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Enhancing Workforce Stability through Data-Driven Selection: An AHP-TOPSIS Approach for Healthcare HRM

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ABSTRACT:

Recruitment challenges in private healthcare, particularly in Sulaimani, Iraq, stem from manual hiring processes that introduce bias and inefficiency, compromising service delivery and increasing turnover. This study proposes an integrated AHP-TOPSIS framework to enhance objectivity in competency-based selection. Three criteria—Medical Knowledge, Clinical Experience, and Patient Care—were weighted via AHP using expert pairwise comparisons, with Medical Knowledge (weight = 0.769) emerging as the most critical for doctors (CR = 0.062, validating consistency). TOPSIS then ranked candidates, prioritizing practical skills (e.g., interpreting lab results, CCi = 0.873; leadership, CCi = 0.934) over conventional metrics like board certification (CCi = 0.131). However, Patient Care (weight = 0.127) and Patient Satisfaction Scores (CCi = 0.064) scored poorly, revealing a gap in human-centric evaluation. The methodology section delineates a rigorous framework of quantitative methodologies, embedding AHP and TOPSIS under the umbrella of MCDM methods. For empirical validation, 10 private hospitals in Sulaimani were selected out of 15, excluding very small facilities functioning more like clinical centers; ultimately, only 7 hospitals agreed to participate and provided responses to the administered questionnaires. The findings of this study establish that, as a framework, it serves to reduce subjective bias, enhance candidate job alignment, and finally, stabilize retention of the workforce. This data driven model offered a replicable solution for HRM in healthcare besides the fact that future applications should integrate psychosocial variables and public health systems for alignment with patient-centered care paradigms. Such efforts contribute to the emerging practices that focus on addressing both technical competencies and systemic inefficiencies, thereby balancing organizational needs with quality care delivery.

Keywords: HRM, AHP-TOPSIS Integration, Employee Selection and Healthcare Sector.

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1 INTRODUCTION

HRM, particularly in today's world, is one of the most important and indispensable instruments in making sure that employees are the most vital and actual contributors in attaining their goals [1]. Truly, employees are valuable assets in assisting the organizations in sustaining growth, competitiveness, and profitability. HRM plays an important role in institutions in general and in the health care sector in particular, which provide high-quality services and rely on a skilled workforce to meet objectives. Yet, although there have been moves towards computerized selection methods, many organizations stick to manual means of evaluating candidates that inevitably lead to inefficiencies and inaccuracies within the recruitment process, most times compromising the objectivity of the selection process. The situation is worsened with the involvement of external parties that scramble to maintain fairness [3]. Workers and employees, especially in the private company, may decide to change their jobs and leave their organizations once they have another opportunity, often without deep thought on how their negative organizational influences such as perceived injustice or work pressure create impact on their change by largely affecting attitudes and behaviors organizationally [4]. In order to address these challenges, there is a growing need for objective and competency-based selection systems involving multi-criteria decision-making methods (MCDM) such as Analytical Hierarchy Process (AHP) as well as techniques for preference ordering by similarity to ideal treatment (TOPSIS) structured approach offer insights to enhance decision-making capacity in selecting the most appropriate candidate [5]. This study examines the use of these methods to improve the recruitment and selection process in private healthcare sectors in Sulaimani. By implementing these approaches, the study aims to contribute to more effective and neutral HR practices in the healthcare sector to reduce employee turnover. Furthermore, this study (9) analyzes the criteria. For illustration, the study delineates specific evaluation criteria tailored to each professional category: for doctors, the dimensions include Medical Knowledge, Clinical Experience, and Patient Care; for nurses, the framework emphasizes Clinical Knowledge, Work Ethics, and Teamwork; while for administrators, the focus encompasses Customer Service, Professional Experience, and Managerial Competence). Additionally, this study (9) uses a combined method (AHP-TOPSIS) to find the connections between the criteria and rank the important alternatives.

Selection of employees is a key step in human resource management functions and it plays an important role in organizing and consolidating the workforce and ensuring that the selected candidates are appropriate and in line with the needs and procedures of the organization the purpose of the organization and the effectiveness of working in them [6]. The quality of human resources has a significant impact on the sustainability of organizations. It is important to follow structured procedures correctly during the selection process and include more technology-based systems such as decision support tools and HR software to improve efficiency and accuracy during the process [7]. These advancements will also significantly help organizations to properly streamline the assessment process and make data driven decisions which are very important and essential in to maintain competitiveness in dynamic business and service environments.

However, the selection process usually involves the existence of multiple criteria to evaluate candidates in order to ensure alignment with the organization's objectives. For example, in the process of selecting doctors and employees in the private and public sectors, the level of stress was analyzed using a three-point scale. Medical knowledge, clinical experience, patient care) that they are a basis for forming the AHP weight assignment process [8]. And the researchers can say that a structured approach of this method ensures a fully comprehensive assessment of the criteria that affect performance.

To better manage hospitals and better implement the service process of private hospitals, the researchers worked on identifying a number of criteria, which can also have a significant impact on the selection of skilled nurses. To avoid the issue of support and resignation of employees in hospitals, these problems are a cause of damage to the reputation of hospitals and a lot of costs, and the criteria are communication skills, work ethic, and teamwork [9].

In the context of comprehensive personnel selection, (MCDA) therefore facilitates the process of evaluating multiple criteria, each with its own weight and level of importance. Key factors such as experience, professional skills, customer service are critical in how to determine the most suitable candidate [10]. The integration of these criteria is a factor in promoting the decision support system and promotes a structured and unbiased selection process, which ultimately contributes to further improvement in organizational performance.

AHP is a decision tool developed by Thomas Sati and designed for problem solving that combines several interrelated criteria to structure complex decisions in a hierarchical manner and then divides them into criteria, sub-criteria and alternatives for systematic analysis [10]. One of the main strengths of the AHP is its ability to determine the relative importance or weight of different criteria which makes it a reliable method of prioritizing factors in the decision-making process. For example, AHP has been more successfully used to weigh criteria in hiring new employees within organizations to further ensure that decisions and decision-making processes are based on clearly defined standards [11]. With the AHP method, the problem tends to be analyzed in a hierarchical manner. They include objectives, criteria and alternatives with built-in hierarchical structures that make complex problems easier to understand [12].

TOPSIS was first developed by Huang and Yoon in 1981 and further refined and improved by [13], [14], [15]. This method is a reason to solving multi-criteria decision problems by assessing alternatives in terms of their proximity to the (positive ideal solution) and their distance from the (negative ideal solution) [16]. A distinctive characteristic of TOPSIS is its ability to concurrently account for both distances, which guarantees a fair and suitable assessment of alternatives. This method enhances the effectiveness of the method in ranking and selecting options especially in complex decision-making situations. For example, within the staff selection process TOPSIS can objectively rank alternatives based on their alignment with predefined criteria, which helps organizations to identify the best for their needs while reducing subjective bias [17]. Therefore, the basic idea is that the best alternative should have the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS) [18].

It presents employee turnover as one of the significant challenges in the healthcare sector which leaves a crushing impact on organizational efficiency as well as quality of services. High turnover rates are not only a factor that leads to higher financial costs but also a factor that disrupts operations and reduces the quality of care provided to patients. Recent studies have identified key factors that influenced employee turnover and job satisfaction in general that are considered important to understand this issue [19]. The negative effects of change are considered to be much greater than the financial losses and cause the removal of valuable resources and disruption of organizational work as well as a cause of reduced efficiency and effectiveness [20]. Despite all the advances in personnel management practices, many organizations still rely on outdated manual selection processes that fail to address the underlying causes of change such as burnout, limited opportunities for career advancement and inadequate compensation.

The presence of biases among healthcare professionals and the effect on quality of clinical care is a cause for concern for (HRM) in the healthcare sectors [21]. In addition, the bulk of previous research has focused on empirical outcomes in talent management such as those affecting individual employees but while primarily discussing firm-level outcomes [22]. The existence of this gap in understanding is considered to be an obstacle in organizations and in developing effective strategies to retain talented employees and maintain a stable workforce. Therefore, organizations are in dire need of an objective and competency-based selection system that can help improve the recruitment process and minimize bias.

The following research objectives are designed to advance these goals and contribute to the development of more effective and equitable human resource practices within healthcare organizations.

- To select staff by identifying and defining key criteria in health care organizations, taking into account important factors.
- To implement the AHP method to determine the relative importance of each selection criterion ensuring an objective comparison of factors influencing staffing decisions within hospitals.
- To implement the TOPSIS method for ranking as well as selecting candidates based on the weighted criteria established by the AHP method.
- To reduce the incidence of employee turnover by improving the alignment between selected candidates with organizational requirements then ensuring that the selected employees are well suited to both the role and the long- term objectives of the company.
- To evaluate the effectiveness of the integrated AHP-TOPSIS approach in improving the overall accuracy and fairness of the personnel selection process namely in comparison with the traditional methods prevalent today.

This study aims to investigate the use of multi-criteria decision-making methods, especially AHP and TOPSIS, to further improve the recruitment and selection process in private health care institutions in Sulaimani, Kurdistan Region of Iraq. By identifying several important sub-criteria for evaluating candidates, this study attempts to contribute to HRM practices, which can ultimately be one of the factors to reduce employee turnover and improve organizational performance in the health care sector. In order to address the aforementioned issues, this paper seeks to answer the following questions:

- What are the key criteria for selecting new employees in project-based environments within healthcare sectors?
- How can the AHP method be used to determine the relative importance of these selection criteria?
- How can TOPSIS method are used to rank alternatives based on weighted criteria.

- To what extent does the integrated methods approach (AHP and TOPSIS) affect the selection of appropriate candidates for project roles as well as reducing staff turnover and bias in private healthcare sectors and other types of organizations?

2 LITERATURE REVIEW

2.1 IMPORTANCE OF HRM IN ORGANIZATIONAL SUCCESS

Human Resource Management (HRM) is essential and complex in fulfilling corporate objectives by matching the organization's plans with its workforce competencies. It entails the alignment of business operations with human resources objectives, ensuring the effective fulfillment of the requirements of both the organization and its employees [22].

HRM is responsible for critical functions such as managing workforce diversity, maintaining legal compliance, overseeing performance management, and promoting ongoing professional development through training and leadership opportunities. These actions enhance employee performance and are essential for achieving organizational objectives and guaranteeing sustained success [23].

Employees, as essential assets, are pivotal to fostering an organization’s growth, competitiveness, and profitability. Effective HRM strategies offer employees opportunities for career growth, skill enhancement, and leadership training, so increasing their job satisfaction, engagement, and overall productivity. When employees perceive value and support, their motivation and dedication enhance, resulting in improved organizational performance [24].

Traditional HR methods, especially in the recruitment and selection process, are being challenged by rapid technological advances. Therefore, the transition from traditional recruitment methods to e-recruitment has transformed HR operations by implementing more efficient as well as scalable and paperless processes. Although such advances provide various benefits, such as optimizing hiring processes and expanding access to a great talent pool, they also present challenges related to adapting to new technologies, maintaining consistency in selection processes and ensuring effective use of these digital platforms. As companies adopt digital HRM, it is critical for practitioners and HR across the institution to carefully navigate these transitions, matching the demand for technical advances with maintaining conventional HR principles and practices [25], [26].

2.2 EMPLOYEE SELECTION AS A CRITICAL HR FUNCTION

The performance of any organization fundamentally depends on its ability to attract, retain and manage qualified human resources especially as the globalized economy requires an increase in specialized talent much more than before. Therefore, in this environment, the process of selecting skilled employees is considered very important, especially in industries such as health care, where human resources play an important role in developing economic infrastructure and production and subsequently creating jobs [27].

Furthermore, (HRM) is essential for optimizing internal processes and client services benefiting both employees and management by improving operational efficiency and cultivating a strategic partnership that advances the organization’s overarching objectives [28].

One of the key factors in the success of an organization is the performance of the workforce, because employees play a very important role in achieving the goals of the organization. This result is therefore particularly important in the context of virtual teams, where the HRM function is becoming increasingly important and important. In virtual environments, HRM strategies must guarantee that teams, established by leaders to accomplish specified objectives, are efficiently managed and work at their best [29]. One difficulty business encounter in the selection process is the existence of implicit biases, which can distort hiring decisions and adversely affect the efficacy of manual selection procedures.

Implicit bias refers to all unconscious opinions or prejudices that affect decision-making processes, such as hiring. For example, here a study indicates that prejudices related to race, ethnicity, or other protected factors often compromise the fairness and objectivity of employee selection, leading to harmful outcomes for particular groups [30].

This underscores the need for rectifying biases in the selection process to ensure fairness and justice. Procedural remedies, such as the Rooney Rule, which require diverse candidates to participate in recruitment processes, have been proposed to reduce such biases and promote equality in decision-making [27].

The only issue of bias in manual selection techniques is worsened by the typical inefficiency at work. Manual assessment of candidates is boring most times, subjective and fraught with errors in judgment. Such type of inefficiency harms both the value of selected candidates and the chances for firms to use a more diverse and skilled workforce.

This increases the tendency of companies towards a methodical data informed recruitment process that could significantly lower bias touch in the selection process while also rendering efficiency. This naturally makes Human Resource Management an important strategic partner in promoting and executing effective yet impartial and efficient employee selection practices.

2.3 OVERVIEW OF MCDM IN HRM

MCDM, also known as Multi-Criteria Decision Analysis (MCDA), is one of the most accurate and revolutionary methodologies for decision-making. Historically, Benjamin Franklin presented one of the initial conceptual frameworks of MCDM through his investigation of moral algebra. Since the 1950s, empirical and theoretical scholars have thoroughly investigated the mathematical modeling potential of MCDM methodologies to create organized frameworks that enhance decision-making and allow for the ranking of various possibilities. Due to the variety of MCDM methodologies, each differing in methodology and application, next sections will offer a comparative examination of different approaches [31].

MCDM is extensively utilized in diverse domains such as supply chains, social sciences, medicine, economics, and consumer behavior, since it facilitates the resolution of intricate decision-making challenges that encompass many, frequently conflicting, criteria [32]. MCDM approaches are regarded as a crucial domain within operations research, providing systematic frameworks for the assessment and prioritization of alternatives.

Despite the substantial advantages that improvements in MCDM research provide to HR practitioners, a notable obstacle persists: numerous HR professionals may lack the requisite knowledge to evaluate and use newly established MCDM approaches. Thus, although these advanced MCDM techniques are extensively published and publicly available, they may still be regarded as intricate and unattainable by HR managers, hindering their practical application [33].

The application of MCDM approaches is of very significant value in both theoretical research and actual decision-making scenarios. Many comprehensive academic studies highlight the implications of MCDM methods in coping with complex decision-making issues, namely by helping decision-makers identify the most appropriate solutions in uncertain contexts. These approaches generally provide a systematic evaluation of option alternatives, greatly improving the accuracy and effectiveness of decision-making. In addition, current research emphasizes the development and reliance on mathematical models to enhance and improve decision-making strategies, especially in human resource management. In the human resource management process multi-criteria decision-making procedures are especially useful in staff selection processes, since decision-makers must evaluate multiple alternatives against various criteria in order to achieve appropriate recruitment results [34].

2.4 AHP APPROACH IN EMPLOYEE SELECTION

AHP is a systematic decision-making approach commonly used in personnel selection and AHP greatly improves the objectivity and dependability of hiring decisions by systematically evaluating alternatives based on established criteria [35]. In Decision Support System (DSS), AHP is one of the essential tools for companies to identify the most suitable and best employees by converting complex decision processes into hierarchical frameworks [36].

AHP is characterized by its ability to integrate both qualitative and quantitative factors into the decision-making process and distinguishes it from conventional selection approaches that rely solely on numerical data, empirical evidence and logical reasoning Candidates must be evaluated [37]. Furthermore, the hierarchical framework of AHP allows firms to assess numerous criteria concurrently, rendering it an essential instrument for human resource management (HRM).

It has been used in evaluating recruitment resources by examining criteria such as performance as well as diversity and cost-effectiveness [38]. Its adaptability and direct deployment have significantly facilitated its use in healthcare organizations serving as a valuable decision support tool in the human resource management process [39].

The AHP methodologies hold significant promise for improving decision making processes, particularly in marketing contexts. However, traditional AHP faces limitations when handling imprecise or ambiguous data, which have been mitigated through the integration of set theory, resulting in the development of AHP. This hybrid approach combines logic principles with AHP to address vagueness, enabling decision-makers to leverage qualitative and quantitative attributes for more reliable and accurate outcomes [40]. As a widely recognized MCDM technique, AHP employs pairwise comparisons to systematically assign weights to variables based on their relative importance [41]. Its simplicity and adaptability to both qualitative and quantitative evaluations have led to extensive applications in healthcare, including efforts to enhance diagnostic precision through AHP [42]. Recent advancements in AHP incorporate logic to account for uncertainties, thereby refining decision-making under ambiguous conditions. The foundational AHP framework, as proposed by [40], involves the following key steps:

- **Construct a Decision Hierarchy** by systematically decomposing the problem into a hierarchical structure of interconnected decision elements, as illustrated in Figure 1.
- **Calculate the Prioritization Vector** using established arithmetic operations, followed by an evaluation to validate the matrix's coherence through consistency ratio analysis.
- **Determine the Relative Weights** of hierarchical elements using eigenvalue methods, ensuring alignment with the problem's objectives. Concurrently,

Across the hierarchy by computing the Consistency Index (C.I), a critical step to mitigate contradictions in pairwise comparisons.

$$C.I = \lambda_{max} - \frac{n}{n-1} \tag{1}$$

In this framework, λ_{max} represents the principal eigenvalue of the pairwise comparison matrix, n denotes the order of the matrix, and CI quantifies deviations from perfect consistency. The Consistency Ratio (CR) is derived by normalizing CI against the Random Index (RI), a benchmark value reflecting the average consistency of randomly generated pairwise matrices. A CR value below the threshold of 10% indicates acceptable consistency in the decision-making model, thereby validating the results [32]. If CR exceeds this threshold, the pairwise comparisons must be revised to resolve inconsistencies.

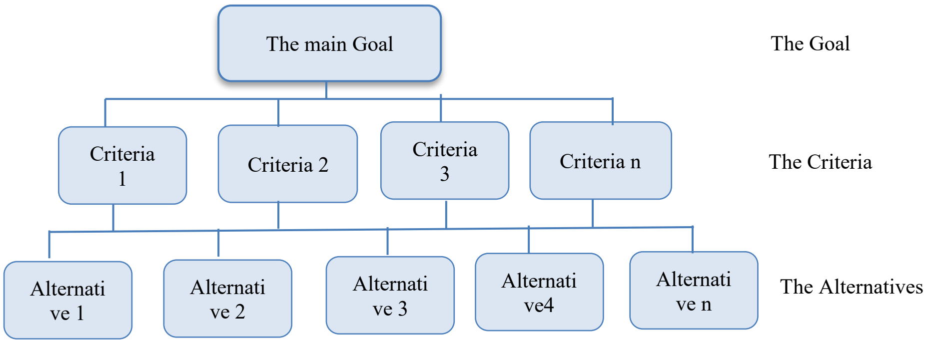

FIGURE 1. AHP decision components shape

2.5 TOPSIS APPROACH IN EMPLOYEE SELECTION

TOPSIS is a well-known MCDM commonly used across various sectors in order to rank different options based on specified criteria and TOPSIS has also shown significant effectiveness in several applications, including staff selection and identifying best candidates for charitable giving [14]. In human resources management (HRM), particularly in organizational contexts, the function of human resources especially employees are essential for enhancing productivity and attaining the organization's objectives. This research intends to utilize the TOPSIS approach to discover the best appropriate employee by evaluating numerous alternatives against established criteria [43].

TOPSIS possesses the adaptability to incorporate various weighting methods and distance measures. This allows academics and practitioners to evaluate the outcomes of different weight assignments applied to previously gather multi criteria data [44]. By modifying the weightings, decision-makers can more accurately represent the significance of various criteria when assessing alternatives. Such a new implementation greatly ensures precision in the entire process of making more relevant decisions. The other feature that reduces subjective bias in TOPSIS is fairness weights that cause a change in the influence of criteria likely to produce distorted or irregular results. Disparity facilitates more balanced and comparable assessments by quantifying proximities of different alternatives to both the optimal and most unfavorable solutions. Logarithmic transformation also deals with problems like non-convexity of utility scores and advances the robustness and fairness of the selection process. [45].

Through different applications, one can show how adaptable TOPSIS in handling complex decision processes in different sectors, especially in human resource management in a healthcare setting. This is made possible by comprehensive documentation on TOPSIS applications in various industries mostly showing its common use and impacts concerning multi-criteria decision-making processes [46]. This is an approach effective in multiple scenarios; it possesses the ability to combine equity and objectivity making it an ideal tool to enhance decision making in human resources and other fields.

2.6 SYNERGY BETWEEN AHP AND TOPSIS

Multiple evaluation metrics were established for the purpose of evaluating the systems based on the outcomes of certain metrics and were chosen through AHP and TOPSIS [47]. AHP-TOPSIS integration was suggested as a framework for software selection, considering it to be a multi-criteria decision-making evaluation. The model cleverly utilized systematic decision-making through AHP-TOPSIS. The framework is particularly suitable for evaluating multi-attribute open-source software (OSS) and presents a systematic method with clearly defined criteria for software selection [48].

The approach of combining AHP and TOPSIS has been thoroughly studied in many decision areas. This merger uses the capability of AHP to obtain the priority ranking across criteria by way of pairwise comparisons, while TOPSIS evaluates the alternatives according to their relative proximity to the optimal solution [49]. In the domain of forest management planning, the combination of two methods AHP and TOPSIS served as a means to assess multiple strategic plans by integrating the preferences of various stakeholders, thus ensuring a robust decision-making process [50].

The AHP-TOPSIS integrated decision support system has been designed to improve the generation of efficient policy and strategies in countering the challenges of reverse logistics. In the presented framework, the AHP technique is used for determining the relative importance of the choice criteria, while the TOPSIS serves as a support system for ranking the options for more efficient and effective decision making [51]. AHP is best suited to derive the criterion weights, while its use for alternative evaluations may not be as apt due to the subjectivity built into it. Therefore, AHP is usually combined with TOPSIS, which is selected for its conceptually simple and mathematically efficient approach and an unambiguous and logical evaluation of probabilities [52].

Integrated AHP-TOPSIS methods, which apply weighted criteria and objective data to assess relative distances among given alternatives, form a powerful classification system. The method is useful in a variety of decision-making situations, with the flexibility to incorporate other techniques into the decision support process, thereby enhancing the robustness and reliability of the results [53].

2.7 EMPLOYEE TURNOVER IN THE HEALTHCARE SECTOR

Employees are affected by many variables in health care including aspect of turnover like poor training and limited professional growth opportunities, in addition to inadequate managerial support. It means low training and poor job clarity foster an environment of dissatisfaction that compels workers to search for alternatives [54],[55]. Along with occupational stress, heavy workloads and poor skill mix further exacerbate the problem of turnover. Nurses are hence subjected to increasing stress on account of low staffing levels on one hand while they have limited participation in the decision-making and patient care activities on the other, all factors resulting in extremely high staffing stress and job dissatisfaction [56]. Furthermore, there are barriers associated with leadership such as poor relationships between managers and employees and inadequate support systems which also adversely affect retention [54].

From a financial perspective, constant change can be a factor in creating barriers to an organization’s profitability which is especially true in smaller healthcare facilities where sustaining adequate staffing levels is already problematic [57]. In addition to leadership challenges and staff dissatisfaction consistently being associated with high turnover rates among nurses, along with remuneration and educational attainment also affect job satisfaction [58]. The turnover of seasoned employees hinders the transfer of professional values and standards to junior staff, resulting in diminished service [59]. The exodus of experienced personnel adversely impacts team cohesion, the efficiency of patient treatment, and the overall functioning of the hospital [60].

2.8 Gaps in Existing Literature

Conventional employee selection methods face significant criticism for relying on manual, subjective assessments, leading to biased, inconsistent, and inaccurate hiring outcomes [61]. These approaches lack systematic, evidence-based frameworks, hindering data-informed decisions and resulting in inefficient recruitment, poor candidate-job alignment, and delayed processes [62]. Despite technological advancements offering tools to enhance decision-making, traditional methods fail to integrate these innovations, limiting adaptability to modern workplace needs [63]. Researchers advocate for data-driven methodologies linked to job-specific standards to improve recruitment efficiency, candidate suitability, and organizational performance [64].

MCDM techniques like AHP and TOPSIS are proven effective in fields such as medical diagnosis and hospital performance evaluation [65]. However, a significant research gap persists in their application to healthcare employee selection, despite their potential to systematize recruitment [66]. While AHP prioritizes diagnostic criteria and TOPSIS assesses service quality, their combined use for healthcare personnel decisions remains understudied [67].

Integrating AHP and TOPSIS offers a transformative opportunity for healthcare HRM, enabling objective, data-driven hiring through structured evaluation of criteria like performance and training needs [67]. This synergy corrects deficiencies in traditional practices and leverages technologies (e.g., workforce analytics) to enhance decision support systems. Successful implementation requires ongoing refinement aligned with evolving organizational demands and commitment to technological adoption in HR operations.

3 THE METHODOLOGY

This study Apply quantitative methods combined into the (MCDM) framework, particularly the AHP and TOPSIS model, to optimize employee selection and reduce turnover in Private Hospitals in Healthcare sector in Sulaimani Kurdistan region, Iraq. The research design will be oriented toward tackling the issue of high turnover rate problems, bias, poor recruitment processes, and mismatching between the candidates (Alternatives) and organizations as a problem statement, while systematically making an answer to the research questions and hence achieving the objectives.

3.1 DATA SOURCE

The private health sector in Sulaimani, Kurdistan region, Iraq plays a crucial role in providing health services, with a plethora of privately owned hospitals working to satisfy the increasing demands of the population. Not all of these institutions have upgraded their systems; many still use manual means of collecting data, particularly in areas of recruitments and evaluations of employees. Such dependence usually results in issues like biases during selection and higher employee turnover rates, thereby affecting the service quality and stability of the organization. In this study, 10 private hospitals in Sulaimani, Kurdistan region, Iraq were included out of 15 hospitals, because some of the hospitals were very small or like a clinical center, and only 9 of the 10 private hospitals were willing to answer our questionnaires. Over the past decade, the private hospital sector in Sulaimani; Kurdistan region, Iraq / has expanded rapidly, due to increased demand for specialized care, weak public health care infrastructure, and government policies that encourage private investment [68], [69] Advanced due to its relative stability and skilled human resources [70].

3.2 DATA TYPES AND COLLECTION

In this research, two different sets of data are used:

AHP criteria: structured evaluations for three professional groups of doctors with three defined criteria.

TOPSIS alternatives: alternative performance metrics derived from standardized assessments.

Primary data were collected using self-constructed questionnaires by using both methods:

AHP questionnaires by expert pairwise comparisons of criteria importance.

TOPSIS evaluation forms ranked by alternative with respect to the said criteria.

In Sulaimani Governorate, the data gathering was focused on private hospitals, utilizing purposive sampling for the respondents of the AHP (i.e., healthcare administrators and senior clinicians) and stratified sampling for the alternative in TOPSIS (by professional category). The raw data were then systematically processed through various steps, including consistency validation for AHP judgments ($CR < 0.1$), normalization of the TOPSIS performance scores, a sensitivity analysis for verifying robustness, and the subsequent application of these processed datasets within the analytical framework as detailed in the later sections [32], [71]

3.2.1 SELECTION OF KEY CRITERIA (AHP WEIGHTING)

All these components fall into the threefold structure of the study: an overview of doctors personnel which translate to three evaluation criteria per occupational group.

Nothing is easy in the whole medical institution because treatment of diseases starts with communication between departments relating to the doctors. Thus, there is communication between doctors and patients. The doctor can get an idea about a patient's disease status from his or her explanation [8]. The patient also can comprehend his or her disease status by the doctor's explanation and be aware of the treatment method and other important aspects. Precisely, judges are directed by information acquired through conversing with patients, leading to directions in medical judgments and treatments. Generally, patients would heed the doctor's diagnosis in addition to the prescription when a doctor explains the treatment process positively. Therefore, well conceiving that doctor-patient communication is vital in effecting accurate diagnosis and treatment [72].

3.2.1.1 MEDICAL KNOWLEDGE CRITERIA

To judge the quality of medical service, the sub-items of professionalism have been taken to comprise accuracy in diagnosing and prescribing, with an emphasis on the medical knowledge of the doctor at the professional level and the latest information, and the high awareness of the patient about the treatment process [73].

3.2.1.2 EXPERIENCE CRITERIA

This partnership can best be informed as a discrete type of human relationship, as established in other relevant works that distinguished the dynamic interactive dimensions of relationships somewhat from the mental associations made by people 'in' relationships-'historically derived representations of experience. This, therefore, marks great import, but without a conceptual frame through which the patient-physician relationship could be viewed, we are not likely to realize the value of the diverse parts and how they affect patient care [74], [75].

3.2.1.3 PATIENT CARE CRITERIA

A more thorough understanding of the components of patient-doctor relations that facilitate patient care is crucial for the support and training of doctors and for organizing health care. For example, if continuity is viewed as a unique contribution to patient-doctor relations, it may be unwise to emphasize diagnostic skills in isolated consultations with the physician, but instead to stress the organizational systems through which consistency can be better achieved [76]. Figure 2 illustrate the selected criteria of the Doctor as AHP method.

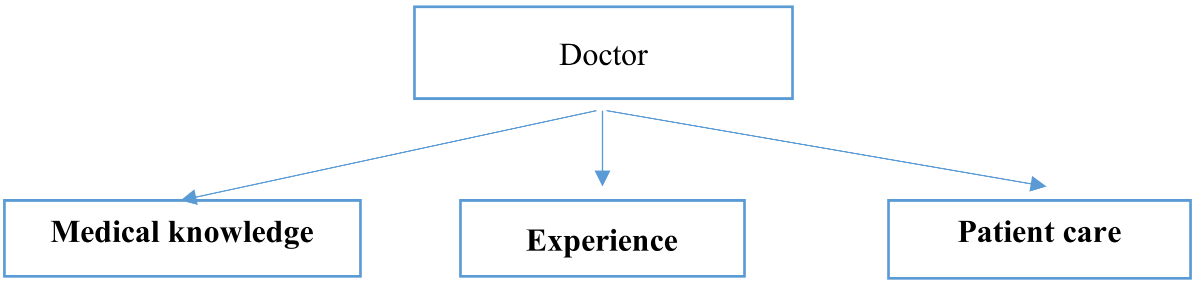

FIGURE 2. Doctor Criteria

3.2.2 SELECTION OF TOPSIS FOR ALTERNATIVES DOCTOR CRITERIA

This section outlines the alternatives matched against each criterion for the doctor (medical knowledge, experience, and patient care) along the AHP-TOPSIS methodology with empirical and methodological justifications for the selection of alternatives. Alternatives chosen are mostly grounded on evidence-informed practices and are operable to address critical gaps in recruitment precision and retention as far as the private healthcare sector in Sulaimani is concerned.

3.2.2.1 TOPSIS ALTERNATIVES FOR MEDICAL KNOWLEDGE

To measure alternative using TOPSIS, five alternatives were chosen corresponding to the medical knowledge criterion under the doctor category. These alternatives were derived from outstanding validated metrics in actual clinical practice, which are aligned with the focus of this study on diagnostic accuracy and [77], [78], [79], [80]: Accuracy in interpreting lab/imaging results.

1. Accuracy in interpreting lab/imaging results.
2. Board certification exam score.
3. CME hours completed annually.
4. Case presentation quality score.
5. Medication error rate (inverse score).

3.2.2.2 TOPSIS ALTERNATIVES FOR EXPERIENCE

In the same vein, five alternatives were chosen according to the empirical baselines that have been established in evaluating real-world clinical performance for assessing candidate performance on experience criteria using TOPSIS. These criteria correspond to what has been referred to before in competency evaluation studies as being diagnosis-related and clinically accurate[77], [79], [81]

1. Years of post-residency practice.
2. Annual procedure volume.
3. Complex case success rate.
4. Teaching/mentoring activities.
5. Leadership roles held.

3.2.2.3 TOPSIS ALTERNATIVES FOR PATIENT CARE

The TOPSIS assessment of patient care proficiency utilizes five validated alternatives: (1) patient satisfaction scores, (2) inverse-scored average consultation time to prioritize efficient yet thorough care, (3) patient follow-up adherence rates, (4) peer-assessed communication ratings, and (5) inverted patient complaint frequency. These metrics collectively evaluate therapeutic effectiveness, care continuity, and interdisciplinary collaboration, aligning with evidence-based frameworks for healthcare quality while addressing critical patient-centered outcomes identified in cross-cultural clinical contexts [77], [78], [82]

1. Patient satisfaction score.
2. Average consultation time (inverse score).
3. Patient follow-up adherence rate.
4. Peer communication rating.
5. Patient complaint frequency (inverted).

3.3 APPLYING THE AHP METHOD

AHP Process is a popular approach for (MCDM) problems [83]. It effectively accesses qualitative and quantitative data using a structured pairwise comparison matrix, while breaking decision problems into hierarchical scenarios [84], [85], [86]. Classical pairwise comparison matrices from Saaty (1980) were used to design a three-tier hierarchy consisting of: (1) a main objective (top level); (2) evaluative criteria (secondary level); and (3) candidate (alternatives) (tertiary level). These are systematically shown in Table 1.

Table 1. The Scale of Relative Importance with Pairwise Comparison Matrix.

Definition	Intensity of importance
Equally important	1
Moderately important	3
Strongly important	5
Very strongly important	7
Extremely important	9
Intermediate values	2, 4, 6, 8
Values of inverse comparison	1/3, 1/5, 1/7 and 1/9

Within this study, the application of AHP and TOPSIS approaches was tested for personnel selection in the private healthcare sector and was narrowed down to three professional categories: doctor, nursing staff, and administrative staff. The evaluation was carried out on a specific three set of criteria, with the associated weight of these criteria playing an important role in the decision-making. Since the validity of any outcome of a multi-criteria decision analysis largely depends on the correctness of the criterion weights, special emphasis was laid on methodological rigor during the weighting process.

The AHP framework has thus been applied in the present work to address subjectivity and uncertainty in expert judgment. Data were collected from a sample of 185 physicians responding to structured questionnaires by pairwise comparisons of decision elements according to their respective professions. The participants expressed comparative judgments about the criteria's relative importance verbally with terms like 'moderately more important', which were later converted into numerical values using standard conversion scales.

The analytical process includes four major phases; that is:

1. Construction of pairwise comparison matrices for expressing expert opinions.
2. Deployment of fuzzification methods to place numerical values on verbal evaluations.
3. Normalization of matrix entries to ensure consistency along rows.
4. Geometric averaging of individual responses to compute group weightings.

The entire process was organized to take into account the subjective nature of the human judgment while allowing minimum loss of information during the quantification of qualitative assessments. Greater applicability of the criteria weights in regard to healthcare workforce selection would have been given by separation of the evaluation groups for clinical and non-clinical staff drawing on expertise from within the sector.

3.4 APPLYING THE TOPSIS METHOD

The most employed method of solving the MCDM problems is TOPSIS, through which a satisfactory solution is derived to approximate the positive ideal solution (PIS) and the negative ideal solution (NIS) [87]. The current study implements the hierarchical TOPSIS method for linguistic variables that facilitate decision making, dynamic and imperialistic, against the use of vague intermediate values [88]. The following are the steps TOPSIS [32].

Step 1: The TOPSIS problem is constructed into the matrix $[\widetilde{X_{ij}}]_{m*n}$ by crafting its weight vector $[\widetilde{w}_1, \widetilde{w}_2, \widetilde{w}_3, \ldots, \widetilde{w}_n]$, where "~" denotes the sets and presumes there's K alternative in the group.

	A1	A2	. . .	An
C1	X11	X12	. . .	X1m
C2	X21	X22	. . .	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
Cm	Xm1	.	. . .	Xmn

$$\tilde{X}_{ij} = \frac{1}{k}\left[\tilde{X}_{ij}^{1} \oplus \tilde{X}_{ij}^{2} \oplus . \quad . \quad . \tilde{X}_{ij}^{k}\right] \; i = 1,2,\ldots,m \text{ and } j = 1,2,\ldots,n \tag{2}$$
$$\widetilde{w}_j = \left[w_j^1 \oplus w_j^2 \oplus . \quad . \quad . \oplus w_j^k\right], j = 1,2,. \; . \; ., n \tag{3}$$

Step 2: The decision matrix is normalized, taking into consideration the Equations (4– 8). All datasets are designed to operate under one platform where measurement criteria are equal, thus, a vector method is adopted for matrix normalization. Eventually, the decision matrix $(\tilde{R})$ is established through a linear scale transformation.

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{m*n} \tag{4}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \quad j \in B \tag{5}$$
$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \quad j \in C \tag{6}$$

$$C_j^* = \max_i C_{ij,}, \qquad if \; j \in B \tag{7}$$
$$a_j^- = \min_i \; a_{ij}, \qquad if \; j \in C \tag{8}$$

Where, the set of alternatives is presented by B and the set of positive and negative ideal solutions is presented by C.

Step 3: Calculate the weighted normalized decision matrix, (Vij).

$$\tilde{V} = \left[\tilde{V}_{ij}\right]_{m,n}, \qquad i = 1,2,\ldots n, \tag{9}$$
$$\tilde{V}_{ij} = \tilde{r}_{ij} \otimes \widetilde{w}_{ij,} \; i = 1,2,\ldots,m \text{ and } j = 1,2,\ldots,n \tag{10}$$

where wj is the weight of the jth criterion and $\sum_{j=1}^{n} w_j = 1$.

Step 4: Equations (11 - 14) achieve the ideal solution. Each objective and criterion is each alone maximized to obtain the standard solution using the ideal solution. The minimized values then distance the decision.

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+) \text{ an idel solution} \tag{11}$$

$$V_j^+ = \left(max_i. \; V_{ij}, \; min_i.V_{ij}\right), \quad j \in B \tag{12}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-) \text{ negative idel solution} \tag{13}$$
$$V_j^- = \left(min_i. \; V_{ij}, \; max_i.V_{ij}\right), \quad j \in C \tag{14}$$

Step 5: Expressions (15 - 17) serve to quantify distances of each alternative from the positive and negative ideal solutions. The distance between two TNs $\tilde{A}_1(a_1, b_1, c_1)$ and $\tilde{A}_2(a_2, b_2, c_2)$ is determined as follow

$$d(\tilde{A}_1, \tilde{A}_2) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \quad (15)$$

$$d_i^+ = \sum_{j=1}^{k} d(\tilde{V}_{ij}, \quad V_j^+), \quad i = 1, 2, \dots, m. \quad (16)$$

$$d_i^- = \sum_{j=1}^{k} d(\tilde{V}_{ij}, \quad V_j^-), \quad i = 1, 2, \dots, m. \quad (17$$

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Step 6: Two analytical methods for computing the closeness coefficient (CCi); the first method computes it directly, while the second is based upon the per-table ranking method of computing assertion strength.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}, \quad i = 1, 2, \ldots, m. \tag{18}$$

3.5 Integration of AHP and TOPSIS in Employee Selection

The amalgamation of both (AHP) and (TOPSIS) constitutes a good framework for decision making in employee selection that integrates subjective criteria weighting with an objective ranking of alternative. Described below is the explicit link between the two methods as developed in the study.

1. Establishing Criteria and Weights Using AHP The process starts with AHP, which hierarchically structures the decision problem. Three professional groups in private hospitals are evaluated regarding the criteria by which employees are to be selected.

These experts, such as a hospital administrator and senior clinician, will conduct a pairwise comparison of each of the criteria using Saaty's scale (1-9) in establishing the relative importance of each criterion. These comparisons are then compiled into matrices, normalized, and checked for consistency (CR < 0.1). The geometric mean of the expert responses will give final weights for each criterion, thereby ensuring systematic quantification of these subjective judgments.

2. Linking AHP Weights to TOPSIS Decision Making

Once the criteria weights are determined using AHP, they will directly be used in the TOPSIS method to provide a ranking of alternative as per the prioritized criteria. Integration proceeds in the following manner:

- Building the Decision Matrix: Organizing all alternative performance data (i.e. board exam scores, patient satisfaction ratings, years of experience) into a matrix with rows comprising the alternatives and columns, the criteria.
- Normalization: The matrix is normalized to remove scale differences (for example, with reference to test scores and years of experience).
- Weighting the Matrix: The weights derived from AHP are multiplied by the normalized scores; hence most important criteria (e.g., "Medical Knowledge" for doctors) will have a more considerable effect on the final ranking.
- Normalization: The matrix is normalized to remove scale differences (for example, with reference to test scores and years of experience).
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3. Rank Alternative via TOPSIS

For each criterion considered, the weighted decision matrix will be used to compute the positive ideal solution (PIS) and negative ideal solution (NIS) using TOPSIS. The Euclidean distances of each alternative from these two points of reference are calculated and the final ranking will be based on the Closeness Coefficient (CCi).

Validation: Model validation is carried out with the commonly used AHP-TOPSIS selection for jobs being compared against the traditional hiring outcomes (such as interview and hiring decisions) in terms of improvement in selection accuracies and turnover reduction.

4. Ensuring Robustness and Practical Application

- Sensitivity Analysis: The rankings remain stable by adjusting (±10%) the AHP weights, thereby confirming the reliability of the model.
- Real Life Application: The alternative list is adopted in hospitals for employment decisions while with concentrations on turnover rate validation of the model for aiding better employee-organization fits.

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As a result, AHP and TOPSIS have succeeded in transforming an inherently subjective hiring criterion into an objective and date-based hiring criterion. The general weighting of selection factors with AHP is done under the influence of experts, while TOPSIS bypasses all experts and, through mathematical computations, ranks alternative on the basis of their fit with the organization's needs. A hybrid system will therefore be more targeted at recruitment and addressing high turnover by matching candidates to the hospital's long-term needs.

4 RESULTS AND DISCUSSION

4.1 AHP ANALYSIS

In this section, the AHP was applied to determine the relative importance of selection criteria for three major healthcare professions Doctor. The pairwise comparison matrices systematically measure and prioritize profession specific competencies, setting a structured framework for objective decision making. Validation of consistency in the AHP methodology provides a sound basis for any MCDM analysis that follows it in the selection of healthcare personnel.

The decision-making process is directly linked to the importance of relevant criteria. In this study, the criterion weights of Doctor such a (Medical Knowledge, Clinical Experience and Patient Care) were derived by the use of AHP method defined with the pairwise comparison matrix in Table 2.

Table 2. **AHP Comparison Matrix for Doctor Criteria**

Criteria	1	2	3
1. Medical Knowledge	1	5	7
2. Clinical Experience	0.2	1	3
3. Patient Care	0.1429	.33	1

Table 3 shows the weights. Medical Knowledge is given the highest weight for the doctor criterion, followed by Patient Care and Clinical Experience.

Table 3. **Weight of Each Criterion Calculated by AHP**

Criteria	The Weight Priorities	
1. Medical Knowledge	0.769	
2. Clinical Experience	0.104	CR= 0.062
3. Patient Care	0.127	

[89] states that CR in AHP should be equal to or less than 0.1 (CR ≤ 0.1). In this study, it was found that CR stands at 0.062, indicating that matrix consistency is quite acceptable. In turn, the most significant criterion for doctor criterion is Medical Knowledge, which has the highest weight criterion (0.769), while Clinical Experience has the least weight criterion (0.104). Such weights are essential for solving MCDM problems. Figure 3 exhibits the weight of each criterion using AHP calculated as radar-chart.

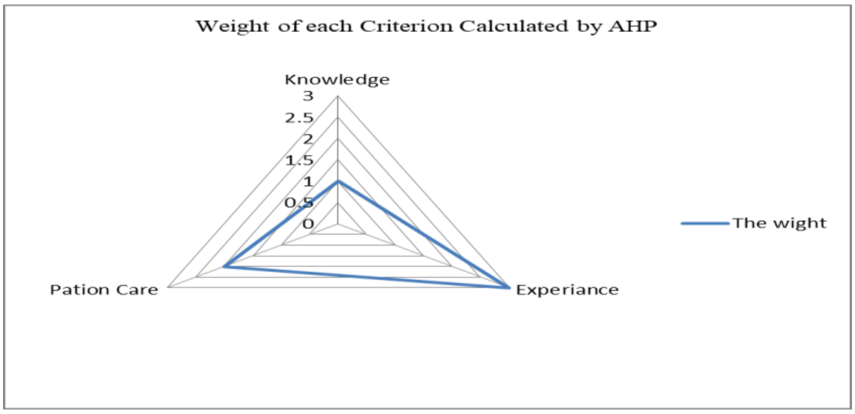

FIGURE 3. The Doctor Criterion weight calculated by AHP

4.2 TOPSIS ANALYSIS

This section clarifies the TOPSIS method to determine the ranking of the alternatives of each selection criteria for three major healthcare professions of doctor.

The systematic procedure, following which the TOPSIS methodology was implemented, included: first constructing the normalized decision matrix for positive and negative ideal solutions using Equations (5) and (6). Then, the weights were incorporated to yield Equation (10), which resulted in the weighted normalized decision matrix with respect to each sub criterion. Equations (11) and (13) then provided the identification of the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) for all alternatives. This then led to the computation of the separation measures between each alternative and the PIS/NIS by means of Equations (15) through (17). Finally, the closeness coefficient (CCi) as derived from Equation (18) gave the alternatives an ordering supplied with the basic criteria.

It is considered that TOPSIS had been used for evaluating and ranking alternatives for the Doctors as per three main criteria, namely Medical Knowledge Clinical Experience and Patient Care which have further alternatives for each of them. Below is the elaboration of the standardized procedure followed to enable the effect of any possible methodological fault through the closeness coefficient (CCi) while ranking alternatives across both primary criteria and their constituent sub criteria:

4.2.1 MEDICAL KNOWLEDGE ALTERNATIVES

Table 4 presents the Medical Knowledge rankings of the five candidate alternatives, (Accuracy in interpreting lab/imaging results) emerged as the highest-ranked alternative (CCi = 0.873) in Medical Knowledge sub criteria and (Board certification exam score) ranked the lowest (CCi = 0.131). This assignment in prioritization indicates that the evaluators are placing greater emphasis on diagnostic accuracy among them when they judge the medical knowledge for personnel selection. Noteworthy is that significant variation in ranking distribution was recorded based on aggregation through all criteria in Medical Knowledge. The graphical alternative distribution representation across Medical Knowledge appears in Figure 4.

Table 4. **The rank of the Medical Knowledge alternatives based on the criterions**

Alternatives	CC_i	The rank
Accuracy in interpreting lab/imaging results	0.873	First
Board certification exam score	0.131	Fifth
CME hours completed annually	0.417	Fourth
Case presentation quality score	0.782	Second
Medication error rate (inverse score)	0.758	Third

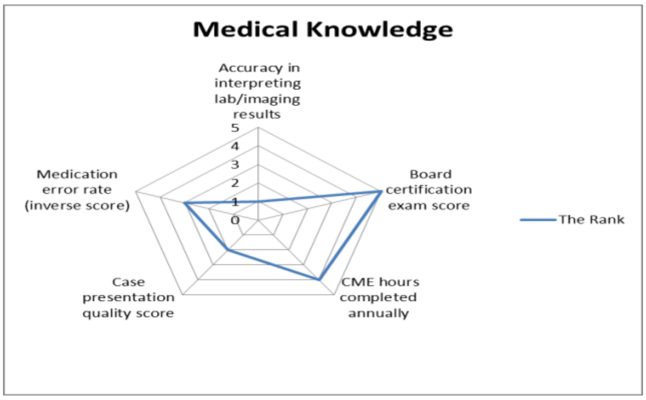

FIGURE 4. **Radar chart of the Medical Knowledge alternatives.**

4.2.2 EXPERIENCE ALTERNATIVES

The ranking against the Clinical Experience sub criteria of the five candidate alternatives is given in Table 5. Thus, the analysis shows that the highest priority was given to (Leadership roles held) (CCi = 0.934); the lowest priority rated was (Teaching/mentoring activities) (CCi = 0.06). Thus, it would seem that evaluator's judge's clinical experience for personnel selection; comparatively favor demonstrated leadership ability to contributions in education. This also tells upon the relative ranking distribution of the composite all Clinical Experience criteria. This is graphically represented by Figure 5 showing relative performance of alternatives across the Clinical Experience dimension.

Table 5. The rank of the Clinical Experience alternatives based on the criterions.

Alternatives	CC_i	The rank
Years of post-residency practice	0.507	Fourth
Annual procedure volume	0.508	Third
Complex case success rate	0.884	Second
Teaching/mentoring activities	0.06	Fifth
Leadership roles held	0.934	First

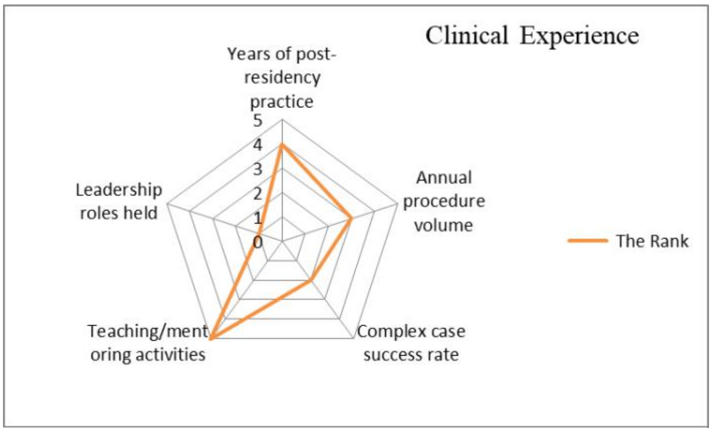

FIGURE 5. Radar chart of the Clinical Experience.

4.2.3 PATIENT CARE ALTERNATIVES

Table 6 made a comparative ranking of five alternatives versus sub criteria on Patient Care. From the analysis, the highest priority goes to 'Patient follow-up adherence rate' (CCi = 0.926), and the lowest rank was assigned to 'Patient satisfaction score' (CCi = 0.064). This spread denotes a greater preference for longitudinal care metrics than retrospective satisfaction measures in the evaluation of Patient Care competencies for personnel selection. The composite ranking from all Patient Care criteria gives further evidence to this evaluative preference.

Table 6. The rank of the Patient Care alternatives based on the criterions.

Alternatives	CC_i	The rank
Patient satisfaction score	0.064	Fifth
Average consultation time (inverse score)	0.5	Fourth
Patient follow-up adherence rate	0.926	First
Peer communication rating	0.508	Third

Patient complaint frequency (inverted)	0.909	Second

In the figure attached to 6, the relative performance of alternatives against dimensions of Patient Care is summarized. The quantitative findings are verified by this graphical representation, particularly the marked difference between adherence and satisfaction measures. Thus, this serves also as an interpretational aid in understanding how different sub criteria roll up to produce the ultimate rankings of alternatives.

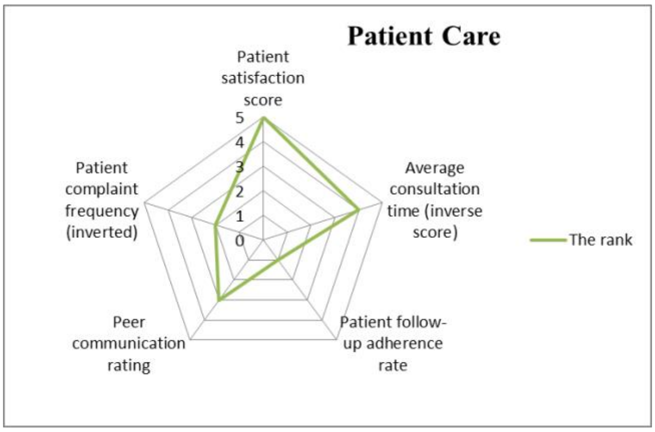

FIGURE 6. Radar chart of the Patient Care.

Discussion

The integrated AHP-TOPSIS framework introduced in this study offers a systematic and effective approach for prioritizing technical competencies in the selection of healthcare staff. Our results indicate that Medical Knowledge (AHP weight = 0.769) is the most critical criterion for selecting doctors. This finding aligns with the work of [8], who also identified core medical expertise as a fundamental pillar for healthcare professionals, particularly in high-stress environments. The high prioritization of practical skills such as accuracy in interpreting lab/imaging results (CCi = 0.873) over traditional metrics like board certification exam score (CCi = 0.131) further supports the growing shift toward demonstrable, competency-based selection models, a principle that is central to modern HRM strategies as discussed in [6, 7].

However, the relatively low weight assigned to Patient Care (0.127) and the poor performance of Patient Satisfaction Scores (CCi = 0.064) suggest a persistent institutional bias toward technical proficiency at the expense of humanistic and psychosocial dimensions of care. This finding presents a notable contrast with prior literature. For instance, [72] and [75] emphasized the critical importance of doctor-patient communication and the therapeutic relationship in achieving positive health outcomes, suggesting that these factors should be more heavily weighted. Furthermore, [9] established a clear link between teamwork, communication, and the quality of care, particularly in nursing, which implies that undervaluing these aspects in selection could inadvertently negatively impact service delivery.

This undervaluation may reflect a broader trend in data-driven HRM where quantitative, easily measurable criteria are favored over qualitative, relationship-based indicators. This aligns with criticisms raised by [21], who noted that implicit biases in healthcare systems often lead to the systematic undervaluation of "soft skills." Our study thus reinforces the need for future MCDM frameworks to incorporate more holistic evaluation criteria that balance technical and humanistic competencies, a challenge acknowledged in the broader MCDM field [31, 34].

The excellent consistency ratio (CR = 0.062) confirms the reliability of our AHP weighting process, which is consistent with the methodological standard (CR ≤ 0.1) established by [89]. However, the divergence between our results and those advocating for greater emphasis on patient-centered care suggests that contextual factors—such as organizational priorities in private healthcare or regional practices in Sulaimani [68, 70] may significantly influence criterion weighting. This underscores the importance of adapting generic MCDM models to specific institutional and cultural contexts, a flexibility that is a noted strength of the AHP-TOPSIS methodology [47, 53].

In summary, while our AHP-TOPSIS model effectively reduces subjective bias and enhances candidate-organization fit by leveraging a structured, data driven approach [5, 64], its current formulation may overlook critical aspects of patient-centered care. Future iterations should integrate psychosocial factors and qualitative feedback mechanisms to better align with contemporary healthcare paradigms that value both technical excellence and human connection, thereby creating a more resilient and effective workforce [22, 59].

Theoretical & Practical Implications

Indeed, in theory, MCDM literature development gained momentum with confirming AHP-TOPSIS streaks for ever-operating contexts of HRM concerning weighing of qualitative measures and ranking by distances to turn subjective judgments into structured decisions. Thereby, this adds theories to competency-based selection. Such silence in Patient Care indicates the incompleteness of MCDM frameworks on the holistic view, and thus calls for psychosocial factors integration.

In practice, this also offers hospitals chances to exchange such tools that lessen differential hiring and turnover. Much as these elements would be at play for correct diagnosis and leadership, it is still left to administrators to alter these weights in preference to mentorship and better patient communication. Furthermore, implementation will also mean contextualization of the model to local settings (public hospitals, for instance,) and effective HR analytics to upscale.

Conclusion

The AHP-TOPSIS model provides a data-driven solution to enhance the stability of the workforce in Sulaimani's private healthcare sector, emphasizing technical skills and leadership to reduce mismatches and turnover. Under prioritization of such metrics as Patient Care can compromise the strength of those objectives because it is nonetheless rigorous (CR = 0.062). Future implementations should also involve public health systems and qualitative feedback such as peer/patient evaluations besides testing robustness through sensitivity analyses. This balances HR effectiveness in the present with organizational resilience over the long term but will require ongoing adjustment to reflect changes in the healthcare value system.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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