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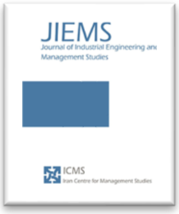

Prioritizing Sales Competencies Using the Best–Worst Method: Evidence from Firms in the Isfahan Science and Technology Town

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Abstract

Performance appraisal of sales teams plays a critical role in organizational effectiveness; however, many existing appraisal systems suffer from subjectivity, inappropriate weighting of indicators, and a lack of role-specific competency prioritization. In particular, limited empirical research has applied structured multi-criteria decision-making approaches to prioritize sales competencies across different organizational levels. To address this gap, this study develops a competency-based performance appraisal framework and empirically prioritizes sales competencies for managers and sales experts in commercial firms located in the Isfahan Science and Technology Town using the Best–Worst Method (BWM). Based on an extensive literature review and expert consultations, performance indicators were identified across four competency dimensions: technical, behavioral, core, and managerial. Expert judgments were collected from twelve experienced sales professionals through pairwise comparison questionnaires, and the BWM was employed to derive indicator weights, while the geometric mean was used to aggregate expert opinions and ensure consistency. The results reveal clear role-specific differences in competency priorities, with managerial competencies emerging as the most critical dimension for supervisors, whereas technical competencies were assigned the highest importance for sales experts, highlighting the need for differentiated performance expectations across hierarchical roles. This study contributes to the human resource management literature by providing a quantitative, role-specific, and replicable framework for competency-based sales performance appraisal and offers practical guidance for designing fair appraisal systems, aligning training and development programs with weighted competencies, and supporting data-driven human resource decisions to enhance employee performance and organizational effectiveness.

Keywords: Performance Appraisal, Competency, BWM, Human Resource Management, Employee Assessment

Paper Type: Original Research

1. Introduction

Employee performance appraisal, as one of the key tools of human resource management, plays a crucial role in enhancing productivity and organizational effectiveness. In recent years, the competency-based approach to performance evaluation has attracted considerable attention, as it provides a more comprehensive and realistic picture of individual and team performance by focusing on employees' capabilities, behaviors, and skills (Pulakos et al., 2015). In contrast, traditional performance evaluation systems, which primarily rely on historical criteria such as work experience, educational background, and general qualitative scores, suffer from structural shortcomings (Murphy et al., 2018). These limitations not only undermine the validity and reliability of evaluation results but may also lead to organizational injustice, reduced employee motivation, and the misallocation of human resources (Aguinis, 2023). The theoretical foundations of the competency-based approach can be traced back to the research of David McClelland (1973), who, in his seminal work, criticized conventional assessment criteria. He argued that factors such as intelligence quotient and academic scores were weak predictors of job success and instead introduced "competency" as a set of underlying characteristics—including motives, personality traits, skills, and knowledge—that determine successful performance in a specific job role (McClelland, 1973). To operationalize this concept, Gary Hammel and colleagues (1990) proposed the four-dimensional competency framework. Accordingly, both organizational and individual competencies are categorized into four main domains: technical competencies, referring to knowledge and technical skills specific to a given field; behavioral competencies, encompassing attitudes, personality traits, and individual motives; core competencies, representing fundamental organizational values and culture; and managerial competencies, related to leadership, decision-making, and resource management abilities. This framework serves as a comprehensive model for identifying, categorizing, and evaluating the competencies required across various job roles (Hamel & Prahalad, 1990). Performance appraisal systems usually consist of multiple indicators that must be integrated to produce a comprehensive evaluation (Kibira et al.,

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2017). One of the main challenges in the appraisal process is determining appropriate weights for these indicators. Improper weighting not only jeopardizes the validity and reliability of the evaluation system but also reduces its overall credibility (Mohammed et al., 2021). In this regard, multi-criteria decision-making (MCDM) methods provide a scientific and systematic approach, enabling the determination of indicator weights based on expert judgment and empirical data (Yılmaz & Harmancioğlu, 2010). Among various MCDM techniques, the Best-Worst Method (BWM), introduced by Rezaei in 2015 (Rezaei, 2015), has gained prominence due to its ease of implementation, reduced number of required comparisons, and more consistent results compared with methods such as AHP (Yildirim & Şişman, 2025). This method is based on selecting the best and worst criteria and comparing other criteria with them, ultimately producing the optimal weights of indicators (Ganguly et al., 2025). Commercial firms operating within the Isfahan Science and Technology Town, particularly those engaged in the distribution of chemical, agricultural, textile, and pharmaceutical products, require systematic and competency-based frameworks for evaluating sales performance. This study identifies key performance indicators across four competency dimensions—technical, behavioral, core, and managerial—and determines their relative importance using the Best–Worst Method (BWM). Expert evaluations were collected, the data were processed in a Python environment, and aggregated mean weights were reported as the final criteria. The results of this research not only enhance the performance appraisal process for sales teams within these firms but also offer a practical framework for other organizations seeking to implement competency-based evaluation models.

2. Literature Review

Albino (2018), in their study on Petrang Company in Angola, examined the key competencies required in employee performance evaluation. Using interviews and questionnaires with organizational leaders, the findings revealed that the main competencies included collaboration, organization, task delivery, and complexity. Quantitative analysis indicated that 75% of the emphasized competencies were behavioral, while only 25% were technical. This important conclusion highlights those behavioral competencies play a more significant role than technical skills in achieving career success in this company, emphasizing the need for managers to give special consideration to these aspects in their planning. Heydarpour et al. (2022) developed a hybrid AHP–DEA framework to evaluate and rank contractors' performance in an industrial project at Zarand Iranian Steel Company. In their model, contractor evaluation criteria were identified from the literature and weighted using AHP based on expert judgments, and the resulting weights were incorporated into an input-oriented CCR DEA model to assess the efficiency of 20 contractors. The findings showed that nearly half of the contractors were fully efficient, while the others exhibited performance gaps, emphasizing the usefulness of the proposed hybrid approach in enhancing objectivity, identifying benchmark contractors, and supporting managerial decision-making in contractor selection and performance improvement. Ayough et al. (2022) developed an interactive multi-criteria decision-making approach for solar power plant site selection by integrating Interactive Simple Additive Weighting (ISAW) with PROMETHEE-based preference functions. The proposed method enhances transparency and decision-maker involvement by iteratively refining alternative rankings through interaction, rather than relying on predefined preferences. A real-world case study and comparisons with established MCDM methods confirmed the effectiveness and flexibility of the approach in addressing complex renewable energy location problems. Ayough et al. (2023) introduced an integrated multi-criteria decision-making approach for supplier selection by combining the Base Criterion (BC) and Utility Additive (UA) methods. The proposed BCUA model simultaneously determines criteria weights and alternative rankings, reducing pairwise comparisons while enhancing consistency. Formulated as a nonlinear programming model and validated through a real-world case study in the electronics industry, the approach demonstrated robust and reliable results. Comparative and sensitivity analyses against established MCDM methods, including FUCOM, OPA, LBWA, and DIBR, confirmed the stability and effectiveness of the proposed method for complex decision-making problems. Baghbani et al. (2023), in an analytical study, identified, weighted, and examined the correlations of employee performance evaluation indicators in assembly lines of a manufacturing company. Initially, after consulting with managers and specialists, 12 final indicators were selected for performance assessment. Then, using the modified Analytical Hierarchy Process (AHP), the weight of each indicator was determined by 10 experts. The results of a three-month employee performance evaluation revealed significant positive and negative correlations among certain indicators. By scientifically weighting the indicators and analyzing their interrelationships, this research contributed to a deeper understanding of performance evaluation in human resource management. Ergülen and Çalık (2024) researched the impacts of the COVID-19 pandemic on the performance of the top 500 industrial companies of Turkey using a hybrid MCDM approach. F-BWM was utilized to define the importance of indicators, while the ranking of company performance was performed by applying the MARCOS method. It was obtained that the pandemic significantly affected the performance of the companies and some of them faced revenue declines, while the others managed to maintain or increase their revenues, and even a change in rank was observed regarding the first two companies. This research, despite a number of drawbacks, such as sample size and time frame, is valuable because it gives practical insights for decision-makers in investment, recruitment, and operations, and introduces a new MCDM-based framework for crisis condition analysis for improving managerial decisions. Adu Sarfo et al. (2024), based on the AMO (Ability–Motivation–Opportunity) framework, examined the effects of GHRM on the environmental performance of small and medium-sized enterprises in Ghana, using Green Employee Empowerment as a mediating variable. Using data from 320 firms and analyzing it through the method of structural equation modeling, it emerged that GHRM has a significant effect on environmental performance, an effect that is mediated through GEE. These results underline that employees' empowerment is crucial to enhance green commitment and behaviors, acting as a key mechanism in the transmission of green HRM policy effects toward improved environmental performance. Although limited to testing only one mediator, this study offers several insights for the development of managerial strategies that pursue organizational sustainability and green growth. Barasin et al. (2024) proposed a novel MCDM-based retail warehouse evaluation framework for western Saudi Arabia. This framework incorporated the G-BWM to weight criteria and RATMI to rank warehouses. Based on key criteria such as cost, quality, and productivity, four warehouses were evaluated. The strengths and weaknesses of each warehouse were identified, and practical recommendations were given to make strategic decisions. With this structured and comprehensive methodology, the paper helps managers enhance operational efficiency in logistics management and paves the way for future studies in this area. Otoo (2024) examines whether employee performance is a mediator in the relationship between HRM practices and organizational effectiveness in a police force setting. The findings from 800 police officers showed that among these practices, only career planning was positively related to employee performance, but not self-managed teams and performance management. Furthermore, employee performance was found to have a significant effect on organizational effectiveness and to be a mediator. The findings of this study indicate that police force managers need to improve their skills and motivation through effective HRM practices of career planning in order to be more effective. Nayebpour and Sehhat (2024), employed a mixed-methods approach based on paradox theory to design a competency framework for HR managers in the information and communication technology (ICT) sector. The framework, designed using thematic analysis, fuzzy Delphi, and the perspectives of 11 experts, consisted of three levels: managerial, organizational, and individual, and 15 dimensions. The important dimensions were paradoxical thinking and ICT literacy. The authors recommended that HR managers in this sector pursue technical and engineering education at the undergraduate level and HRM education at the graduate level. The unique aspect of this research is that it is paradox-based, which helps in conflict management in a sector that is complex and constantly changing. Ghedabna et al. (2024), through a literature review and qualitative analysis, examined the role of artificial intelligence (AI) in transforming human resource management. Their study highlighted how AI reshapes processes such as recruitment, performance appraisal, and employee development. By analyzing large datasets, AI reduces human bias in decision-making and enhances efficiency. Additionally, it enables real-time feedback, predictive performance trend analysis, and personalized learning pathways, which contribute to employee professional growth and the strengthening of organizational human capital. Despite these advantages, the study also identified challenges such as privacy concerns and algorithmic bias. Ultimately, the findings emphasize that integrating AI into HRM not only improves efficiency but also fosters innovation and organizational competitiveness. Latif and Wahyuning (2024) conducted a study aimed at selecting the best raw material supplier for PT. Sinergi Gula Nusantara uses the Analytic Hierarchy Process (AHP) and Expert Choice 11 software. Evaluation criteria included quality, price, supply volume, and agricultural land size. AHP analysis revealed that quality, with a weight of 0.565, was the most important decision-making factor, followed by price, supply volume, and land size. Among the five suppliers assessed, Farmer No. 5 was identified as the best supplier with a weight of 0.293. This study provides a structured framework that assists managers in improving their supply chains, with AHP offering transparency, precision, and data-driven decision-making. Hazrati et al. (2024), through a qualitative study based on grounded theory, proposed a model for organizational performance evaluation in higher education with a focus on creativity and innovation. Semi-structured interviews were conducted with 12 faculty members, and the data were analyzed using thematic analysis in MAXQDA software. The results identified a comprehensive model encompassing six categories: causal conditions, contextual conditions, core phenomena, intervening factors, strategies, and outcomes. The model highlights the role of factors such as HR encouragement and a learning culture in enhancing performance and demonstrates that this approach can lead to improved university rankings, higher productivity, and greater responsiveness to societal needs. By filling a gap in academic performance evaluation models, this study provides a valuable tool for managers aiming to strengthen competitive advantage and organizational development in dynamic higher education environments. Khaleghi Forghani et al. (2024) developed a framework for assessing corporate accelerators. The framework was developed using the Balanced Scorecard method. A systematic literature review and semi-structured interviews with 12 experts were conducted. The data was analyzed using thematic analysis. The framework includes four dimensions: innovation and technology performance, startup satisfaction, internal processes of the accelerator, and learning and growth. The framework allows for a more comprehensive assessment of corporate accelerators than the current financial focus. Mehmankhah et al. (2024) developed a hybrid approach to design an assessment tool for performance evaluation in assessment centers using cognitive dimensions. Applying meta-synthesis to 50 selected articles out of 608, and validating through fuzzy Delphi, the researchers designed a localized model comprising six dimensions, 20 components, and 115 indicators. These dimensions emphasized cognitive constructs such as decision-making, cognitive abilities, problem-solving, and interactive cognition. The findings suggest that incorporating cognitive factors into assessment provides a more accurate and holistic understanding of managerial capabilities.

Rony et al. (2024), using multiple regression analysis, examined the impact of HR competencies and work motivation on employee performance. The results revealed that both variables individually and jointly exerted significant positive effects on performance. HR competencies and motivation were both identified as key factors for improvement, with an R^2 indicating that 31% of employee performance variance was explained by these two predictors. The study underscores the importance of strengthening competencies and motivation to enhance organizational outcomes. Chukwuka and Dibie (2024), in a qualitative exploratory study, investigated the strategic role of AI in employee performance evaluation. The research compared the positive and negative experiences of AI-based versus manual evaluation methods. The findings revealed that traditional approaches, relying heavily on human judgment, were time-consuming and lacked precision, whereas AI systems provided greater transparency, accuracy, real-time productivity alerts, and timely reward mechanisms. The study concluded that AI significantly enhances both productivity and employee satisfaction, and when more fully integrated into entrepreneurial ecosystems, it can substantially improve HR. Rezaei Manesh et al. (2025), using a foresight approach, identified and prioritized drivers of sustainable performance optimization in the oil, gas, and petrochemical industry. Data were gathered through cross-impact/structural analysis and expert interviews with 24 specialists, analyzed using MiqMaq software. The findings showed that drivers such as digital technology-enhanced process improvements, strategic alignment with sustainability, and HR training had the greatest influence. In contrast, waste management, environmental impact reduction, and compliance with safety standards had higher dependency and lower influence. This research offers a strategic framework for managers in these industries to enhance organizational sustainability. Khamar et al. (2025) studied the impact of High-Performance Work Systems (HPWS) on job satisfaction among Sepah Bank employees in Sistan and Baluchestan province. This descriptive-correlational and applied research collected data via questionnaires from 245 employees. Results demonstrated that HPWS and its components had significant positive effects on job satisfaction. By examining the role of these systems, the study contributed to a better understanding of their importance in improving organizational and HR performance. Mutmainah et al. (2025), through a systematic literature review, examined the critical role of HR policies in achieving environmental sustainability. The study confirmed the significant positive effects of two core elements—green training and employee participation—on enhancing environmental performance. The authors argued that embedding environmental considerations into all levels of HR policies not only increases awareness but also strengthens sustainable organizational culture and environmental accountability. San Román-Niaves et al. (2025), employing the AMO framework, analyzed the relationship between Green HRM practices and green psychological climate. Reviewing 16 studies, the findings demonstrated that GHRM strategies—such as green rewards and training—enhance employees' perceptions of organizational commitment to sustainability, directly and indirectly fostering voluntary green behaviors and organizational performance. The study emphasizes the importance of integrating the three AMO dimensions to create synergy and reinforce a sustainability-oriented organizational culture. In the present study, the Best–Worst Method (BWM) was employed to incorporate expert judgments from the sales department of Baspar Chemi Sepidan Company with the aim of calculating the weights of predefined performance indicators, which form the basis for monthly individual performance evaluations of the sales team. This approach views performance appraisal not merely as a tool for measuring employee productivity, but also as a mechanism for enhancing motivation, improving job satisfaction, and promoting organizational justice. Fairness in performance appraisal processes is widely recognized as a critical factor in retaining human capital and directly influencing employee loyalty and organizational commitment. Accordingly, the need to improve employee satisfaction and to establish a fair and motivating work environment at Baspar Chemi Sepidan underscores the importance of designing and implementing a scientific and coherent evaluation system for the sales team. The application of BWM enables the systematic integration of expert insights, reduces subjectivity in decision-making, and enhances the accuracy of indicator weighting, thereby facilitating the development of a fair, transparent, and effective performance appraisal framework.

Table 1: Literature review

Authors	Employee Competence	Performance Evaluation	Indexing	Method	Case Study
Albino (2018).	*			Questionnaire Analysis	*
Heydarpour et al. (2022)		*	*	AHP–DEA	*
Ayough et al. (2022)			*	ISAW–PROMETHEE	*
Ayough et al. (2023)			*	BCUA	*
Baghbani et al. (2023).		*	*	AHP	*
Ergülen and Çalık (2024).		*		F-BWM	
Adu Sarfo et al. (2024).	*	*		SEM	*
Barasin et al. (2024).		*	*	G-BWM	
Otoo (2024).	*	*		Questionnaire Analysis	
Nayebpour and Sehhat (2024).	*		*	Fuzzy Delphi	
Ghedabna et al. (2024).	*	*		Qualitative Analysis	
Latif and Wahyuning (2024).			*	AHP	*

Authors	Employee Competence	Performance Evaluation	Indexing	Method	Case Study
Hazrati et al. (2024).	*	*		Thematic Analysis	
Khaleghi Forghani et al. (2024).		*	*	-	
Mehmankhah et al. (2024).		*	*	Fuzzy Delphi	
Rony et al. (2024).	*	*		Multiple Regression	
Chukwuka and Dibie (2024).		*	*	-	
Rezaei Manesh et al. (2025).	*	*	*	Cross-Impact Matrix	
Khamar et al. (2025).		*		Questionnaire Analysis	*
Mutmainah et al. (2025).	*	*		-	
San Román-Niaves et al. (2025).	*	*		Systematic Analysis	
This Study	*	*	*	BWM	*

Despite the growing body of research on employee competencies, performance appraisal, and the use of MCDM techniques, few studies have applied a structured, competency-based weighting approach specifically to sales teams, whose performance dynamics differ from those of other organizational units. Moreover, existing literature has rarely applied the Best–Worst Method (BWM) in human resource management (HRM) contexts, and almost no studies have compared competency priorities across different hierarchical roles, such as managers and sales experts. This gap underscores the need for a role-specific, data-driven framework that prioritizes competencies within sales departments using BWM in a real organizational setting.

3. Research Methodology

In the research methodology section, the process of identifying and extracting performance evaluation indicators in four main domains—technical, core, behavioral, and managerial—is elaborated in detail to provide a comprehensive framework for employee performance evaluation. Subsequently, the mechanism for calculating the weight of each indicator is explained. To achieve this goal, the chosen methodology and its implementation phases are introduced, followed by a detailed explanation of the weight allocation process according to the relative significance of each evaluation indicator. This approach enables accurate prioritization of indicators and provides a scientific basis for a fair and systematic evaluation of employee performance. The Best-Worst Method (BWM), first introduced by Rezaei (2015), is one of the modern multi-criteria decision-making (MCDM) methods that determines the weights of criteria with a minimal number of pairwise comparisons, achieving high precision and acceptable consistency. The steps of this method are as follows (Rezaei, 2015):

1. **Identifying criteria:** A set of criteria (or indicators) to be weighted is determined.
2. **Selecting the best and worst criteria:** The decision-maker selects one criterion as the best (most important) and one as the worst (least important).
3. **Best-to-others comparisons (BO vector):** The relative importance of other criteria compared to the best criterion is determined, usually using a scale of 1 to 9, where larger values indicate greater importance of the best criterion over the compared criterion. The result is the BO vector.
4. **Others-to-worst comparisons (OW vector):** The relative importance of the criteria compared to the worst criterion is determined. The result is the OW vector.
5. **Formulating the optimization model:** Using the BO and OW vectors, a linear programming model is established to extract the final weights. The objective of the model is to minimize the maximum deviation (ξ) between the BO and OW comparisons.

   The main linear programming formulation of BWM is as follows:

$$
\begin{aligned}
&\min \ \xi \\
&\text{Subject to:} \\
&\left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, j = 1, \dots, n \\
&\left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi, j = 1, \dots, n \\
&\sum_{j=1}^{n} w_j = 1, w_j \geq 0
\end{aligned}
\tag{1}
$$

6. **Deriving the final weights**: Solving the model yields the optimal weights of the criteria, characterized by uniqueness and high consistency.

7. **Consistency index (ξ):** The optimal ξ value represents the minimum deviation from full consistency. A smaller ξ indicates higher consistency of judgments.

8. **Consistency ratio (CR):** To evaluate the reliability of judgments, the consistency ratio is calculated as follows:

$$CR = \frac{CI}{\xi} \tag{2}$$

where CI denotes the maximum possible inconsistency in the selected scale. In this study, following Salimi and Rezaei (2018), the acceptable threshold for CR is set at 0.15 (Salimi & Rezaei, 2018). This approach is particularly suitable given the multidimensional nature of performance evaluation and the qualitative features of expert judgments.

9. **Aggregation of expert opinions**: After calculating the weights for each expert, the geometric mean of the weights is computed and then normalized to obtain the final weight vector. This method reduces individual bias and provides a valid and fair basis for decision-making.

3.1. Identification of Performance Evaluation Indicators

Performance evaluation of sales teams is one of the critical factors for the success of modern organizations. Identifying and implementing appropriate performance indicators not only enhances individual and team performance but also plays a key role in achieving organizational strategic goals. Based on research conducted to identify the four categories of indicators, several companies were examined, and relevant articles were reviewed to derive suitable performance indicators for sales teams. Key Performance Indicators (KPIs) are vital measures for evaluating an organization's success in achieving its objectives (Aithal & Aithal, 2023). KPIs not only reflect past results but also serve as a guide for future actions aimed at performance improvement. Badawy et al. (2016) emphasized in their study that many companies mistakenly use inappropriate measures as KPIs due to their inability to distinguish them from other performance indicators. An effective KPI should possess attributes such as actionability, alignment with strategic goals, and simplicity, so that it can correctly guide employee behavior and lead to real improvements (Badawy et al., 2016). In sales, KPIs are defined as measurement tools that assess how closely the performance of the sales team aligns with predefined goals and the overall impact of their performance on the business (Tieber, 2019). In this study, through reviewing articles and sources, the performance evaluation indicators for sales teams were identified.

3.1.1. Technical Indicators

Technical indicators focus on measurable and task-specific aspects of sales performance:

- Sales Target Achievement: Measures the extent to which predefined sales objectives are met. Research has identified this as one of the most critical sales performance measures (Insight, 2025).
- Collection Rate: Indicates the team's ability to collect receivables and secure revenue from completed sales (Mukhoma, 2014).
- Customer Development: Reflects the team's capability in acquiring new customers, retaining existing ones, and enhancing customer lifetime value (NetSuite, 2024).

3.1.2. Behavioral Indicators

Behavioral indicators emphasize observable behaviors and soft skills of employees. They act as a shared framework for attracting, retaining, developing, and recognizing top talent:

- Professional Appearance: Maintaining an appropriate and professional appearance that reflects commitment to organizational standards.
- Teamwork and Collaboration: Ability to collaborate effectively with others (University, 2025).
- Punctuality: Adherence to working hours and discipline in attendance, reflecting commitment and responsibility (Santhose & Anisha, 2023).
- Respect and Interpersonal Relations: Ability to build effective relationships with colleagues and foster a positive work environment (Albu, 2017).

3.1.3. Core Indicators

Core indicators emphasize the fundamental values and essential behaviors of the organization (Van Rekom et al., 2006):

- Ethics and Professional Conduct: Adherence to ethical standards and professional behavior, forming the foundation of trust among customers and colleagues.
- Integrity and Organizational Loyalty with Active Participation: Combining loyalty to the organization with active engagement in organizational activities and continuous improvement of processes.
- Adaptability to Business Model Changes: Flexibility and adaptability to evolving business models are essential capabilities in today's dynamic and competitive environment.

3.1.4. Managerial Indicators

Managerial indicators are specifically designed for managers and sales team leaders (Domínguez et al., 2019):

- Leadership and Team Guidance: Ability to effectively lead the team and guide it toward achieving organizational goals.
- Strategic Thinking: Capability to analyze the business environment, identify opportunities and threats, and develop appropriate strategies.
- Motivation and Team Spirit: Skill in motivating team members and maintaining high morale to achieve optimal performance.

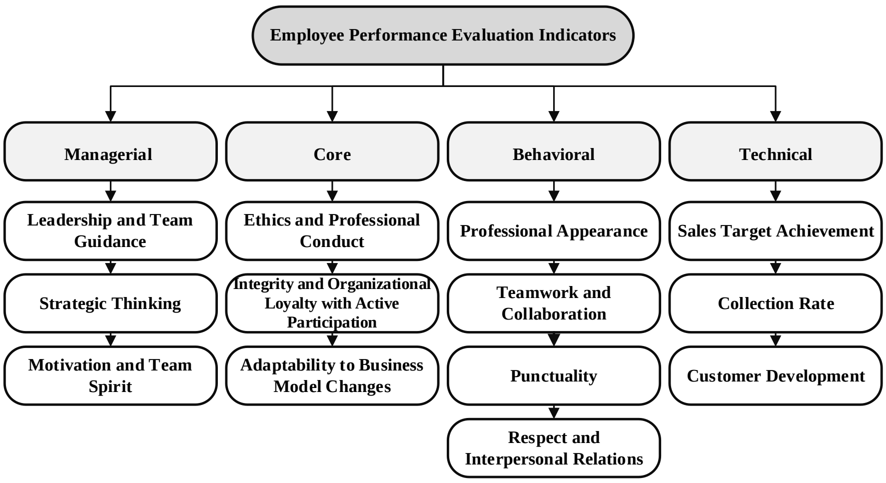

Figure 1: Indicators for Competency-Based Performance Appraisal

Figure 1 investigates the resulting indicators used for competency-based performance evaluation.

3.2. Calculation of Performance Evaluation Criteria Weights

In this study, the Best–Worst Method (BWM), a multi-criteria decision-making (MCDM) approach, was employed to determine the weights of performance evaluation indicators for sales managers and experts. To this end, the opinions of twelve sales domain experts were collected. Each expert completed six pairwise comparison questionnaires concerning four main criteria, including technical, core, behavioral, and managerial dimensions. The BWM relies on selecting the best and worst criteria by each expert and comparing them with the remaining criteria, thereby enabling the derivation of optimal weights through a linear programming model. In this model, the objective is to minimize the inconsistency level (ξ) in the experts' judgments. All computation, optimization, and aggregation procedures were implemented in Python, and the logical and computational structure of the process is presented in the following section:

Input:

Set of criteria $C = \{c_1, c_2, \dots, c_n\}$;

Experts' pairwise comparisons: Best (A_B), Worst (A_W)

Output:

Final normalized weights $W^* = (w_1^*, w_2^*, \dots, w_n^*)$;

Average consistency ratio ξ_{avg}

Procedure:

1. For each expert $e = 1,2,\dots,m$:

a. Define decision variables $w_1, w_2, \dots, w_n$.

b. Formulate and solve the following linear programming model:

Minimize ξ_e

subject to

$$|\frac{w_B}{w_j} - A_{B_e}(j)| \leq \xi_e, \forall j \in C$$
$$|\frac{w_j}{w_W} - A_{W_e}(j)| \leq \xi_e, \forall j \in C$$
$$\sum_j w_j = 1, w_j \geq 0$$

c. Obtain expert-specific weights W_e and record ξ_e.

2. Aggregate experts' weights using the geometric mean:

$$\widetilde{w}_j = (\prod_{e=1}^{m} w_{je})^{1/m}$$

3. Normalize aggregated weights to obtain W^*.

4. Compute the average consistency ratio:

$$\xi_{avg} = \frac{1}{m}\sum_{e=1}^{m} \xi_e$$

Return: (W^*, ξ_{avg}) (3)

After calculating individual weights for each expert, the results were aggregated using the geometric mean method to ensure consistency and collective integration of the experts' judgments. This aggregation approach, widely adopted in the MCDM literature, provides a valid means of combining multiple expert opinions. The resulting weights were then normalized so that their sum equaled one. In addition, the consistency ratio (ξ) was calculated for each expert, and the average consistency value was considered as an indicator of the reliability and stability of the judgments. Table 2 presents the performance evaluation indicators for managers, categorized into four main groups: Technical, Core, Behavioral, and Managerial. Expert opinions were collected through structured questionnaires, and the corresponding consistency ratio was measured and reported in the table.

Table 2: Evaluation Criteria for Managers and Supervisors

			Best Indices				Worst Indices					
Person	Best Index	Worst Index	Managerial	Behavioral	Core	Technical	Managerial	Behavioral	Core	Technical	ξ	CR
1	Managerial	Technical	1	2	4	6	6	2	5	1	0.3571	0.11
2	Managerial	Technical	1	2	3	8	8	5	4	1	0.3429	0.07
3	Core	Technical	2	3	1	8	4	3	8	1	0.4138	0.09
4	Managerial	Behavioral	1	6	5	4	6	1	2	3	0.4478	0.14
5	Managerial	Technical	1	5	3	9	9	2	6	1	0.4369	0.08
6	Technical	Technical	4	1	3	8	3	8	6	1	0.4138	0.09
7	Managerial	Technical	1	4	6	8	8	2	3	1	0.4800	0.10
8	Managerial	Core	1	4	7	3	7	3	1	4	0.4615	0.12
9	Managerial	Technical	1	2	4	6	6	3	2	1	0.3529	0.11
10	Technical	Behavioral	6	7	3	1	2	1	3	7	0.3889	0.10
11	Technical	Behavioral	2	6	3	1	4	1	3	6	0.3333	0.12
12	Managerial	Core	1	5	8	4	8	4	1	5	0.4651	0.10

Table 3 presents the weighting assigned to the three key competency-based performance evaluation indicators for experts, namely Technical, Core, and Behavioral. Unlike the previous set of indicators shown in Table 2, this category does not include managerial criteria.

Table 3: Evaluation Criteria for Experts

Person	Best Index	Worst Index	Best Indices			Worst Indices			ξ	CR
			Behavioral	Core	Technical	Behavioral	Core	Technical		
1	Technical	Behavioral	7	3	1	1	2	7	0.5122	0.13
2	Core	Technical	2	1	6	4	6	1	0.4286	0.13
3	Technical	Core	3	8	1	5	1	8	0.5217	0.11
4	Technical	Core	3	7	1	3	1	7	0.5122	0.13
5	Technical	Core	2	6	1	3	1	6	0.4286	0.14
6	Technical	Behavioral	7	3	1	1	2	7	0.5122	0.13
7	Behavioral	Technical	1	2	6	6	4	1	0.4286	0.14
8	Behavioral	Core	1	8	6	8	1	2	0.6316	0.14
9	Technical	Core	2	6	1	4	1	6	0.4286	0.14
10	Technical	Behavioral	9	3	1	1	2	9	0.5294	0.10
11	Technical	Behavioral	7	3	1	1	3	7	0.5122	0.13
12	Technical	Behavioral	8	3	1	1	5	8	0.5217	0.11

Following the measurement and collection of expert opinions regarding the main performance evaluation indicators for both managers and experts, Table 4 presents the weighting of the sub-indicators within the Technical domain. The examined indicators include Sales Target Achievement (C1), Collection Rate (C2), and Customer Development (C3), together with the respective scores assigned by each expert.

Table 4: Technical domain indicators

Person	Best Index	Worst Index	Best Indices			Worst Indices			ξ	CR
			C3	C2	C1	C3	C2	C1		
1	C1	C2	4	8	1	3	1	8	0.5714	0.12
2	C1	C3	9	5	1	1	5	9	0.6164	0.11
3	C2	C3	7	1	3	1	7	2	0.5122	0.13
4	C1	C2	5	8	1	2	1	8	0.6061	0.12
5	C1	C2	4	7	1	2	1	7	0.5600	0.15
6	C3	C2	1	7	4	7	1	3	0.5600	0.15
7	C1	C2	4	8	1	3	1	8	0.5714	0.12
8	C1	C3	7	5	1	1	2	7	0.5932	0.15
9	C1	C3	6	2	1	1	3	6	0.4286	0.14
10	C2	C1	4	1	7	2	7	1	0.5122	0.13
11	C1	C3	8	6	1	1	2	8	0.6316	0.14
12	C1	C3	6	2	1	1	3	6	0.4286	0.14

Table 5 shows the weighting of the indicators within the Behavioral domain. The indicators considered include Professional Appearance (G1), Teamwork and Collaboration (G2), Punctuality (G3), and Respect and Interpersonal Relations (G4).

Table 5: Behavioral domain indicators

Person	Best Index	Worst Index	Best Indices				Worst Indices				ξ	CR
			G4	G3	G2	G1	G4	G3	G2	G1		
1	G1	G3	4	7	3	1	5	1	6	7	0.4091	0.10
2	G2	G3	3	6	1	4	4	1	6	3	0.4000	0.13
3	G2	G1	3	6	1	7	5	2	7	1	0.4375	0.11
4	G4	G1	1	2	3	5	5	4	2	1	0.3261	0.14
5	G2	G3	3	6	1	4	5	1	6	3	0.4000	0.13
6	G2	G3	3	7	1	4	4	1	7	3	0.4078	0.10
7	G4	G1	1	2	3	6	6	3	2	1	0.3333	0.11
8	G4	G3	1	9	4	3	9	1	5	4	0.4186	0.08
9	G4	G3	1	9	3	4	9	1	8	6	0.4211	0.08
10	G2	G3	4	7	1	5	5	1	7	3	0.4575	0.12
11	G2	G1	3	4	1	7	4	2	7	1	0.4078	0.10
12	G1	G3	2	6	3	1	3	1	2	6	0.3333	0.11

Table 6 shows the weighting of the indicators within the Core domain. The considered indicators include Ethics and Professional Conduct (E1), Integrity and Organizational Loyalty with Active Participation (E2), and Adaptability to Business Model Changes (E3).

Table 6: Core area indicators

Person	Best Index	Worst Index	Best Indices			Worst Indices			ξ	CR
			E3	E2	E1	E3	E2	E1		
1	E1	E3	9	4	1	1	2	9	0.5806	0.11
2	E2	E1	3	1	7	5	7	1	0.5122	0.13
3	E1	E3	7	5	1	1	4	7	0.5932	0.15
4	E1	E2	4	7	1	2	1	7	0.5600	0.15
5	E3	E2	1	7	4	7	1	4	0.5600	0.15
6	E1	E3	7	3	1	1	2	7	0.5122	0.13
7	E2	E3	9	1	5	1	9	3	0.6164	0.11
8	E2	E3	8	1	3	1	8	5	0.6061	0.13
9	E1	E2	5	7	1	3	1	7	0.5932	0.15
10	E1	E3	8	4	1	1	4	8	0.5714	0.12
11	E1	E3	7	5	1	1	4	7	0.5932	0.15
12	E3	E2	1	9	5	9	1	4	0.6164	0.11

Table 7 shows the weighting of the indicators within the Managerial domain. The considered indicators include Leadership and Team Guidance (M1), Strategic Thinking (M2), and Motivation and Team Spirit (M3).

Table 7: Management Area Indicators

Person	Best Index	Worst Index	Best Indices			Worst Indices			ξ	CR
			M3	M2	M1	M3	M2	M1		
1	M1	M2	5	8	1	2	1	8	0.6061	0.13
2	M1	M3	7	3	1	1	3	7	0.5122	0.13
3	M2	M3	9	1	4	1	9	3	0.5806	0.11
4	M1	M2	4	7	1	3	1	7	0.5600	0.15
5	M3	M2	1	8	4	8	1	3	0.5714	0.12
6	M3	M2	1	7	3	7	1	4	0.5122	0.13
7	M2	M3	8	1	5	1	8	2	0.6061	0.13
8	M1	M2	4	7	1	2	1	7	0.5600	0.15
9	M2	M1	3	1	7	2	7	1	0.5122	0.13
10	M2	M3	7	1	2	1	7	4	0.4375	0.11
11	M3	M2	1	8	3	8	1	3	0.5217	0.11
12	M2	M1	3	1	7	3	7	1	0.5122	0.13

In the expert surveys conducted using the BWM approach, the consistency ratio (ξ, CR) was calculated to ensure the validity and reliability of the collected judgments and the resulting weight estimations.

4. Discussion

The discussion section provides an interpretation of the results and offers deeper insights into the practical implications of the competency-based performance appraisal model developed for sales teams in commercial firms based in the Isfahan Science and Technology Town. Through an examination of the weighting distribution across competency categories obtained using the Best–Worst Method (BWM), this section illustrates how differences in indicator priorities correspond to the varying roles and responsibilities of managers and subject-matter experts within these firms. Table 8 illustrates the competency-based performance appraisal framework developed for sales managers and supervisors. Given that these individuals are responsible for leading subordinates and managing team operations, managerial competencies play a particularly significant role in their performance evaluation. Four overarching categories of indicators—managerial, core, behavioral, and technical—were considered for this group, and the corresponding weights were derived based on expert assessments using the Best–Worst Method (BWM). As shown in Table 8, managerial indicators carry the highest weight, followed by core and behavioral indicators, with technical indicators considered the least important in assessing managerial performance. This pattern reflects the core responsibilities of managerial positions, where strategic thinking, leadership, and team motivation are prioritized over technical proficiency.

Table 8: Evaluation Criteria for Managers and Supervisors

Indicators	Weights (percent)	Indicators	Weights (percent)
Technical	16.08%	Sales Target Achievement	49.18%
		Collection Rate	26.89%
		Customer Development	23.93%
Behavioral	20.78%	Professional Appearance	20.27%
		Teamwork and Collaboration	33.12%
		Punctuality	15.35%
		Respect and Interpersonal Relations	31.26%
Core	24.23%	Ethics and Professional Conduct	44.06%
		Organizational Loyalty with Active Participation	31.07%
		Adaptability to Business Model Changes	24.87%
Managerial	38.91%	Leadership and Team Guidance	38.70%
		Strategic Thinking	30.89%
		Motivation and Team Spirit	30.41%

Table 9 presents the competency-based performance appraisal results for sales experts. Unlike managers and supervisors, these employees do not oversee subordinates; therefore, managerial indicators are excluded from their evaluation framework. As shown, technical competencies constitute the most important and influential category for experts, followed by core and behavioral indicators. This finding suggests that, at the expert level, the accurate execution of assigned tasks and the achievement of operational goals are the primary determinants of performance. The emphasis on technical proficiency underscores its pivotal role in driving sales outcomes and organizational success. Moreover, since the same sub-indicators were applied across all technical dimensions, a single consolidated survey was sufficient to capture expert opinions and determine the corresponding weights.

Table 9: Evaluation Criteria for Experts

Indicators	Weights (percent)	Indicators	Weights (percent)
Technical	42.22%	Sales Target Achievement	49.18%
		Collection Rate	26.89%
		Customer Development	23.93%
Behavioral	27.94%	Professional Appearance	20.27%
		Teamwork and Collaboration	33.12%
		Punctuality	15.35%
		Respect and Interpersonal Relations	31.26%
Core	29.84%	Ethics and Professional Conduct	44.06%
		Organizational Loyalty with Active Participation	31.07%
		Adaptability to Business Model Changes	24.87%

4. Managerial Recommendations

Based on the findings and competency weightings derived from the BWM, several managerial recommendations are proposed to enhance the efficiency and fairness of the competency-based performance appraisal system:

1. **Role-Specific Evaluation Framework:**
   Performance appraisal should be tailored to the job hierarchy. Managerial roles must emphasize leadership, strategic decision-making, and behavioral competencies, while expert positions should focus on technical proficiency, goal achievement, and customer development. This differentiation ensures that evaluation criteria accurately reflect the core responsibilities of each role.
2. **Competency-Based Career Path Design:**
   Employee career progression should be structured so that the focus gradually shifts from technical expertise at the expert level to leadership, communication, and ethical competencies at managerial levels. This approach supports effective succession planning and helps identify individuals with both technical and managerial potential.
3. **Targeted and Tiered Training Programs:**
   Training and development initiatives should be aligned with the weighted competencies identified in this study. Experts require continuous technical and sales-oriented training, whereas managers should receive advanced courses in leadership, negotiation, and team motivation.
4. **Multi-Level and 360-Degree Evaluation System:**
   Implementing a multi-level appraisal framework with differentiated weights for each competency category can improve fairness and objectivity. The inclusion of multi-source feedback (from peers, subordinates, and supervisors) can further enhance accuracy and acceptance of performance evaluations.
5. **Strategic Integration of Competency Weights:**
   The derived competency weights should be incorporated into broader HR functions such as recruitment, compensation, and promotion policies. Aligning these processes with data-driven competency models promotes organizational justice, transparency, and employee engagement.

In summary, adopting these managerial recommendations enables organizations to strengthen their competency-based performance management systems, align individual capabilities with strategic goals, and foster a culture of continuous learning and professional growth.

5. Conclusion

The findings of this study offer significant insights into the competency-based performance appraisal model implemented for sales teams in commercial firms based in the Isfahan Science and Technology Town. The results obtained through the Best–Worst Method indicate varying competency priorities between managerial and expert roles, demonstrating how hierarchical structures influence the emphasis placed on different performance indicators. At the managerial level, the highest weight was assigned to managerial competencies, followed by core and behavioral indicators, while technical factors had the least influence. This pattern highlights that effective managers must possess strong leadership and decision-making abilities, demonstrate alignment with the organizational culture and core values, and uphold ethical and professional standards to unify their teams and achieve sustainable performance. Thus, success in managerial roles depends not only on operational knowledge but also on the ability to inspire, coordinate, and strategically guide subordinates. Conversely, at the expert level, technical competencies were identified as the most critical and influential category, followed by core and behavioral indicators. This finding indicates that experts' performance is primarily determined by their technical proficiency, goal-oriented execution, and ability to achieve sales targets, ensure timely collection, and develop new customers. In other words, specialists contribute to organizational success by excelling in the operational and technical dimensions of their work. Overall, the study confirms that a role-specific and competency-based performance appraisal system enhances fairness, transparency, and alignment between individual capabilities and organizational objectives. By differentiating between the competencies required at each hierarchical level, organizations can more effectively design targeted training programs, career development plans, and succession strategies. Ultimately, adopting a structured competency-based evaluation approach enables human resource managers to improve both individual productivity and collective organizational performance. This research makes several unique contributions to the literature on human resource management and performance appraisal. First, it operationalizes the Best–Worst Method (BWM) as a quantitative and structured tool for determining competency weights within a real-world organizational context, thereby demonstrating its practical applicability in performance evaluation. Second, by integrating both behavioral and technical dimensions into a unified framework, the study bridges the gap between subjective managerial judgments and objective data-driven assessments. Finally, it provides a replicable model that can guide other organizations in designing fair, transparent, and competency-based appraisal systems. Despite its valuable contributions, the study is not without limitations. The research was done as a single-case study in one organization, which may not permit a generalization of findings across industries or cultural contexts. The weighting procedure required expert judgments, which, even with the structuring by BWM, cannot avoid a degree of subjectivity. Furthermore, this study focused exclusively on sales personnel; extending the model to other functional departments may provide wider insights. Future studies can expand on the present findings by applying the proposed framework across different industries and organizational sizes to test its robustness and generalizability. Integrating fuzzy logic or hybrid MCDM techniques could also enhance precision and handle uncertainty in expert evaluations. Moreover, incorporating longitudinal data would allow researchers to examine how competency weights evolve over time in response to strategic or environmental changes. Finally, combining BWM-based weighting with AI-driven performance analytics could pave the way for more adaptive and intelligent human resource management systems.

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