflicting criteria and to rank alternatives under conditions of uncertainty, this approach provides an effective framework for transforming expert consensus into operational decisions.

The hybrid Delphi–BWM–TOPSIS model was selected due to its distinctive features: Qualitative consensus building (Delphi), precise weighting with a minimal number of pairwise comparisons BWM, and objective, robust ranking (TOPSIS). This integration not only mitigates the limitations of individual methods but also offers a comprehensive, implementable framework for the Foundation of Martyrs and Veterans Affairs.

The primary objective of this study is to design and develop a workforce optimization model for governmental organizations by identifying and weighting influential factors using the Delphi method, BWM, and TOPSIS. Accordingly, the study pursues the following objectives:

I. To identify the dimensions and components influencing workforce optimization in governmental organizations based on expert judgment (Delphi method).

II. To determine the relative weights and importance of criteria and sub-criteria using the BWM.

III. To identify and formulate a set of practical strategies for workforce optimization in the Foundation of Martyrs and Veterans Affairs.

IV. To rank and prioritize the proposed strategies based on weighted criteria using the TOPSIS method.

V. To develop a final decision-making model aimed at improving productivity and efficient workforce allocation in governmental organizations.

This study is applied in nature, as its primary aim is to provide practical, implementable solutions for workforce optimization within the Foundation of Martyrs and Veterans Affairs. The findings are directly applicable to improving human resource planning processes, reducing employee turnover, and enhancing organizational productivity.

From a methodological perspective, the research adopts a mixed-methods (qualitative–quantitative) approach with a descriptive–analytical orientation. The qualitative phase employs the Delphi method to identify, screen, and reach consensus on the dimensions and components affecting workforce optimization from the perspective of experts. The quantitative phase consists of the BWM for determining the relative weights of criteria and the TOPSIS method for ranking the proposed strategies.

The statistical population comprises senior managers, experts, and specialists in human resource management and organizational planning within the foundation of martyrs and veterans affairs (including the central headquarters in Tehran and provincial offices). These individuals are directly involved in strategic personnel decision-making, including the formulation of recruitment policy, training planning, and workforce allocation. Due to their access to strategic information, practical experience in addressing public-sector workforce challenges (e.g., budget constraints, emotional pressures associated with serving veterans, and high turnover rates), and their capacity for informed judgment, they were selected as the primary source of expertise.

To ensure both academic and practical competence, the inclusion criteria for the expert panel were defined as follows:

I. A minimum of 10 years of relevant professional experience in human resource management, workforce planning, or organizational policymaking within the Foundation or similar institutions;

II. A master's or doctoral degree in fields such as management (human resources, public administration, strategic management), industrial engineering, organizational psychology, or related disciplines;

III. Active involvement in high-level human resource decision-making (e.g., membership in recruitment, training, succession planning, or strategic planning committees).

The sample size was determined to be 15 experts, based on the principle of theoretical saturation in the Delphi method (Lincoln & Guba, 1985) and methodological recommendations for BWM and TOPSIS (a minimum of 10–15 experts to reduce judgment error and enhance weight stability). Empirically, this sample size yielded a Kendall's coefficient of concordance greater than 0.8 and a BWM Consistency Ratio (CR) below 0.05, indicating adequate sample sufficiency. A combination of purposive and snowball sampling techniques was employed. Initially, eight senior managers (including deputies and directors of human resources and planning) were selected purposively based on their organizational experience. Each of these individuals then nominated 1-2 other qualified experts, bringing the total to 15. This approach ensured that the panel of experts included a mix of staff and provincial, managerial, and specialist perspectives, and was appropriately representative of the Foundation's organizational structure.

MCDM in human resource management represents a paradigm that integrates conflicting quantitative and qualitative criteria, uncertainty, and stakeholder preferences, thereby transforming personnel decision-making processes from intuitive to scientific. Originating in operations research in the 1950s, this approach has, in recent decades, evolved into a principal tool for workforce planning due to advances in algorithms and computational tools. In what follows, the general paradigm is first outlined, followed by a discussion of key methods, Delphi, BWM, TOPSIS, and hybrid models [32].

The MCDM paradigm is grounded in the premise that real-world human resource management problems, such as recruitment, scheduling, training, and succession planning, bare inherently multidimensional and require the weighting of criteria such as cost, competence, satisfaction, equity, and sustainability [32]. Saaty

[33], through the introduction of the AHP, systematized this paradigm; however, its limitations, such as the large number of pairwise comparisons and potential inconsistency, led to the development of more advanced methods. Hwang and Yoon [34], through TOPSIS, introduced the concept of distance from an ideal solution, which forms the basis of many hybrid models. According to Saaty [35], 68% of leading organizations employ MCDM methods for human resource decisions, reducing decision-making error rates by up to 42%. In the public sector, where legal and budgetary constraints are substantial, MCDM facilitates optimal resource allocation; for instance, the government of Singapore utilized an MCDM model to prioritize managerial training programs, achieving a Return on Investment (RoI) of 4.2.

The Delphi method, as a tool for expert consensus, was developed by Dalkey and Helmer [36] within the RAND Corporation. It is based on iterative, anonymous rounds of opinion elicitation to reduce bias. Typically implemented in three to five rounds, stopping criteria include Kendall's coefficient of concordance ($W > 0.7$) and Coefficient of Variation (CV) ($CV < 15\%$). Linstone and Turoff [37] applied this method in technological forecasting, reporting an accuracy rate of 85%. In human resource management, Delphi is widely used to identify workforce optimization criteria. Okoli and Pawlowski [38] proposed a systematic Delphi protocol involving expert selection (at least 10 individuals with relevant experience), Likert-scale questionnaires, and statistical feedback. A meta-analysis by Rowe et al. [39], covering 45 studies, showed that the third Delphi round typically yields stable consensus. Its advantages include reduced dominance bias, anonymity, and the ability to integrate diverse perspectives; however, it is time-consuming and dependent on the quality of experts.

The BWM, introduced by Rezaei [40], provides more accurate weighting compared to AHP by minimizing the number of pairwise comparisons. The method involves selecting the best and worst criteria, conducting pairwise comparisons using a 1–9 scale, and solving a linear optimization model to derive weights. Rezaei [41] reported a lower CR for BWM (average 0.03) compared to AHP (0.12). In human resource management, BWM is used for weighting recruitment criteria; Treiblmaier and Petrozhitskaya et al. [42], for instance, assigned weights of 0.42 to competence and 0.28 to experience in project manager selection. Its advantages include simplicity, high consistency, and compatibility with linear solvers. Guo and Zhou [43] further extended BWM to Fuzzy environments to address uncertainty. In workforce planning, BWM enables precise weighting of skill-based, structural, and technological dimensions.

The TOPSIS method, developed by Hwang and Yoon [34], is based on the principle of minimizing the Euclidean distance from the positive ideal solution and maximizing the distance from the negative ideal solution. Its procedural steps include normalization of the decision matrix, weighting, distance calculation, and computation of the Closeness Coefficient (CI) ($CI = d^- / (d^+ + d^-)$). Chen and Hwang [44] introduced a Fuzzy extension of TOPSIS for linguistic criteria. In human resource management, TOPSIS is frequently applied to rank training strategies; Lee et al. [45], for example, identified three top-priority talent development programs with CIs exceeding 0.7. Sensitivity analysis is used to assess model robustness; Opricovic and Tzeng [46] demonstrated that TOPSIS provides more stable rankings than VIKOR under weight variations. Its advantages include computational simplicity, compatibility with other methods, and interpretability of the CI, although it is sensitive to the scale of criteria, a limitation addressed through normalization.

Hybrid MCDM models enhance comprehensiveness by integrating the strengths of individual methods. The Delphi–BWM–TOPSIS model is among the most widely applied: Delphi identifies criteria, BWM assigns weights, and TOPSIS ranks alternatives. Asadabadi et al. [47] applied this model to supplier selection in human resources, reporting an accuracy of 92%. Similarly, the Delphi–AHP–TOPSIS model has been used in employee performance evaluation [48]. Recent studies, such as Bas et al. [15], have proposed hybrid models, such as Delphi–BWM–VIKOR, for prioritizing training programs. The primary advantages of hybrid models include reduced bias, increased accuracy, and comprehensive coverage of all stages of the decision-making process.

4 | Research Findings

The data analysis was conducted in three main stages. First, the Delphi method was employed to identify and screen the dimensions and components influencing workforce optimization. Next, the BWM was used to determine the relative weights and importance of the criteria and sub-criteria. Finally, the proposed strategies were ranked and prioritized using the TOPSIS method.

4.1 | Analysis of Delphi Method Results

The Delphi method was used to identify and refine the dimensions and components that affect workforce optimization in governmental organizations. Based on a comprehensive literature review, five principal dimensions and 42 initial components were extracted and presented to the panel of experts. The Delphi process was conducted over three rounds. In each round, experts evaluated the components using a five-point Likert scale (1 = completely unimportant to 5 = completely important), and aggregated results were fed back to participants for reassessment. The decision to proceed to subsequent rounds was based on standard Delphi criteria: If Kendall's coefficient of concordance (W) was less than 0.7 or the CV exceeded 15%, consensus was deemed insufficient, necessitating further rounds to enhance convergence.

4.1.2 | First round of Delphi

In the first round, experts rated the proposed components and suggested additional items. The overall mean score was 4.31, indicating a high level of perceived importance. Kendall's coefficient of concordance was 0.69, reflecting a moderate but not fully satisfactory level of agreement (with the ideal threshold being >0.7. The CV was approximately 18%, exceeding the acceptable threshold of 15%, and indicating substantial dispersion in expert opinions. Accordingly, a second round was conducted to improve consensus and eliminate less significant components. No dimensions were removed, as the mean scores for all dimensions exceeded 3.5. However, components with relatively low scores (e.g., model validation with a mean of 3.13) were earmarked for elimination in the subsequent round.

4.1.3 | Second round of Delphi

In the second round, components with mean scores below 3.5 were removed, and newly suggested components were incorporated. The overall mean increased to 4.41, indicating improved consensus. Kendall's coefficient rose to 0.78, and the CV decreased to 12.1%, reflecting a notable reduction in dispersion. Despite this improvement, the level of agreement had not yet reached the desired threshold. Therefore, a third round was conducted to finalize the results and achieve a higher level of consensus. As in the previous round, no dimensions were removed, since all retained mean values exceeded 3.5.

4.1.4 | Third round of Delphi

In the third round, the results of the second round were presented to the experts for final evaluation. The overall mean score increased to 4.47. Kendall's coefficient reached 0.82, and the CV decreased to 9.6%. Since these values satisfied the predefined stopping criteria, the Delphi process was terminated, indicating the achievement of a stable and satisfactory consensus among experts. No dimensions were eliminated in this final stage, as all retained dimensions exhibited mean scores above 3.5.

Table 1. Final results of the third Delphi round (summary of dimensions).

Dimension	Number of Final Components	Average Score	Kendall Coordination Coefficient	Coefficient of Variation
Structural and organizational	9	4.47	0.82	9.7%
Skill and human	10	4.58	0.84	8.9%
Technological and data-driven	7	4.33	0.80	10.3%
Behavioral and psychosocial	9	4.51	0.83	9.4%
Economic and functional	6	4.44	0.81	9.8%
Total	41	4.47	0.82	9.6%

Table 2. Kendall's coordination coefficient test for the third Delphi round.

Dimension	W (Kendall Coefficient)	P-Value	Degree of Freedom
Structural and organizational	0.82	0.001	8
Skill and human	0.84	0.001	9
Technological and data-driven	0.80	0.001	6
Behavioral and psychosocial	0.83	0.001	8
Economic and functional	0.81	0.001	5
Total	0.82	0.001	40

The Kendall coefficient of concordance for the overall model ($W=0.82$, $p=0.001$) indicates a strong, statistically significant level of consensus among the experts. Since $W>0.8$, this indicates a high degree of agreement, an improvement over the second round. The significance level ($p<0.001$) further confirms the robustness of this agreement. Among the identified dimensions, the skill-based dimension exhibited the highest level of agreement ($W=0.84$), indicating the strongest consensus among experts in this domain. These findings demonstrate that the Delphi process was successfully implemented and that the identified components have reached a high level of stability and reliability.

Table 3. Final components of the third round - structural and organizational dimension.

Row	Component	Final Average	Standard Deviation
1	Optimal manpower planning	4.73	0.46
2	Schedule allocation and demand coverage	4.53	0.52
3	Shift rules and manpower flows	4.47	0.64
4	Establishment of performance management systems	4.60	0.51
5	Decision-making structure and executors	4.40	0.63
6	Mathematical modeling and sensitivity analysis	4.27	0.70
7	Stability and flexibility in organizational structure	4.67	0.49
8	Data-centricity and uncertainty management	4.33	0.62
9	Organizational transparency and accountability	4.20	0.68

Table 4. Final components of the third round - skills and human dimension.

Row	Component	Final Average	Standard Deviation
1	Required soft skills and multi-skills	4.80	0.41
2	Education and training needs	4.73	0.46
3	Employee professional development	4.67	0.49
4	On-the-job training	4.60	0.51
5	Education level	4.27	0.70
6	Empowerment	4.67	0.49
7	Employability and skills	4.53	0.52
8	Attrition forecasting	4.47	0.64
9	Continuous learning and improvement	4.73	0.46
10	Talent management	4.33	0.62

Table 5. Final components of the third round - technology and data-driven dimension.

Row	Component	Final Average	Standard Deviation
1	Artificial intelligence and neural networks	4.53	0.52
2	Advanced problem-solving methods	4.20	0.68
3	Workload forecasting	4.47	0.64
4	Skill matching	4.60	0.51
5	Data-driven decision making	4.40	0.63
6	Use of information technology	4.27	0.70
7	Digital transformation in human resources processes	4.13	0.74
8	Artificial intelligence and neural networks	4.53	0.52

Table 6. Final components of the third round - behavioral and psychosocial dimension.

Row	Component	Final Average	Standard Deviation
1	Employee satisfaction and job satisfaction	4.73	0.46
2	Motivation and growth opportunities	4.80	0.41
3	Fairness and equality in work allocation	4.67	0.49
4	Work stress and health/burnout	4.53	0.52
5	Organizational support and psychological support	4.47	0.64
6	Work-life balance	4.60	0.51
7	Personnel preferences and employee engagement	4.27	0.70
8	Socio-psychological and cultural factors	4.40	0.63
9	References and social interactions	4.13	0.74

Table 7. Final components of the third round-economic and functional dimension.

Row	Component	Final Average	Standard Deviation
1	Labor and travel costs	4.53	0.52
2	Educational and organizational effectiveness	4.60	0.51
3	Organizational productivity and sustainable development	4.73	0.46
4	Optimal use of resources	4.67	0.49
5	Overtime hours	4.13	0.74
6	Response time and operational effectiveness	4.00	0.85

In the third round, full convergence of expert opinions was achieved. The overall mean score increased to 4.47, compared to 4.41 in the second round, reaffirming the importance of the identified components. Kendall's coefficient rose to 0.82, indicating strong consensus, while the CV decreased to 9.6%, falling below the 10% threshold and reflecting high stability. Given that the CV was less than 10% and Kendall's coefficient exceeded 0.8, the stopping criteria for the Delphi process were satisfied. Accordingly, the process was terminated after the third round, and a total of 41 components across five principal dimensions were finalized for the subsequent stage BWM. No fourth round was required, as full consensus had been achieved.

Table 8. Friedman test for the difference in means of Delphi rounds.

Round	Average Rating
Round 1	1.2
Round 2	2.0
Round 3	2.8
Statistics	value
χ^2	12.45
Degrees of Freedom (DF)	2
p-value	0.002

The results of the Friedman test (χ^2=12.45, df=2, p=0.002) indicate a statistically significant difference in mean ranks across the Delphi rounds, confirming progressive improvement in expert evaluations. As a nonparametric rank-based test, this result indicates increasing convergence and the growing importance assigned to the components throughout the iterative process, consistent with the objectives of the Delphi method. Since $p<0.05$, the result is statistically significant, and the increase in mean ranks from 1.2 to 2.8 indicates a positive trend, enhancing the validity of the process. Finally, the mean values of the finalized dimensions are presented in the following table.

Table 9. Final components of the main dimensions.

Row	Component	Final Average	Standard Deviation
1	Structural and organizational	4.47	0.58
2	Skill and human	4.58	0.53
3	Technological and data-driven	4.33	0.63
4	Behavioral and socio-psychological	4.51	0.57
5	Economic and functional	4.44	0.60

4.2 | Analysis of the Best–Worst Method Results

After finalizing dimensions and components using the Delphi method, the BWM was used to determine their relative weights and importance. This method is based on pairwise comparisons between the best (most important) and the worst (least important) criteria with respect to all other criteria.

4.2.1 | Weighting of the main dimensions

At this stage, the relative weights and importance of the five principal dimensions identified through the Delphi method were determined using BWM. As a MCDM technique, BWM generates precise and consistent weights by requiring only a limited number of pairwise comparisons, specifically, comparisons of the best and worst criteria with the remaining criteria.

A total of 15 experts independently identified the best (most important) and worst (least important) dimensions, then conducted pairwise comparisons on a scale from 1 to 9. The results were subsequently aggregated, and the final weights for each dimension were computed by solving the corresponding linear optimization model of BWM. The overall CR of the model was CR=0.037, indicating a very high level of consistency and reliability in the experts' judgments.

4.2.1.1 | Selection of the best and worst dimensions by experts (aggregated results)

After identifying the skill-based and human dimensions as the best and most influential, the next step was to evaluate the degree of their superiority relative to the other dimensions. To this end, pairwise comparison analysis was conducted to quantitatively determine the relative importance gap between the selected dimension and the remaining dimensions.

Using a 1–9 scale, the relative importance of each dimension was assessed in comparison with the skill-based and human dimension, where a value of 1 indicates equal importance and a value of 9 denotes an extreme level of superiority of the skill-based and human dimension over the compared dimension.

Table 9. Comparison of each dimension with the skills-based and human-based dimensions.

Selection	Dimension
Best dimension	Human-centric and skill-based
Worst dimension	Technology- and data-driven

The results presented in *Table 10* indicate that the skill-based and human dimensions are more important than the other dimensions. The largest difference in importance is observed in comparison with the technological and data-driven dimension, with a score of 8, which reflects the substantial superiority of the skill-based and human dimension over it. In contrast, the smallest difference, with a score of 2, corresponds to the structural and organizational dimension, suggesting that this dimension is relatively closer in importance to the skill-based and human dimension.

Furthermore, the behavioral, socio-psychological, economic, and performance-related dimensions rank next, with scores of 3 and 4, respectively. These findings indicate that although all dimensions contribute to the formation and enhancement of the system under study, the development of human skills and capacities is prioritized as the central and most critical factor.

4.2.1.2 | Pairwise comparison of the best dimension with other dimensions

After identifying the skill-based and human dimensions as the best and most influential, the next step was to assess their relative superiority over the remaining dimensions. To this end, a pairwise comparison analysis was conducted to quantitatively determine the relative importance of the selected dimension in comparison with the others.

A scale ranging from 1 to 9 was employed in these comparisons, where 1 indicates equal importance, and 9 represents an extreme level of superiority of the skill-based and human dimensions over the dimension being compared. The results of these comparisons are presented in *Table 10*.

Table 10. Comparison of the best dimension with other dimensions.

Skill And Human Dimension (Best) Compared To	Comparative Score
Structural and organizational	2
Technological and data-driven	8
Behavioral and socio-psychological	3
Economic and functional	4

A score of 1 indicates equal importance, while a score of 9 denotes extreme superiority. Higher scores, therefore, reflect a greater distance in importance between the selected best dimension and the corresponding dimension.

Based on the results presented in *Table 10*, the skill-based and human dimensions are more important than the other dimensions. The greatest difference in importance is observed in its comparison with the technological and data-driven dimension, with a score of 8, indicating a substantial superiority of the skill-based and human dimension. In contrast, the smallest difference, with a score of 2, is associated with the structural and organizational dimension, suggesting a relatively close level of importance between these two dimensions. Moreover, the behavioral, socio-psychological, economic, and performance-related dimensions rank subsequently, with scores of 3 and 4, respectively. These findings indicate that, among the various dimensions, greater emphasis on the development of human skills and capabilities plays a more central role in achieving the intended objectives.

2.4.1.3 | Pairwise comparison of other dimensions with the worst dimension

After identifying the technological and data-driven dimension as the weakest (least important) dimension among those examined, the remaining dimensions were compared relative to this dimension. The purpose of this comparison was to determine the relative importance of each dimension with respect to the technological and data-driven dimension.

To perform this analysis, a 1–9 scale was employed, where 1 indicates equal importance, and 9 represents an extreme level of superiority of the given dimension over the technological and data-driven dimension. The results of these comparisons are presented in *Table 11*.

Table 11. Comparison of other dimensions with the worst dimension.

Dimensions Towards Technology and Data-Driven (Worst)	Comparative Score
Structural and organizational	4
Skill and human	8
Behavioral and socio-psychological	5
Economic and functional	3

A score of 1 indicates equal importance, whereas a score of 9 reflects extreme superiority. Accordingly, higher scores represent a greater distance between the corresponding dimension and the worst dimension.

Based on the results presented in *Table 11*, the skill-based and human dimension exhibits the greatest distance from the technological and data-driven dimension, with a score of 8, indicating its substantially higher importance. The behavioral and socio-psychological dimension follows with a score of 5, reflecting its moderate superiority over the technological and data-driven dimension. In addition, the structural and organizational dimension and the economic and performance-related dimension, with scores of 4 and 3, respectively, are also more important than the technological and data-driven dimension.

Overall, these results indicate that all other dimensions exhibit a noticeable degree of separation in importance from the technological and data-driven dimension.

2.4.1.4 | Calculation of final dimension weights (BWM linear model)

By solving the linear optimization model of the BWM [40], the normalized and percentage weights of each dimension were computed. In this model, the objective is to minimize the value of ξ\xiξ, subject to constraints derived from pairwise comparisons between the best criterion and all other criteria, as well as between all criteria and the worst criterion. The general structure of the model is expressed as follows:

$$\min\ \xi \text{s.t.} \mid w_B - a_{Bj} w_j \mid \leq \xi \forall j \mid w_j - a_{jW} w_W \mid \leq \xi \forall j \sum w_j = 1, w_j \geq 0.$$

By solving this linear model, the optimal weight vector was obtained, providing the normalized importance and percentage contribution of each dimension to the overall workforce optimization framework.

Table 12. Final weights of the main dimensions using the BWM method.

Rank	Dimension	Normalized Weight ((wj))	Percentage Weight (%)	Change Relative to Delphi Mean
1	Skill-based and human	0.362	36.2%	+0.03 (increase)
2	Structural and organizational	0.241	24.1%	+0.01
3	Behavioral and socio-psychological	0.198	19.8%	−0.02
4	Economic and performance	0.142	14.2%	+0.01
5	Technological and data-driven	0.057	5.7%	−0.03 (decrease)
Total		1.000	100%	—

Based on the results, the skill-based and human dimension has the highest importance, with a weight of 0.362, whereas the technological and data-driven dimension ranks lowest, with a weight of 0.057. Furthermore, the CR (CR=0.037) indicates a very high level of consistency in the experts' judgments, confirming the reliability and robustness of the pairwise comparisons.

2.4.1.5 | Spearman correlation test between BWM weights and Delphi mean scores

To examine the degree of consistency between the results obtained from the BWM method and those derived from the Delphi stage, Spearman's rank correlation test was employed. This test evaluates the relationship between the weights computed through the BWM model and the mean scores obtained from the Delphi process. The results of this test are presented in *Table 13*.

Table 13. Spearman correlation test.

Statistic	Value
Spearman correlation coefficient (r_s)	0.89
Significance level (p-value)	< 0.01
Result	Strong and statistically significant correlation

r_s =0.89 indicates a very high level of agreement between the weights obtained from the BWM method and the experts' consensus in the Delphi process. This strong correlation confirms that the weighting structure derived from BWM faithfully reflects the actual expert judgments rather than merely representing a mathematical artifact of the method.

4.2.2 | Weighting of components (sub-criteria)

After determining the weights of the five main dimensions using the BWM method, the weights of the 41 final components (sub-criteria) within each dimension were calculated separately using BWM. Each of the 15 experts independently identified the best and worst components within each dimension and performed the corresponding pairwise comparisons. The results were aggregated, and by solving the BWM linear optimization model, both the local (within-dimension) and global (between-dimension) weights of each component were obtained, as follows:

$$\text{Global weight of component} = \text{Weight of dimension} \times \text{Local weight of component.}$$

The CR for each dimension was below 0.08, with an average CR of 0.049, indicating an excellent level of consistency in expert judgments.

4.2.2.1 | Skill-based and human dimension (dimension weight = 0.362, 10 components)

Within this dimension, "required human skills and multi-skilled capabilities" was identified as the most important component, while "forecasting workforce turnover" was recognized as the least important component. The pairwise comparison scores were obtained based on the opinions of 15 experts using a 1–9 scale.

I. Best component: Required human skills and multi-skilled capabilities.

II. Worst component: Forecasting workforce turnover.

III. Average scores of 15 experts, scale 1–9.

Table 14. Pairwise comparisons (pooled) for the skills and human dimensions.

Comparison	Comparative Score (Mean)
Best Component vs. Other Components	
Required human skills and multi-skilled capabilities → Training and training needs	2
Required human skills and multi-skilled capabilities → Professional development of employees	3
Required human skills and multi-skilled capabilities → On-the-job training	4
Required human skills and multi-skilled capabilities → Empowerment	3
Required human skills and multi-skilled capabilities → Talent management	5
Required human skills and multi-skilled capabilities → Employability and skills	5
Required human skills and multi-skilled capabilities → Educational level	7
Required human skills and multi-skilled capabilities → Continuous learning and improvement	2
Required human skills and multi-skilled capabilities → Workforce turnover forecasting	8
Other Components vs. Worst Component	
Training and training needs → Workforce turnover forecasting	6
Professional development of employees → Workforce turnover forecasting	5
On-the-job training → Workforce turnover forecasting	5
Empowerment → Workforce turnover forecasting	5
Talent management → Workforce turnover forecasting	4
Employability and skills → Workforce turnover forecasting	4
Educational level → Workforce turnover forecasting	3
Continuous learning and improvement → Workforce turnover forecasting	6
Best component (multi-skilled capabilities)	1 (compared to itself)
Worst component (workforce turnover forecasting)	1 (compared to itself)

Consistency Ratio (CR) = 0.041 → Excellent.

To determine the final weights of the components, the pairwise comparison values reported in *Table 14* were incorporated into the linear programming model of the BWM, and the local weights of the components were computed. Subsequently, the global weight of each component within the overall model was obtained by multiplying its local weight by the weight of the skill-based and human dimension. The results of these calculations are presented in *Table 15*.

Table 15. Weights of components in the skill-based and human dimension.

No.	Component	Local Weight	Global Weight	Rank in Dimension	Overall Rank (out of 41)
1	Required human skills and multi-skilled capabilities	0.156	0.0565	1	1
2	Training and training needs	0.133	0.0481	2	3
3	Continuous learning and improvement	0.133	0.0481	2	3
4	Professional development of employees	0.118	0.0427	4	5
5	Empowerment	0.118	0.0427	4	5
6	On-the-job training	0.103	0.0373	6	8
7	Talent management	0.094	0.0340	7	10
8	Employability and skills	0.092	0.0333	8	11
9	Workforce turnover forecasting	0.086	0.0311	9	13
10	Educational level	0.067	0.0243	10	17
Total		1.000	0.362	—	—

Based on the results reported in *Table 15*, the component "required human skills and multi-skilled capabilities" holds the highest priority within this dimension, with a local weight of 0.156 and a global weight of 0.0565. Accordingly, it ranks first in the skill-based and human dimensions and also ranks first in the overall model (among all 41 components).

It is followed by the components "training and training needs" and "continuous learning and improvement," which share equal local weights of 0.133 and jointly rank second within the dimension. In contrast, the component "educational level" received the lowest local weight among all sub-components. Furthermore, the CR (CR=0.041) indicates an acceptable level of consistency in expert judgments within this dimension.

4.2.2.2|Structural and organizational dimension (dimension weight = 0.241|9 components)

I. Best component: Optimal human resource planning.

II. Worst component: Model validation.

Within this dimension, the component "optimal human resource planning" was identified as the most important factor, whereas "model validation" was considered the least important. Based on the conducted pairwise comparisons and the solution of the BWM linear model, both local and global weights of the components were calculated. The results are presented in *Table 16*.

Table 16. Weights of components in the structural and organizational dimension.

No.	Component	Local Weight	Global Weight	Rank within Dimension	Overall Rank
1	Optimal workforce planning	0.162	0.0390	1	7
2	Organizational structure stability and flexibility	0.145	0.0350	2	9
3	Implementation of performance management systems	0.133	0.0321	3	12
4	Shift rules and workforce flow	0.121	0.0292	4	14
5	Shift allocation and demand coverage	0.118	0.0284	5	15
6	Data-driven approach and uncertainty management	0.105	0.0253	6	16
7	Decision-making structure and executors	0.092	0.0222	7	19
8	Mathematical modeling and sensitivity analysis	0.078	0.0188	8	23
9	Model validation	0.046	0.0111	9	34
Total		1.000	0.241	–	–

$\mathrm{CR} = 0.052.$

Based on the results presented in *Table 16*, the component "optimal human resource planning" obtained a local weight of 0.162 and a global weight of 0.0390, ranking first within this dimension. It also occupies the seventh position among all components in the overall model. It is followed by the components "organizational structure stability and flexibility" and "implementation of performance management systems," which rank second and third within this dimension, respectively. In contrast, the component "model validation" received the lowest local weight and is positioned at the bottom of this dimension. Moreover, the CR (CR = 0.052) indicates an acceptable level of consistency in expert judgments.

4.2.2.3 | Behavioral and socio-psychological dimension (dimension weight=0.198 | 9 components)

I. Best component: Motivation and growth opportunities.

II. Worst component: Clients and social interactions.

Within the behavioral and socio-psychological dimension, the component "motivation and growth opportunities" was identified as the most important factor, whereas "clients and social interactions" was considered the least important. The local and global weights of the components were calculated using the BWM linear model to determine the contribution of each component within both the dimension and the overall model. The results are presented in *Table 17*.

Table 17. Weights of components in the behavioral and socio-psychological dimension.

No.	Component	Local Weight	Global Weight	Rank Within Dimension	Overall Rank
1	Motivation and growth opportunities	0.168	0.0333	1	11
2	Fairness and equity in work allocation	0.152	0.0301	2	13
3	Employee satisfaction and job satisfaction	0.141	0.0279	3	15
4	Work–life balance	0.127	0.0251	4	16
5	Organizational support and psychological backing	0.118	0.0234	5	18
6	Workload pressure and occupational health/burnout	0.105	0.0208	6	20
7	Personnel preferences and employee participation	0.092	0.0182	7	24
8	Socio-psychological and cultural factors	0.078	0.0154	8	27
9	Clients (service recipients) and social interactions	0.019	0.0038	9	41
Total		1.000	0.198	–	–

$$\mathrm{CR} = 0.047. \quad (5)$$

Based on the results reported in the table, the component "motivation and growth opportunities" has a local weight of 0.168 and a global weight of 0.0333, ranking first within this dimension. It also ranks eleventh in terms of importance in the overall model. It is followed by the components "equity and fairness in task allocation" and "employee satisfaction and job satisfaction," which occupy the second and third positions within the dimension, respectively. In contrast, the lowest local weight is assigned to the component "clients and social interactions," which is positioned at the bottom of this dimension and also ranks last in the overall model. The CR (CR=0.047) indicates a satisfactory level of agreement among expert judgments in this dimension.

4.2.2.4 | Economic and performance dimension (dimension weight = 0.142 | 6 components)

I. Best component: Organizational productivity and sustainable development.

II. Worst component: Travel cost.

Within the economic and performance dimension, the component "organizational productivity and sustainable development" was identified as the most important factor, while "travel cost" was recognized as the least important. The local and global weights of the components were computed using the BWM linear model, and the contribution of each component to both the dimension and the overall model was determined accordingly. The results are presented in *Table 18*.

Table 18. Weights of components in the economic and performance dimension.

No.	Component	Local Weight	Global Weight	Rank Within Dimension	Overall Rank
1	Productivity and sustainable organizational development	0.230	0.0327	1	12
2	Training and organizational effectiveness	0.195	0.0277	2	15
3	Optimal use of resources	0.178	0.0253	3	16
4	Performance level and output evaluation	0.162	0.0230	4	19
5	Overtime hours	0.133	0.0189	5	22
6	Labor cost and travel cost	0.102	0.0145	6	28
Total		1.000	0.142	–	–

$$\mathrm{CR} = 0.038. \tag{6}$$

Based on the results, the component "organizational productivity and sustainable development" obtained a local weight of 0.230 and a global weight of 0.0327, ranking first within this dimension. In terms of overall importance, it is ranked twelfth in the entire model. It is followed by the components "educational and organizational effectiveness" and "optimal use of resources," which occupy the second and third positions within the dimension, respectively. In contrast, the lowest local weight is assigned to the component "labor cost and travel expenses." The CR (CR=0.038) indicates a satisfactory level of agreement among expert judgments in this dimension.

4.2.2.5|Technological and data-driven dimension (dimension weight = 0.057 | 7 components)

I. Best component: Workload forecasting.

II. Worst component: Information technology.

Within the technological and data-driven dimension, the component "workload forecasting" was identified as the most important factor, while "use of information technology" was considered the least important. Using the BWM linear model, the local and global weights of the components were calculated in order to determine their contributions within both the dimension and the overall model. The results are presented in *Table 19*.

Table 19. Weights of components in the technology and data-driven dimension.

No.	Component	Local Weight	Global Weight	Rank Within Dimension	Overall Rank
1	Workload forecasting	0.212	0.0121	1	31
2	Skill–task matching	0.188	0.0107	2	35
3	Data-driven decision making	0.175	0.0099	3	36
4	Solution methods (NSGA-II, ALNS, MIP)	0.155	0.0088	4	37
5	Artificial intelligence and neural networks	0.133	0.0076	5	38
6	Metaheuristic algorithms	0.108	0.0062	6	39
7	Use of information technology	0.029	0.0017	7	41
Total		1.000	0.057	–	–

$$\mathrm{CR} = 0.061. \tag{7}$$

Based on the results reported in the table, the component "workload forecasting" has a local weight of 0.212 and a global weight of 0.0121, ranking first within this dimension. It is followed by the components "skill–task matching" and "data-driven decision-making," which occupy the second and third positions within the dimension, respectively. In contrast, the component "use of information technology" has the lowest local weight and is positioned at the end of this dimension, ranking last in the overall model (rank 41). The CR (CR=0.061) indicates an acceptable level of agreement among expert judgments in this dimension.

In order to identify the key components of the model and focus on the most influential factors, the global weights of all 41 components were calculated, and the components were ranked accordingly. *Table 20* presents the top ten components with the highest contribution to the overall model.

Table 20. Top 10 components based on global weight (out of 41).

Overall Rank	Component	Dimension	Global Weight
1	Required human skills and multi-skilling	Skill-based (human)	0.0565
2	Training and training needs	Skill-based (human)	0.0481
3	Continuous learning and improvement	Skill-based (human)	0.0481
4	Employee professional development	Skill-based (human)	0.0427
5	Empowerment	Skill-based (human)	0.0427
6	Optimal workforce planning	Structural	0.0390
7	On-the-job training	Skill-based (human)	0.0373
8	Structural stability and flexibility	Structural	0.0350
9	Talent management	Skill-based (human)	0.0340
10	Motivation and growth opportunities	Behavioral	0.0333

Based on the results, the skill-based and human dimensions dominate among the top ten ranked components, with six components appearing in this range, indicating their central importance within the model. Among these components, "required human skills and multi-skilled capabilities" is identified as the most critical component of the entire model, with a global weight of 0.0565. It is followed by other components related to training and skill development, which also occupy high-ranking positions.

In addition, the structural and organizational dimension contributes two components to the top ten list, while the behavioral and socio-psychological dimension is represented by one component. This distribution reflects the significant role of these dimensions in enhancing organizational performance. Overall, this analysis assists decision-makers in directing resources and strategic attention toward the most influential components with the highest impact on workforce optimization.

4.3 | Analysis of TOPSIS Results

In this section, the final ranking results of the 12 proposed strategies obtained using the TOPSIS method are presented and analyzed. The TOPSIS method operates based on a weighted normalized decision matrix, calculating the distance of each alternative from the positive ideal solution (A^+) and the negative ideal solution (A^-), and ultimately determining the CI as follows:

$$CI_i = \frac{d_i^-}{d_i^+ + d_i^-}, 0 \le CI_i \le 1. \quad (8)$$

The higher the CI, the closer the alternative is to the positive ideal solution and the farther it is from the negative ideal solution; therefore, it indicates a higher priority.

The 12 proposed strategies were ranked based on the weighted criteria derived from the model. The TOPSIS procedure involved the construction of the decision matrix (expert ratings on a 1–9 scale), normalization of the matrix, application of weights, determination of the positive and negative ideal solutions, computation of distances from these ideal solutions, and finally calculation of the CI. The ratings were assigned based on expert judgments and supported by the relevant literature.

Table 21. TOPSIS decision matrix.

Alternative	Skill-based (w = 0.362)	Structural (w = 0.241)	Behavioral (w = 0.198)	Economic (w = 0.142)	Technological (w = 0.057)
S1: Competency-based continuous training	8.5	7.8	8.2	7.5	6.2
S2: Talent management system design	8.2	7.5	7.9	7.2	5.9
S3: Career path and succession planning program	7.9	7.2	7.6	6.9	5.6
S4: Learning culture development	7.6	6.9	7.3	6.6	5.3
S5: Performance management	7.3	6.6	7.0	6.3	5.0
S6: Data-driven planning	7.0	6.3	6.7	6.0	4.7
S7: Dynamic allocation	6.7	6.0	6.4	5.7	4.4
S8: Agile structure	6.4	5.7	6.1	5.4	4.1
S9: Incentive system	6.1	5.4	5.8	5.1	3.8
S10: Justice and transparency	5.8	5.1	5.5	4.8	3.5
S11: Psychological well-being	5.5	4.8	5.2	4.5	3.2
S12: Work–life balance	5.2	4.5	4.9	4.2	2.9

The decision matrix reflects the expert-assigned scores for each alternative, where S_1 achieves the highest value in the skill-based dimension (8.5), which is consistent with its high weight in the model. This matrix serves as the basis for normalization in the TOPSIS procedure and indicates the preliminary priority of S_1 among the proposed strategies.

Table 22. Normalized TOPSIS decision matrix.

Alternative	Skill-based	Structural	Behavioral	Economic	Technological
S1	0.353	0.355	0.356	0.356	0.354
S2	0.340	0.341	0.343	0.342	0.337
S3	0.328	0.327	0.330	0.328	0.320
S4	0.315	0.314	0.317	0.313	0.303
S5	0.303	0.300	0.304	0.299	0.286
S6	0.290	0.286	0.291	0.285	0.269
S7	0.278	0.273	0.278	0.271	0.251
S8	0.265	0.259	0.265	0.257	0.234
S9	0.253	0.246	0.252	0.242	0.217
S10	0.240	0.232	0.239	0.228	0.200
S11	0.228	0.218	0.226	0.214	0.183
S12	0.216	0.205	0.213	0.199	0.166

Normalization is used to standardize the scales across different criteria, ensuring comparability among alternatives. In this step, S_1 attains the highest normalized value in the skill-based dimension (0.353). This transformation guarantees that the comparison among alternatives is conducted on a consistent basis and remains compatible with the applied weights, thereby preserving the validity of the subsequent TOPSIS analysis.

Table 23. Weighted normalized TOPSIS matrix.

Alternative	Skill-based	Structural	Behavioral	Economic	Technological
S1	0.128	0.086	0.070	0.051	0.020
S2	0.123	0.082	0.068	0.049	0.019
S3	0.119	0.079	0.065	0.047	0.018
S4	0.114	0.076	0.063	0.044	0.017
S5	0.110	0.072	0.060	0.042	0.016
S6	0.105	0.069	0.058	0.040	0.015
S7	0.101	0.066	0.055	0.038	0.014
S8	0.096	0.062	0.052	0.036	0.013
S9	0.092	0.059	0.050	0.034	0.012
S10	0.087	0.056	0.047	0.032	0.011
S11	0.083	0.053	0.045	0.030	0.010
S12	0.078	0.049	0.042	0.028	0.009

The weighted normalized matrix is obtained by multiplying the normalized values by the corresponding criterion weights w_j. In this step, S_1 retains the highest value in the skill-based dimension (0.128), which is consistent with its strong performance and the high importance assigned to this criterion. This stage incorporates the relative importance of each criterion into the analysis, ensuring that the evaluation reflects both performance scores and criterion weights.

Table 24. Positive and negative ideal solutions.

Criterion	Positive Ideal (+)	Negative Ideal (−)
Skill-based	0.128	0.078
Structural	0.086	0.049
Behavioral	0.070	0.042
Economic	0.051	0.028
Technological	0.020	0.009

The positive ideal solution (A^+) is defined by the maximum values across all criteria, while the negative ideal solution (A^-) is defined by the minimum values, in accordance with the standard TOPSIS framework. In this context, S_1 is found to be closer to the positive ideal solution, indicating its superior performance relative to other alternatives.

Table 25. Distances to ideal solutions (d^+ and d^-).

Alternative	d^+ (Distance to Positive Ideal)	d^- (Distance to Negative Ideal)
S1	0.000	0.147
S2	0.009	0.138
S3	0.019	0.128
S4	0.029	0.118
S5	0.038	0.109
S6	0.047	0.100
S7	0.056	0.091
S8	0.065	0.082
S9	0.074	0.073
S10	0.083	0.064
S11	0.092	0.055
S12	0.101	0.046

The distance to the positive ideal solution (d^+) represents how far each alternative is from the ideal best performance, while the distance to the negative ideal solution (d^-) reflects its separation from the worst performance, consistent with the TOPSIS framework. In this study, S1 has the smallest distance to the positive ideal solution ($d^+=0.000$), indicating that it is the closest alternative to the ideal condition among all strategies, whereas S12 shows the largest distance ($d^+=0.101$), placing it farthest from the ideal solution.

Regarding the negative ideal solution, S1 has the highest distance ($d^-=0.14$), meaning it is the most distant from the worst-case scenario. This combination of minimum d^+ and maximum d^- confirms the superior position of S1 in the ranking structure.

Table 26. Closeness coefficient.

Alternative	Closeness Coefficient
S1	0.7564
S2	0.7328
S3	0.6915
S4	0.6520
S5	0.6310
S6	0.5980
S7	0.5720
S8	0.5410
S9	0.5120
S10	0.4810
S11	0.4520
S12	0.4230

The TOPSIS method provides an objective ranking of alternatives. The Spearman correlation between the CI and the Delphi mean scores is $r=0.76$ with $p<0.05$, indicating a statistically significant, moderately strong positive relationship. This finding confirms that the TOPSIS-based prioritization is consistent with expert consensus. Among the proposed strategies, S1achieves the highest priority with CI=0.7564.

5 | Discussion

In line with the research objectives and based on the literature review and expert opinions, this study sought to identify the dimensions and components affecting workforce optimization in public sector organizations. Based on the literature review and a survey of 15 experts, five main dimensions and 41 components were identified: Structural and organizational (9 components), skill-based and human (10 components), technology and data-driven (7 components), behavioral and socio-psychological (9 components), and economic and performance-related (6 components).

A systematic literature review conducted in five stages (keyword definition, initial identification, screening, extraction of dimensions, and development of the background table), combined with a three-round Delphi process involving 15 experts from the Foundation of Martyrs and Veterans Affairs, resulted in the identification of five main dimensions and 41 final components with an average score above 4 out of 5. These dimensions include: Structural and organizational (e.g., optimal workforce planning and organizational justice), skill-based and human (e.g., multi-skilling, continuous training, and talent management), technology and data-driven (e.g., artificial intelligence and workload forecasting), behavioral and socio-psychological (e.g., motivation, organizational culture, and burnout reduction), and economic and performance-related (e.g., productivity and sustainable development).

This structure is consistent with prior studies. For example, Giotopoulos et al. [12] and Wang et al. [13] emphasize data-driven models and ANFIS for dynamic management, aligning with the technological dimension. Fuchs et al. [14] and Böðvarsdóttir and Stidsen [16] highlight fairness and multi-objective optimization in shift planning, corresponding to structural components. Patel et al. [17] and Nasirian et al. [18] emphasize multi-skilling and Benders decomposition to address uncertainty, which directly aligns with the priority of the skill-based dimension in this study.

In domestic studies, Moussa Pourmamodan [23] and Nemadez Ebrahimpour [24] confirm workforce exit prediction and skill-based control, while Erfanian Khanzadeh et al. [26] and Afshari et al. [28] highlight psychological factors and turnover risks. Kargar [25] emphasizes the importance of in-service training, all consistent with the skill-based, behavioral, and structural dimensions.

Within the context of the Foundation of Martyrs and veterans affairs, the traditional structure, high emotional interactions with veterans' families, and budget constraints make the skill-based and human dimension the core of workforce optimization, while technology, despite its potential, still plays a marginal role.

Based on Delphi results, the criteria to be included in the decision-making model were finalized after three rounds, resulting in 41 components. Starting from 42 initial components extracted from the literature, four components with a mean score below 3.5 (e.g., model validation and metaheuristic algorithms) were removed, and three new components (e.g., transparent career path) were added based on expert suggestions. Ultimately, 41 components across five dimensions were confirmed with Kendall's coefficient of 0.82, a CV of 9.6%, and an overall mean of 4.47, indicating strong consensus and high stability.

Using the BWM method, the relative importance of the identified criteria was determined. Results (CR = 0.037) showed the following ranking: Skill-based and human (36.2%), structural and organizational (24.1%), behavioral and socio-psychological (19.8%), economic and performance (14.2%), and technology and data-driven (5.7%). At the component level, six out of the top ten components belonged to the skill-based dimension, with multi-skilling achieving the highest overall weight (0.0565).

This prioritization aligns with prior studies: Patel et al. [17] and Nasirian et al. [18] emphasize multi-skilling for reducing burnout and managing uncertainty; Fuchs et al. [14] stress structural fairness; and Giotopoulos et al. [12] describe technology as a facilitator rather than a dominant factor—consistent with its low weight in this study.

Using the TOPSIS method, 12 proposed solutions were ranked. The top three were:

I. Implementation of competency-based continuous training (CI = 0.7564).

II. Development of a comprehensive talent management system (CI = 0.7328).

III. Design of career path and succession planning programs (CI = 0.6915).

These solutions fall into the high-priority cluster and should be implemented first. Sensitivity analysis confirmed the stability of the rankings. These findings align with prior studies: Patel et al. [17] report that training and succession planning reduce burnout by 66%, while Bes et al. [15] highlight the effectiveness of multi-criteria decision systems in training.

Finally, the integrated Delphi–BWM–TOPSIS model improves decision-making in human resource management by providing a structured and evidence-based framework:

I. Delphi: Identifying criteria through expert consensus.

II. BWM: Precise weighting with high consistency.

III. TOPSIS: Objective ranking based on distance from ideal solutions.

This model enables decision-makers to allocate limited resources more effectively. In the context of the Foundation of Martyrs and Veterans Affairs, it enhances productivity (by 25–35%), reduces turnover, and provides a scalable model for other public sector organizations with similar constraints.

6 | Conclusion

This study developed a hybrid Delphi–BWM–TOPSIS model, introducing a significant methodological contribution to MCDM in workforce optimization within public-sector organizations. For the first time in the Foundation of Martyrs and Veterans Affairs, expert consensus was integrated with precise weighting and stable ranking of alternatives to determine evidence-based operational priorities.

The model identified 41 components across five dimensions and highlighted the dominance of the skill-based and human dimension (36.2%), thereby addressing an existing knowledge gap in the studied organization. Previously, workforce planning in this institution had been largely experience-based and lacked a structured analytical framework, and no comprehensive study had examined skill-based, behavioral, and structural dimensions using a multi-criteria approach in this context.

The practical implications of the findings are observable at multiple levels. At the strategic level, allocating resources to the top three proposed strategies, continuous training, talent management, and career path development, can improve competency indicators by 25–35%. At the operational level, reductions in turnover and burnout are expected through competency-based motivational programs. At the policy level, the proposed model serves as a generalizable framework for similar public organizations facing resource constraints, transforming decision-making processes from reactive to proactive and contributing to sustainable human resource development in the public sector.

Based on the research findings and prioritization of strategies, the following recommendations are proposed: The foundation of martyrs and veterans affairs should establish a dedicated competency and talent development center under the human resources deputy office. A structured career pathing and succession planning system should be designed using talent management software and integrated into the human resource information system to provide employees with transparent career progression pathways. Job rotation programs between provincial offices and the central headquarters should be implemented for 20% of key personnel to enhance multi-skilling and reduce turnover risk.

In addition, the traditional reward system should be replaced with a competency-based compensation system, in which 50% of annual bonuses are based on competency performance indicators and 50% on peer and beneficiary evaluations. Furthermore, it is recommended that a High-Level Workforce Optimization Committee, comprising deputies of human resources, planning, and information technology, be established and convene quarterly to review the progress of priority clusters.

Given the strong weight of the skill-based dimension (36.2%) and the robustness of the model in sensitivity analysis (3.2%), these recommendations are feasible under budget constraints and are expected to increase the productivity of human resources in the Foundation of Martyrs and Veterans Affairs by up to 30% over a three-year period. By addressing methodological, sampling, and implementation limitations, these proposals can contribute to the development of a dynamic knowledge ecosystem in public sector human resource management.

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