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Performance Measurement of Financial Officer Recruitment of a Company Using PIVN-AHP & PIVN-TOPSIS

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Abstract. When it comes to building and sustaining a company's financial base, financial officers (FOs) are indispensable. Consequently, hiring FOs should be fair and efficient to guarantee continuous economic growth. Evaluating their performance is crucial. The main objective of this research is to find the best financial officer. The research developed an innovative method based on the parametric representation of interval numbers to handle the uncertainty in real-life multi-criteria decision-making (MCDM) scenarios. This research considers all the essential characteristics of an FO to find the best candidate. We provide a new approach to determining the weight of each criterion and sub-criterion, the Parametric Interval Number-Analytic Hierarchy Process (PIVN-AHP). The next step in finding the best FO is to use a hybrid algorithm called PIVN-TOPSIS, which stands for Parametric Interval Number-Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Several MCDM approaches, such as Simple Additive Weighting (SAW), Weighted Aggregated Sum Product Assessment (WASPAS), and the Weighted Sum Model (WSM), were used in a comparative study to confirm the ranks. We could also conduct a sensitivity study by shifting the weight of specific criteria. An FO's evaluation focuses on key criteria and sub-factors, with PIVN-AHP used

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to calculate weights. “Accounts Knowledge” (C5) is the most significant criterion, while “Growth of Customer” (CW31) holds the highest sub-criterion weight.

Key words: performance measurement, financial officers, decision-makers, PIVN, AHP, TOPSIS.

1. Introduction

FOs are crucial to every organisation. The FO is responsible for overseeing the company’s finances. Therefore, a fair and effective method of recruiting FOs is required. Because there are so many competing factors to consider when hiring an FO, an exhaustive and methodical MCDM strategy is necessary. Incomplete, unclear, or unhelpful information is often required to solve MCDM challenges. Interval numbers help depict and handle imprecision better in FO recruiting since experts evaluate many traits subjectively. A definite numeric crisp value may not be acceptable. Ascribing weights to the criteria is essential to choosing the finest choice; hence, a new approach capable of tolerating imprecision is necessary. Recruiting under ambiguous circumstances will become easier for various service industries, including education, hospitality, healthcare, and tourism. It is one way the service industry consistently surpasses itself, but it cannot be quantified similarly to product-based sectors. It makes it more interesting and challenging to study. For instance, decision-makers may evaluate the efficiency of an FO in various ways specific to that individual’s personality, discipline, motivating role, communication skills, account knowledge, professionalism, and technical expertise. The interview performance of an FO may not lend itself to a point estimate of subjective appraisal. With this in mind, the research employs MCDM techniques using the Parametric form of Interval Numbers (PIVN) and assigned weights to the criteria (Alaa *et al.*, 2019).

Several MCDM methods exist for computing the weights. This research integrates the views of several decision-makers. It uses an arithmetic-mean aggregation technique to standardise the weights assigned to each criterion and sub-criterion for evaluating finance officers’ qualities. The MCDM AHP calculated the weights. Many recruitment procedures involve more than one expert or management representative, each of whom may place varying importance on a given set of traits when seeking a new FO. Problem-solving must address the uneven importance placed on various decision-makers using a method grounded in scientific logic. This research uses a methodology that accounts for the fact that multiple decision-makers place different values on the same factors before arriving at a unified set of weights for the recruiting process as a whole. Interviewees need honest feedback to improve their professionalism and academic development. Evaluation and ranking processes help better understand the strengths and limitations of applicants. Many qualities of an FO are qualitative, and intuitively, evaluating or rating an FO requires translating these qualities into numerical values by applying appropriate scales (Alrashedi, 2024).

1.1. *Related Works*

Dozens of scientific studies illustrate the evolution and integration of MCDM methodologies across diverse applications, reinforcing their significance in decision-making under complex and uncertain conditions when stakeholders and policymakers select personnel. Demirel and Çubukçu (2021) proposed a decision-making system using the fuzzy logic method, one of the AI approaches. The process is related to the performance assessment of employment seekers. Performance measurement includes all applications and develops a rule based on academic qualifications and experience. Esangbedo *et al.* (2021) analysed some vendors' human resource information systems through two novel hybrid MCDM methods that take ordinal data as input. They introduced a Grey-Point-Allocation Full-Consistency (Grey-PA-FUCOM) weighting approach. This approach extends the FUCOM (Pamučar *et al.*, 2018) method with Grey-Point-Allocation. The Grey-PA-FUCOM integrates the straightforward point-allocation technique commonly used by practitioners in human resources with the sophisticated FUCOM method familiar to experts in grey system theory. Ozgormus *et al.* (2021) presented a systematic approach to solving the Turkish textile industry's Personnel Selection Problem (PSP), considering multiple performance objectives and factors. The authors used a fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to assign weights to social criteria. The origins of the DEMATEL technique (Gabus and Fontela, 1972; Fontela and Gabus, 1974) trace back to Leontief's input-output model (Leontief, 1949), a widely recognised framework in economics. A key advantage of the DEMATEL method lies in its ability to construct a structural model of a systematic problem by analysing the strength of binary relationships (pairwise comparisons) between elements. Finally, a ranking among the alternatives is derived using the GRA technique regarding the scores related to each criterion in the previous step. Nong and Ha (2021) proposed an integrated MCDM approach to help select qualified workers in distribution science. They used an integrated methodology consisting of AHP (Saaty, 1977) and TOPSIS (Hwang and Yoon, 1981) to solve the problem of staff selection. AHP was used to obtain the weights for selection criteria, and TOPSIS was applied to rank the available options. Popović (2021) researched applying MCDM approaches in personnel selection. They used the CoCoSo method (Yazdani *et al.*, 2019) to rank possibilities and choose the best candidate. The fuzzy Analytic Hierarchy Process (FAHP) is an extension of the AHP that integrates fuzzy set theory. This integration, which allows decision-makers to use fuzzy membership functions and linguistic variables to address uncertainty, was pioneered by Bellman and Zadeh (1970). They and Zimmermann's (1978) significant advancements laid the foundation for applying fuzzy set theory in decision-making frameworks, marking a crucial evolution in the field. Bellman and Zadeh's (1970) framework utilised the maximin principle, a significant development in the field. This principle focuses on the worst-case scenario and carries a profound weight in decision-making. It influenced seminal works by Yager and Basson (1975) and Baas and Kwakernaak (1977) in fuzzy MADM that proposed additive weighting models. De Graan (1980) and Lootsma (1980) extended Saaty's theory for using fuzzy sets. Van Laarhoven and Pedrycz (1983) introduced the first FAHP method, which used triangular fuzzy numbers (TFNs) in pairwise comparison, significantly contributing to the field. Chen and Hwang (1992) categorised fuzzy methods into two groups: ranking methods, such as Hamming distance and linguistic ranking, and MADM methods like fuzzy simple additive weighting, fuzzy outranking, and FAHP. Uslu *et al.* (2021) aimed to measure the exact criteria for selecting qualified management at a healthcare facility. They employed Fuzzy AHP and MULTIMOORA (Brauers and Zavadskas, 2010) methodologies in choosing a health manager, considering the evaluation of 8 candidates in 12 personnel selection criteria. Several advanced MCDM approaches have been proposed to improve decision-making processes. The study by Zavadskas *et al.* (2010) highlighted the peculiarities of determining attribute weights in MCDM methods, emphasising the variability in expert knowledge across different fields. Keršulienė and Turskis (2011) integrated the ARAS-F and SWARA techniques for architect selection, demonstrating the effectiveness of combining fuzzy and ratio-based methods. Zavadskas *et al.* (2011) proposed a methodology incorporating SWOT analysis, AHP, expert judgment, and QUALIFLEX to determine management strategies for construction enterprises. Further contributions to personnel selection include the hybrid fuzzy MCDM approaches of Keršulienė and Turskis (2014a, 2014b), who integrated ARAS-F, the fuzzy weighted-product model, and AHP to enhance chief accountant selection. Turskis and Keršulienė (2024) introduced the SHARDA-ARAS methodology, effectively prioritising project managers for sustainable development. Ghorabaee *et al.* (2017) extended the EDAS method using interval type-2 fuzzy sets, providing a robust framework for multi-criteria group decision-making under uncertainty. Zavadskas *et al.* (2018) applied the TOPSIS-F method to assess air pollution, demonstrating the applicability of fuzzy MCDM techniques to environmental problems. Hashemi *et al.* (2018) combined grey-intuitionistic fuzzy ELECTRE and VIKOR for contractor assessment, enhancing decision-making in construction management. Erdogan *et al.* (2019) proposed a comprehensive MCDM model for sustainable construction management, integrating AHP and expert judgment to improve project selection processes. Gigović *et al.* (2016) introduced a new technique for multi-criteria decision-making – Multi-Attributive Ideal-Real Comparative Analysis method (MAIRCA). Boral *et al.* (2020) proposed a novel integrated MCDM approach by combining the FAHP with the modified Fuzzy MAIRCA (FMAIRCA). Liou and Wang (1992) suggested modifying the fuzzy weighted average (FWA) method developed by Dong and Wong (1987). Xu and Yager (2006) introduced some geometric aggregation operators based on intuitionistic fuzzy sets. Atanassov (1986, 1989) and Atanassov and Gargov (1989) introduced the concept of an intuitionistic fuzzy set, which is a generalisation of the fuzzy set (Zadeh, 1965). Kara *et al.* (2022) defined the choice of human resources managers in logistics organisations using the Intuitionistic Fuzzy Weighted Averaging (IFWA) technique to assign the weights to the criteria and the FMAIRCA technique to rank candidates for managers. The key determinants influencing the implementation of green human resource management into petrochemical firms by Bushehr City are the integrated approach of fuzzy hierarchical analysis and type-2 DEMATEL by Rajabpour *et al.* (2022). Keršulienė *et al.* (2010) introduced the Stepwise Weight Assessment Ratio Analysis (SWARA) method. Yager (2013a, 2013b) introduced the concept of the Pythagorean fuzzy set, a generalisation of the intuitionistic fuzzy set, offering enhanced capabilities for addressing uncertainty. Following its development, the introduction of Pythagorean fuzzy aggregation operators, such as the Pythagorean fuzzy weighted averaging and Pythagorean fuzzy ordered weighted averaging operators, proposed by Yager and Abbasov (2013), has sparked significant interest and engagement in the research community. Saeidi *et al.* (2022) modified the SWARA method by integrating it with the TOPSIS using Pythagorean fuzzy sets (PFSs) and named it the PF-SWARA-TOPSIS method. Sarucan *et al.* (2022) applied Hesitant Fuzzy AHP, Fuzzy-COPRAS, and Fuzzy-TOPSIS methods for job evaluation research in a food enterprise. This approach helps form an equal compensation policy for increasing employee satisfaction with job evaluation analysis of various positions. Qi (2023) constructed an advanced model of the TOPSIS model to present new approaches to assessing quality performance in public charging service quality. The research ranked alternative options using the TOPSIS combined with the FUCOM method with probabilistic, hesitant and fuzzy concepts. Yiğit (2023) proposed an integrated DSS approach using MCDM to evaluate trainers within organisations and select the best candidate(s) to participate in the training program. The proposed model also considers the training budget and the limitation on the number of assignments. This proposed model comprises three phases: Delphi, the Interval-Valued Neutrosophic AHP (IVN-AHP), and Fuzzy C-Means (FCM). Alrashedi (2024) mentioned that optimising the Human Resources Management Process or HRMP is possible with Markov chain and fuzzy MCDM methodologies. Dhruva *et al.* (2024a) introduced a decision framework for selecting CVs in healthcare sectors. The solution resolves the issue of excessive value hesitation in criteria using the LOPCOW (logarithmic percentage change-driven objective weighting) method, similar to the logarithmic normalisation method (Zavadskas and Turskis, 2008). The ranking system acts as the measure for individual CV appraisal using the CoCoSo methodology. Taylan *et al.* (2024) developed a new set of criteria and sub-criteria to assess twelve candidate pilots. The research explored numerically unmeasurable, imprecise, and non-linear continuous fuzzy linguistic characteristics that made the work distinct and challenging because of differing preferences and variations among the decision-makers (DMs). The application of three different procedures of fuzzy MCDM methods–fuzzy TOPSIS, fuzzy VIKOR, and fuzzy PROMETHEE–has been evaluated through the trapezoidal fuzzy number for ranking different positions in potential pilots.

1.2. *MCDM, Fuzzy-Based MCDM and Interval Numbers in an Uncertain Environment*

Saaty (1977) introduced the Analytic Hierarchy Process (AHP), a systematic and comprehensive approach for addressing complex decision-making problems (Saaty and Bennett, 1977; Saaty and Vargas, 1979; Saaty, 1980). While the AHP effectively structures decision-making processes and prioritises alternatives, it is important to acknowledge that it does not account for the ambiguity or indecisiveness that decision-makers may exhibit in real-world scenarios. A significant limitation should be considered when applying the AHP (Wind and Saaty, 1980; Saaty, 1982, 1996). To address this, researchers employed fuzzy AHP, a technique utilising comparison matrices that incorporate fuzzy integers. Zadeh introduced his concept of fuzzy sets in 1965. Fuzzy set theory solely considers the degree of approval, neglecting the certainty associated with decision-making. Zadeh (1965) founded the basic principles of the intuitionistic fuzzy sets (IFS) notion. Atanassov (1994) developed the IFS, a robust tool for managing ambiguity and uncertainty. The distinguishing characteristic of IFS is its ability to ascertain membership, non-membership, and indeterminacy levels for each element. Peng and Wang (2011) employed the GRA variant of the TOPSIS decision-making approach to address the optimal supplier selection problem utilising interval numbers. Hladík (2012) employed interval numbers to resolve the Linear Programming problem. Liao and Xu (2014) presented a study on Intuitionistic Fuzzy Systems. Classical AHP and Fuzzy AHP terminate at IFS values for comparison matrices, although the AHP extends well beyond this point. A triangular collection of conceptually fuzzy integers was employed for vendor selection using AHP (Kaur, 2014). Pal and Mahapatra (2017) devised a parametric representation of interval numbers in functional form, incorporating arithmetic operations in symmetric, asymmetric, and convex combinations. Wang *et al.* (2015) employed TOPSIS and the Response Surface Method in MCDM scenarios utilising interval data. Nirmala and Uthra (2019) used the AHP with the TIFN methodology of MCDM to solve the supplier selection problem. In recent years, numerous scholars have concentrated on evaluating the efficacy of university instructors. Nikoomaram *et al.* (2009) assessed the efficacy of administration sciences educators by utilising fuzzy set theory, AHP, and TOPSIS. Jana *et al.* (2024) employed fuzzy AHP for the priority-based selection of financial indices for investors. Huang and Feng (2015) advocate for using RAHPTOPSIS, an augmented variant of AHP and TOPSIS, to evaluate the reliability of college physical education courses. Mazumdar *et al.* (2010) assessed the efficacy of individual educators by utilising grey relational analysis (GRA) and the COPRAS technique. Wu *et al.* (2012) employed AHP and VIKOR MCDM to evaluate the 12 private universities designated as a case study by the Ministry of Education. Mondal and Pramanik (2014) employed a neutrosophic methodology and MCDM techniques for faculty recruitment problems. Modification of the extent analysis fuzzy AHP and the proposed fuzzy comprehensive evaluation method for educational performance, as outlined by Chen *et al.* (2015), regarding factor and sub-factor weight estimations. Daniawan (2018) integrated the AHP and SAW methodologies to determine the criterion weights and rank alternatives for evaluating lecturer performance. Alaa *et al.* (2019) developed a Fuzzy Delphi technique and multi-criteria research to assess and rank the English competency of prospective educators. Nandi *et al.* (2023) assessed the therapeutic alternatives for COVID-19 patients employing generalised hesitant fuzzy MCDM methodologies. Hussain *et al.* (2019) employed MCDM methods to evaluate the quality of services rendered by the telecommunications sector. Employing statistical techniques, the writers successfully identified the specific parameters affecting the quality of the service rendered. Ultimately, the Fuzzy RASCH method was employed to compute the weights. Furthermore, the TOPSIS method was employed to ascertain the best minimal quantity of lubrication (MQL), while the fuzzy MCDM approach was applied to evaluate service provider selection. Following the establishment of a correlation between machine output and input through response surface methodology (RSM), Sen *et al.* (2019a) utilised the non-dominated sorting genetic algorithm-II (NSGA-II) to explore potential solutions. Sen *et al.* (2019b) employed the MCDM method NTOPSIS in conjunction with GEP theory and the non-dominated sorting genetic algorithm-II (NSGA-II) to determine the optimal synergy between MQL and vegetable oil. To achieve optimal site selection, Hussain *et al.* (2018) utilised a methodology known as Parametric Interval Valued Intuitionistic Fuzzy Number

(PIVIFN) to evaluate the alternatives based on the criteria. Ghorui *et al.* (2021) utilised MCDM methods with fuzzy interval data to assess school teachers' effectiveness. The authors identified the ideal choice using the fuzzy TOPSIS method. Garg (2016) and Kumar and Garg (2018) enhance a unique generalised scoring function for interval-valued intuitionistic fuzzy sets. The revised scoring system was evaluated and featured four different situations. Ghosh (2021) examined the efficiency of Indian life insurance businesses utilising Data Envelopment Analysis (DEA) and Structural Equation Modelling (SEM). Sarkar (2012) and Sarkar *et al.* (2011) utilised the Euler-Lagrange theory to ascertain the optimal levels of product reliability and production rate inside a defective manufacturing system, focusing on the problem of economic manufacturing quantity (EMQ). Michaelowa (2007) advocates for applying bivariate and multivariate analysis, supplemented by visual aids, to examine the qualitative impacts of lower- and upper-level education on university students. Chien (2007) applied Kano's approach to decision-making to enhance student learning satisfaction. The proposed principles and decision-making approach may assist students, instructors, and administrators. Melón *et al.* (2008) employed the AHP technique, whereby a panel of decision-makers assigns weights to several aspects to identify the most effective educational project. Liao *et al.* (2023) enhanced the EDAS approach by utilising cumulative prospect theory for multi-attribute group decision-making by incorporating probabilistic hesitant fuzzy information Dhruva *et al.* (2024b). It is advisable to elucidate the stability and performance characteristics of the CoCoSo ranking technique in the context of unknown preferences. Yan *et al.* (2024) determined the placement of electric vehicle charging stations using the spherical fuzzy CoCoSo and the CRITIC (Diakoulaki *et al.*, 1995) methodologies.

1.3. *Research Gap*

Many MCDM methods are used for personnel selection and similar selection problems using fuzzy AHP, Fuzzy TOPSIS, IVN-AHP, Pythagorean/intuitionistic fuzzy methods, DEMATEL, FUCOM, CoCoSo, MAIRCA, etc. However, no focused studies are known to have been published that (I) customise the PIVN-AHP+PIVN-TOPSIS pipeline specifically to Finance Officer recruitment and (II) test in practice the PIVN rankings against real post-hire performance in FO roles.

1.4. *Research Questions*

a. How well do PIVN-AHP and PIVN-TOPSIS discriminate among candidates for a Financial Officer role compared with classical AHP–TOPSIS?
b. Does the PIVN-based ranking correlate with post-hire performance indicators better than alternative MCDM methods?

1.5. *Research Objectives*

The objectives of this study are:

I. To identify the best financial officer and
II. To get the ranking of the financial officer.

1.6. *Motivation for the Proposed Study*

Scholars have proposed various MCDM methods to assess, rank, and determine the most viable options. For example, Nikoomaram *et al.* (2009) applied a fuzzy MCDM approach to evaluate administrative sciences instructors, while Mazumdar *et al.* (2010) developed MCDM models for appraising teacher performance. Wu *et al.* (2012) employed a hybrid MCDM model for ranking universities based on performance evaluation. Other studies have focused on specific tools and applications in educational contexts. Huang and Feng (2015) utilised an AHP-TOPSIS approach to evaluate teaching quality in physical education. Mondal and Pramanik (2014) proposed a group decision-making model under a neutrosophic environment for teacher recruitment. Karmaker and Saha (2015) explored recruitment processes for teachers in Bangladesh using MCDM methods.

Additionally, Chen *et al.* (2015) evaluated teaching performance using a combination of fuzzy AHP and a comprehensive evaluation approach. Daniawan (2018) investigated lecturer performance through AHP and SAW methods, and Alaa *et al.* (2019) developed a framework combining fuzzy Delphi and TOPSIS to assess English skills in pre-service teachers. The AHP and TOPSIS methods described in this article rely on interval numbers to aid decision-making by identifying optimal solutions. Typically, interval numbers define the fuzziness of parameters, with triangular fuzzy numbers (TFNs) serving as an extension. When evaluating qualitative characteristics, decision-makers benefit from considering ranges rather than precise numerical values. For instance, the PIVN-based method estimates the highest degree of membership as a range rather than a single point. This approach simplifies the evaluation process, saving time and effort by reducing the need for exact numerical guesses.

In contrast to fuzzy numbers, which decision-makers divide into three intervals (low, medium, and high), interval numbers may be divided into three intervals (low, medium and high). PIVN is a more accurate depiction of reality in certain cases than TFN. For instance, in the Triangular Fuzzy Numbers (TFN) (a, b, c), membership begins at “a”, peaks at “b” with 1 and gradually decreases to 0 at “c”. An expert may be unable to determine the value “b” for an attribute when the maximum membership exists, a difficulty that arises in the actual world while hiring an FO. The notion of interval numbers offers a more confident approach to the expert that can end this hesitation. Considering the range [a, c], it becomes clear that the data is consistent throughout the interval. This research aims to recruit FOs based on an exhaustive set of attributes. The PIVN-AHP methodology helped decision-makers calculate the criteria and sub-criteria weights. After that, the authors used the TOPSIS approach with PIVN to rank the FOs. The parametric form of interval numbers (PIVN) gives decision-makers a great deal of leeway to lessen the degree of ambiguity and indeterminacy in their choices. Due to the paucity of literature on PIVN-AHP and PIVN-TOPSIS, we offer a novel idea to aid decision-makers in rapidly identifying viable options with little effort and time expenditure.

1.7. *Justification of Methodology*

Candidate selection for a Financial Officer is a multi-criteria decision-making problem involving criteria that sometimes oppose one another: financial expertise, regulatory compliance, ethics, analytical prowess, and leadership. The traditional AHP and TOPSIS methods strive to structure criteria and rank alternatives; however, they assume crisp or vague judgments, which do not allow for hesitation, ambiguity, or partial knowledge associated with human decisions.

This research uses the Parametric Interval Number Analytic Hierarchy Process (PIVN-AHP) to form the relative weights of the selection criteria. PIVN-AHP allows experts to express their opinions via interval judgments rather than fixed values, thus preserving the uncertainty of the decision maker while reducing subjectivity. The parametric representation of interval numbers allows the performance of systematic sensitivity analysis in order to verify the robustness of the weight estimates under changes in expert perception.

Once the hierarchy has been found, Parametric Interval Number TOPSIS will rank the Financial Officer candidates. The classical TOPSIS does not allow for interval-valued evaluations; hence, the PIVN extension has also been done to model the closeness of each candidate to both ideal and anti-ideal solutions under uncertainty. The hybrid PIVN-AHP and PIVN-TOPSIS application is particularly appropriate for recruitment settings because it (i) integrates both structured weighting of hierarchical criteria and compensatory ranking of alternatives; (ii) tackles vagueness and hesitation in expert judgment explicitly; and (iii) improves the decision robustness by employing parametric sensitivity analysis.

Thus, the methodology chosen herein allows for performance measurement in Financial Officer recruitment using a rigorous, transparent, and uncertainty-resilient, high-stakes, multi-dimensional framework, and subject to incomplete information.

1.8. *Contributions of This Study*

This study contributes to the literature by theoretically fleshing out Multi-Criteria Decision-Making (MCDM) in two important directions. Firstly, it starts with the incorporation of Parametric Interval Number AHP (PIVN-AHP) and Parametric Interval Number TOPSIS (PIVN-TOPSIS) into high-impact, high-stakes, and commercially more remunerative backgrounds of Financial Officer recruitment, where there stands decision uncertainty, evaluation ambiguity, and accountability for performance. While fuzzy, intuitionistic fuzzy, or Pythagorean fuzzy approaches capture half of the uncertainty only, parametric interval number realms parametrically membership, non-membership, and hesitation degrees, thus furnishing a much richer perspective in the guise of vagueness and judgmental inconsistency in expert evaluations. On the second count, the study advances personnel selection research theoretically by showing that the PIVN-based methods provide more robust and discriminative candidate rankings, in addition to being relatively immune to rank reversal and to sensitivity with changes in parameters, traits long perceived to be theoretical downfalls of classical AHP and TOPSIS. Further reinforcing this study is the fact that, by applying the method to Financial Officer recruitment and associating the rankings obtained with post-hire performance indicators, it establishes a new theoretical linkage bridging interval-based neutrosophic decision modelling with empirical validation in strategic human resource management.

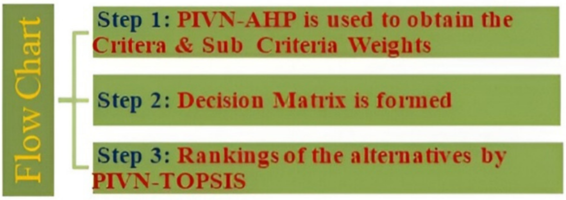

Fig. 1. Flow chart of the study.

1.9. *Novelties of the Proposed Study*

This article describes the parametric interval number (PIVN) theory, and AHP-linked TOPSIS with interval uncertainty was used to select the optimal option.

a) The concept of the parametric representation of interval numbers helps to handle the uncertainties of real-life MCDM problems conveniently.
b) A methodical approach is indispensable when hiring an FO. Decision-makers included all intelligible qualities of an FO, expanding on the criteria and sub-criteria already present in the literature. Consequently, the criteria and sub-criteria of this research provide an extensive set of characteristics.
c) The data were analysed using the TOPSIS and AHP procedures, which included interval uncertainty.

1.10. *Beneficiaries*

In particular, this study will aid company boards, HR managers, and executive recruitment panels by putting forward a systematic framework for the selection of financial officers, who may face uncertainty; policy makers and regulators, in promoting transparency in the recruitment process; academics and MCDM researchers, in extending parametric interval number methods to the problem under study; and consultants and recruitment agencies, in providing support for real-world decision-making.

1.11. *The Sketch of the Proposed Research*

We worked in a practice environment. Seven FOs participated in a simulated job interview. Five decision-makers were present: subject matter specialists, finance officials, and upper management. Figure 1 represents the study's flow chart.

1.12. *Structure of the Paper*

This article continues with the following structure: Mathematical preliminaries with the parametric form of interval numbers are introduced in Section 2, along with some introductory arithmetic operations. The PIVN-AHP and PIVN-TOPSIS methods are outlined in Section 3, along with a basic comparison of Classical-AHP and Classical-TOPSIS. Section 4 shows how PIVN-AHP and PIVN-TOPSIS are used to hire financial officers with numerical representation of calculations. Section 5 examines how various MCDM tools might be compared and contrasted to determine a ranked list. Tables and graphs show the various rankings since Section 6 contains the sensitivity analysis. Sections 7 and 8 present the findings of this research with limitations and suggestions for further research, respectively. Lastly, Section 9 presents conclusions.

2. Mathematical Preliminaries

2.1. *MCDM Methodology for FO Recruitment*

Definition 1. MCDM involves assigning relative importance to each criterion and rating the available options. Criteria are characteristics of the alternatives prioritised or valued by those choosing. Individual or collective decision-makers play critical roles in MCDM.

2.2. *Importance of the Proposed Research*

To achieve its objectives, a corporation must hire a capable FO. The government and private sector can gain from the proposed study in the following ways:

(a) It improves the current quantitative approach to hiring FOs by using an extensive list of criteria, sub-criteria, and various decision-makers.
(b) Both private and public sector organisations can use this method to hire new employees and determine internal promotions.

2.3. *Definition of Interval Number (Pal and Mahapatra, 2017)*

An interval number is a subset of the set of real numbers containing a closed interval of real numbers. It is symbolised as:

$$X = [m_l, m_r] = \{x : m_l \leqslant x \leqslant m_r;\ x \in \mathbb{R}\}, \tag{1}$$

where m_l and m_r denote the lowermost value and uppermost value of the interval, respectively, and $\mathbb{R}$ is the set of real numbers.

2.4. *Definition Parametric Interval-Valued Function (Pal and Mahapatra, 2017)*

Parametric interval-valued Function: Let us assume an interval $[m_l, m_r]$, where m_l, $m_r > 0$.

The parametric interval-valued function for the interval $[m_l, m_r]$ is defined as

$$a(\tau) = m_l^{1-\tau} m_r^{\tau}, \quad \text{where } \tau \in [0, 1]. \tag{2}$$

Cases:

a) if $\tau = 0$, we get the lower value of the interval;
b) if $\tau = 1$, we get the upper value of the interval;
c) for $0 < \tau < 1$, we get different values in the interval.

2.5. *Sum of Two PIVN (Pal and Mahapatra, 2017)*

Let $A = [m_l, m_r]$ and $B = [n_l, n_r]$ be two interval numbers with $m_l, m_r > 0, n_l, n_r > 0$. The Sum of two PIVN is denoted by $S = A + B$ and defined by

$$S(\tau) = m_l^{1-\tau} m_r^{\tau} + n_l^{1-\tau} n_r^{\tau}. \tag{3}$$

2.6. *Difference of Two PIVN (Pal and Mahapatra, 2017)*

Let $A = [m_l, m_r]$ and $B = [n_l, n_r]$ be two interval numbers with $m_l, m_r > 0$ and $n_l, n_r > 0$. The Difference between the two PIVN is denoted by $D = A - B$ and defined by

$$D(\tau) = m_l^{1-\tau} m_r^{\tau} - n_l^{1-\tau} n_r^{\tau}. \tag{4}$$

2.7. *Multiplication of Two PIVN (Pal and Mahapatra, 2017)*

Let $A = [m_l, m_r]$ and $B = [n_l, n_r]$ be two interval numbers with $m_l, m_r > 0$ and $n_l, n_r > 0$. The Multiplication of two PIVN is denoted by $M = A \times B$ and defined by

$$M(\tau) = m_l^{1-\tau} m_r^{\tau} n_l^{1-\tau} n_r^{\tau} = (m_l n_l)^{1-\tau} (m_r n_r)^{\tau}. \tag{5}$$

2.8. *Division of Two PIVN (Pal and Mahapatra, 2017)*

Let $A = [m_l, m_r]$ and $B = [n_l, n_r]$ be two interval numbers with $m_l, m_r > 0$ and $n_l, n_r > 0$. The Division of two PIVN is denoted by $V = \frac{A}{B}$, $B \neq 0$ and defined by

$$V(\tau) = m_l^{1-\tau} m_r^{\tau} \div n_l^{1-\tau} n_r^{\tau} = \left(\frac{m_l}{n_l}\right)^{1-\tau} \left(\frac{m_r}{n_r}\right)^{\tau}. \tag{6}$$

2.9. *Parametric Interval Numbers Weighted Aggregated Operator (PIVNWAO) (Pal and Mahapatra, 2017)*

Let $\tilde{A} = [m_l^{1-\tau} m_r^{\tau}]$ and $\tilde{B} = [n_l^{1-\tau} n_r^{\tau}]$ be two PIVN with weight factors $\tilde{w}^1$ and $\tilde{w}^2$ respectively such that $\tilde{w}^1 + \tilde{w}^2 = 1$. Then PIVNWAO is

$$\text{PIVNWAO}(\tilde{A}, \tilde{B}) = \tilde{w}^1 \left[m_l^{1-\tau} m_r^{\tau}\right] + \tilde{w}^2 \left[n_l^{1-\tau} n_r^{\tau}\right], \quad \text{where } \tau \in [0, 1]. \tag{7}$$

3. Methodology of PIVN-AHP and PIVN-TOPSIS

3.1. *Classical AHP*

Many MCDM practitioners rely on the AHP for weighing criteria. Saaty (1979) introduced this methodology. Both qualitative and quantitative information can benefit from it. AHP is a widely used decision-making tool in various domains, including engineering, economics, sustainability, and management. It provides a systematic, transparent, and mathematically rigorous approach to evaluating and prioritising alternatives based on expert judgment and pairwise comparisons. Ensuring consistency in judgments enhances the reliability and robustness of the decision-making process. Priority weights are obtained from pairwise comparisons using AHP to define the importance of each criterion. The decision maker is guided to the optimal action by the weights collected. In contrast to the possible lack of precision, the conventional AHP employs discrete values for the criteria preference and offers discrete weights. This essay develops the notion of interval numbers and applies it to the issue of hiring finance officers to address the imprecision inherent in qualitative evaluation. An interval represents a range or the extent to which a choice can vary within that range.

3.2. *Some Flaws of Fuzzy AHP*

The fuzzy AHP is a popular method. It is widely used in decision-making, and numerous published papers discuss its applications. However, we believe this approach's logic is flawed (Kèyù Zhü, 2014).

a) Specifically, the definition and operational rules of fuzzy numbers in fuzzy AHP contradict the core principles of fuzzy set theory and deviate from the AHP's basic tenets.
b) When interpreting the outcomes, fuzzy AHP lacks a universally accepted method for ranking fuzzy numbers and verifying the validity of the results.
c) Furthermore, we scrutinise the applicability of the Analytical Hierarchy/Network Process (AHP/ANP) in complex and uncertain environments. Our findings suggest that fuzzy ANP is fundamentally flawed due to the absence of fuzzy priorities in the super matrix, which forms the foundation of the ANP.
d) Despite the widespread application and citation of fuzzy AHP in numerous cases, those utilising this method will recognise its inherent issues.
e) The pairwise comparisons method often uses a matrix to solve an eigenvalue problem. The principal eigenvector determines the leading ranking, while the eigenvalue helps assess inconsistency. Bana e Costa and Vansnick (2008) scrutinised this approach. They establish the conditions of order preservation (COP) and demonstrate that even in consistent matrices, COP may not hold (Kułakowski, 2015).
f) The debate centres around the most effective method for determining priorities. Various matrices, differing in size and accuracy, are created randomly. As the matrix dimension and inconsistencies grow, so do the conflicting rankings. However, these conflicts primarily impact nearby priorities (Ishizaka and Lusti, 2006).

3.3. *PIVN-AHP*

Step 1: Formation of Comparison Matrix
A generalised representation of a comparison matrix in terms of a decision expert's Parametric form of an interval number. Whereas interval numbers include infinite values rather

than a crisp or accurate value, general methods cannot assess them. The interval numbers are chosen here as the numbers within the two values are also included, providing much scope to the decision-makers. Let the decision-makers express their judgment in the form $A_{n\times n}$ where $C_{kt} = [m_{lkt}^{1-\tau} m_{rkt}^{\tau}]$, where $k = 1, 2, 3, \ldots, n$; $t = 1, 2, 3, \ldots, n$ and $\tau \in [0, 1]$ denotes the comparative preference of criteria. In the matrix $C_{ii} = 1$ when $k = t$.

Comparison matrix of criteria in terms of PIVN for different values of τ

$$\begin{bmatrix} [m_{l11}^{1-\tau} m_{r11}^{\tau}] & [m_{l12}^{1-\tau} m_{r12}^{\tau}] & \cdots & [m_{l1n}^{1-\tau} m_{r1n}^{\tau}] \\ [m_{l21}^{1-\tau} m_{r21}^{\tau}] & [m_{l22}^{1-\tau} m_{r22}^{\tau}] & \cdots & [m_{l2n}^{1-\tau} m_{r2n}^{\tau}] \\ \vdots & \vdots & \ddots & \vdots \\ [m_{ln1}^{1-\tau} m_{rn1}^{\tau}] & [m_{ln2}^{1-\tau} m_{rn2}^{\tau}] & \cdots & [m_{lnn}^{1-\tau} m_{rnn}^{\tau}] \end{bmatrix}.$$

Step 2: Crispification of PIVN for all $\tau \in [0, 1]$
It is a set of numbers, one for each τ.

Step 3: Normalisation of Crisp Matrix

$$N_{kt} = \frac{h_{kt}}{\sum_{k=1}^{n} h_{kt}}, \quad \text{where } k = 1, 2, 3, \ldots, n;\ t = 1, 2, 3, \ldots, n. \tag{8}$$

Step 4: Estimation of Criteria Weights

$$w_t = \frac{\sqrt[n]{\prod_{t=1}^{n} N_{kt}}}{\sum_{k=1}^{n} \left(\sqrt[n]{\prod_{t=1}^{n} N_{kt}}\right)}. \tag{9}$$

Step 5: Assess the consistency of pairwise comparisons using the Consistency Index (CI) and Consistency Ratio (CR). Eq. (10) helps to calculate the CI.

$$CI = \frac{\lambda_{\max} - n}{n - 1}. \tag{10}$$

The $\lambda_{\max}$ is the largest eigenvalue of the comparison matrix, and n is the matrix size.

Saaty introduced the Random Consistency Index (RI) of the comparison matrix to validate the consistency of the comparisons. It varies based on the matrix size. There n is the matrix size.

Eq. (11) helps to calculate CR:

$$CR = \frac{CI}{RI}. \tag{11}$$

If $CR < 0.10$, the consistency is acceptable.
If $CR \geqslant 0.10$, the judgments may be inconsistent, and the comparisons should be revised.

Step 6: Sub-Criteria and Global Weights
A similar method follows for the sub-criteria, and finally, the global weights are obtained by multiplying the criterion weight by the respective sub-criterion weight.

3.4. *Classical TOPSIS*

When using MCDM to prioritise options, the TOPSIS technique is commonly employed. The TOPSIS algorithm is based on the idea that the optimal choice is the one that is the most like the Positive Ideal Solution (PIS) and the most unlike the Negative Ideal Solution (NIS). To aid decision-makers in picking the best option, the authors (Kelemenis and Askounis, 2010) created a novel TOPSIS-based multi-criterion technique. Chen *et al.* (2009) explained the benefits of TOPSIS as follows:

a) It makes sense and is easy to understand.
b) It has high computing efficiency.
c) Easy-to-understand quantitative methods for comparing the effectiveness of various solutions.

3.5. *PIVN-TOPSIS*

Step 1: Formation of the Decision Matrix

Step 2: Calculation of Normalised Decision Matrix

$$\overline{x}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}. \tag{12}$$

Step 3: Calculation of Weighted Normalised Decision Matrix

$$\hat{x}_{ij} = \overline{x}_{ij} w_j. \tag{13}$$

Step 4: Determination of the Positive Ideal Solution and Negative Ideal Solution

$$A^+ = (\hat{x}_1^+, \hat{x}_2^+, \dots, \hat{x}_n^+) = \left\{\left(\max_i \hat{x}_{ij} \mid j \in P\right), \left(\min_i \hat{x}_{ij} \mid j \in C\right)\right\}, \tag{14}$$

$$A^- = (\hat{x}_1^-, \hat{x}_2^-, \dots, \hat{x}_n^-) = \left\{\left(\min_i \hat{x}_{ij} \mid j \in P\right), \left(\max_i \hat{x}_{ij} \mid j \in C\right)\right\}, \tag{15}$$

where B represents Profit Type Criteria, and NB denotes Cost Type Criteria.

Step 5: Calculation of the Euclidean Distance from the Ideal Best and Ideal Worst value:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(\hat{x}_{ij} - x_j^+\right)^2}; \quad i = 1, 2, \dots, m; \; j = 1, 2, \dots, n, \tag{16}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(\hat{x}_{ij} - x_j^-\right)^2}; \quad i = 1, 2, \dots, m; \; j = 1, 2, \dots, n. \tag{17}$$

Step 6: Calculation of Performance Score and Ranks

$$K_i = \frac{S_i^-}{S_i^+ + S_i^-}. \tag{18}$$

A higher value of K_i represents better alternatives.

4. Data Description

Data for the study were gathered through a structured questionnaire administered to a panel of domain experts: senior finance managers, HR executives, and academics with knowledge in recruitment and financial management. The experts judged the recruitment criteria and sub-criteria from their perspective and organisational practices.

To reduce the possibility of biases, some of the following steps were taken:

- Ensuring Expert Panel Diversity – Respondents were selected from different organisations and backgrounds to avoid organisational or personal bias.
- Anonymity of Responses – All responses were collected anonymously to prevent conformity bias and to ensure independent judgments.
- Checking for Consistency – During the AHP stage, consistency ratios were found, and inconsistent studies were either recorded back or abandoned to control random and subjective bias.
- Using Parametric Interval-Valued Numbers (PIVN) – Through adopting PIVN for AHP and TOPSIS, uncertainty and vagueness in human judgment were mathematically modelled, reducing individual bias and thus creating a more rigorous decision-making framework.

5. Application of PIVN-AHP and PIVN-TOPSIS in the Recruitment of FO

Table 1 presents the criteria and sub-criteria for financial officer recruitment. These criteria were identified from several studies, each contributing to the framework. Nikoomaram *et al.* (2009) evaluated training performance using a fuzzy MCDM approach. Huang and Feng (2015) applied AHP-TOPSIS to assess teaching quality in physical education. Mazumdar *et al.* (2010) proposed multicriteria decision-making models for evaluating teacher performance. Wu *et al.* (2012) used a hybrid MCDM model to rank universities based on performance evaluation. Mondal and Pramanik (2014) introduced a group decision-making approach for teacher recruitment in a neutrosophic environment. Karmaker and Saha (2015) explored MCDM methods for teacher recruitment in Bangladesh. Chen *et al.* (2015) developed a fuzzy AHP-based approach for evaluating teaching performance. Daniawan (2018) applied AHP and SAW methods to assess lecturer teaching performance. Lastly, Alaa *et al.* (2019) proposed a framework combining fuzzy Delphi and TOPSIS methods to evaluate and rank the English skills of pre-service teachers.

Table 1
Criteria and sub-criteria for FO recruitment.

Criteria	Sub-criteria
C_1: Personality (PT)	C_{11}: Customer Management
	C_{12}: Flexibility
	C_{13}: Kindness
C_2: Discipline (DP)	C_{21}: Punctuality
	C_{22}: Dedication
	C_{23}: Well Organised
C_3: Motivating Role (MR)	C_{31}: Growth of Customer
	C_{32}: Positive Impact
	C_{33}: Financial Advice to Customer
C_4: Communication Skill (CS)	C_{41}: Speaking
	C_{42}: Listening
	C_{43}: Idea
C_5: Accounts Knowledge (AK)	C_{51}: Calculation Ability
	C_{52}: Problem Solving
	C_{53}: Analytical Skill
C_6: Professionalism (PL)	C_{61}: Work Ethics
	C_{62}: Confidentiality
C_7: Technological Knowledge (TK)	C_{71}: PPT
	C_{72}: FT Software

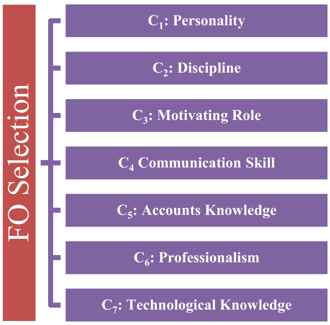

Fig. 2. Hierarchical structure representing the application.

Figure 2 below represents the hierarchical structure of the study.

Table 2 presents a linguistic five-point Likert-type Parametric Interval Number Scale for comparing the importance of a Financial Officer's criteria using the AHP method.

Obtaining PIVN values for different 'τ'.

Table 3 represents different values of 'τ'.

5.1. *Calculations of PIVN-AHP*

Step 1: Formation of a comparison matrix

The decision maker uses different linguistic terms for different criteria and sub-criteria, and Table 4 denotes the comparison of different criteria in linguistic terms. The pairwise

Table 2
Linguistic five-point likert-type parametric interval valued number scale for comparing the importance of a financial officer's criteria and sub-criteria using the AHP method.

Linguistic term	Abbreviation	Parametric interval valued number
Equally Important	$\boldsymbol{EQI}$	1
Moderately Important	MI	$[1^{1-\tau}; 2^{\tau}]$
Strongly Important	SI	$[2^{1-\tau}; 3^{\tau}]$
Very Strongly Important	$\boldsymbol{VSI}$	$[3^{1-\tau}; 4^{\tau}]$
Extremely Important	EXI	$[4^{1-\tau}; 5^{\tau}]$

Table 3
PIVN values for different 'τ'.

τ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
$\boldsymbol{EQI}$	1	1	1	1	1	1	1	1	1	1	1
$\boldsymbol{MI}$	1	1.06	1.13	1.22	1.32	1.43	1.52	1.64	1.76	1.84	2
$\boldsymbol{SI}$	2	2.07	2.14	2.23	2.35	2.44	2.54	2.66	2.77	2.85	3
$\boldsymbol{VSI}$	3	3.08	3.16	3.26	3.36	3.45	3.56	3.67	3.78	3.88	4
$\boldsymbol{EXI}$	4	4.09	4.18	4.27	4.36	4.47	4.57	4.68	4.78	4.89	5
$\boldsymbol{1/MI}$	0.50	0.54	0.57	0.61	0.66	0.70	0.76	0.81	0.88	0.94	1
$\boldsymbol{1/SI}$	0.33	0.35	0.36	0.38	0.39	0.41	0.42	0.45	0.46	0.48	0.50
$\boldsymbol{1/VSI}$	0.25	0.26	0.26	0.27	0.28	0.28	0.29	0.31	0.32	0.32	0.33
$\boldsymbol{1/EXI}$	0.20	0.20	0.21	0.21	0.22	0.22	0.23	0.23	0.24	0.24	0.25

Table 4
Pairwise comparison matrix of criteria in linguistic terms.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
C_1	$\boldsymbol{EQI}$	$1/VSI$	VSI	$1/MI$	$1/SI$	SI	EXI
C_2	VSI	$\boldsymbol{EQI}$	SI	$1/MI$	$1/SI$	$1/MI$	VSI
C_3	$1/VSI$	$1/SI$	$\boldsymbol{EQI}$	$\boldsymbol{EQI}$	$1/VSI$	$1/SI$	SI
C_4	MI	MI	$1/FI$	$\boldsymbol{EQI}$	$1/EXI$	$1/SI$	SI
C_5	SI	SI	VSI	EXI	$\boldsymbol{EQI}$	SI	EXI
C_6	$1/SI$	MI	SI	SI	$1/SI$	$\boldsymbol{EQI}$	SI
C_7	$1/EXI$	$1/VSI$	$1/SI$	$1/SI$	$1/EXI$	$1/SI$	$\boldsymbol{EQI}$

comparison matrix is prepared based on the perception of four authors who contributed to this paper.

Step 2: Crispification of PIVN for all $\tau \in [0, 1]$ (see Table 5)

Conversion of linguistic terms to a 'τ' value decided by a decision expert. The arithmetic mean method aggregates different decision-makers assigned 'τ' values.

Step 3: Normalisation of the crisp matrix (see Table 6)

Step 4: Estimation of Criteria Weights

Table 7 represents the criteria weights obtained by the PIVN-AHP methodology.

Table 7 shows that criterion C_5 scores the maximum weight of 0.331 (rounded off), followed by C_2, C_6, C_1, C_4, C_3 and C_7.

Step 5: Consistency Check

Table 5
Crisp pairwise comparison matrix.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
C_1	1	0.29	3.47	0.69	0.41	2.46	4.48
C_2	3.47	1	2.46	0.69	0.41	0.69	3.47
C_3	0.29	0.41	1	1.45	0.29	0.41	2.46
C_4	1.45	1.45	0.69	1	0.22	0.41	2.46
C_5	2.46	2.46	3.47	4.48	1	2.46	4.48
C_6	0.41	1.45	2.46	2.46	0.41	1	2.46
C_7	0.22	0.29	0.41	0.41	0.22	0.41	1
Sum	9.30	7.35	13.96	11.18	2.96	7.84	20.81

Table 6
Normalisation of crisped matrix.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
w_j	0.139	0.149	0.079	0.111	0.331	0.147	0.047
C_1	0.107	0.039	0.227	0.062	0.138	0.284	0.205
C_2	0.373	0.136	0.176	0.062	0.138	0.088	0.167
C_3	0.031	0.056	0.072	0.130	0.098	0.052	0.118
C_4	0.156	0.197	0.049	0.089	0.074	0.052	0.118
C_5	0.264	0.335	0.227	0.401	0.338	0.284	0.205
C_6	0.044	0.197	0.176	0.220	0.138	0.128	0.118
C_7	0.023	0.039	0.029	0.037	0.074	0.052	0.048

Table 7
Representation of criteria weights.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
w_j	0.139	0.149	0.079	0.111	0.331	0.147	0.047

Table 8
Calculated the weighted sum value (WSV), the ratio of WSV and the CW ratio.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Weighted sum value (WSV)	Criteria weights (w_i)	WSV/w_i
C_1	0.139	0.043	0.274	0.076	0.135	0.361	0.210	1.238	0.139	8.906
C_2	0.482	0.149	0.194	0.076	0.135	0.101	0.163	1.300	0.149	8.725
C_3	0.040	0.062	0.079	0.161	0.096	0.060	0.115	0.613	0.079	7.659
C_4	0.202	0.216	0.054	0.111	0.073	0.060	0.115	0.831	0.111	7.486
C_5	0.342	0.366	0.274	0.497	0.331	0.361	0.210	2.381	0.331	7.193
C_6	0.056	0.216	0.194	0.273	0.135	0.147	0.115	1.136	0.147	7.628
C_7	0.030	0.043	0.032	0.045	0.073	0.060	0.047	0.330	0.047	7.021

For this step, we must take the same crisped pairwise comparison matrix, which is not normalised. Table 8 shows values in each matrix junction after being multiplied by the criteria weights, weighted sum value (WSV), and the ratio of WSV and CW.

Now, $\lambda_{\max} = \frac{8.906+8.725+7.659+7.486+7.193+7.628+7.021}{7} = \frac{54.418}{7} = 7.774.$

Consistency Index (CI) $CI = \frac{\lambda_{max}-n}{n-1} = \frac{7.774-7}{7-1} = \frac{0.774}{6} = 0.129$; in this case, $n = 7$ as we have 7 criteria (see Table 9).

Table 9
Random Index (RI) up to 10 criteria.

Criteria number (n)	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Table 10
Global weights representation.

Criteria weights	Sub-criteria weights	Global weights
$w_1 = 0.139$	$w_{11} = 0.23$	$w_{111} = 0.032$
	$w_{12} = 0.55$	$w_{112} = 0.076$
	$w_{13} = 0.22$	$w_{113} = 0.306$
$w_2 = 0.149$	$w_{21} = 0.22$	$w_{221} = 0.033$
	$w_{22} = 0.36$	$w_{222} = 0.054$
	$w_{23} = 0.42$	$w_{223} = 0.062$
$w_3 = 0.079$	$w_{31} = 0.64$	$w_{331} = 0.050$
	$w_{32} = 0.21$	$w_{332} = 0.016$
	$w_{33} = 0.15$	$w_{333} = 0.012$
$w_4 = 0.111$	$w_{41} = 0.24$	$w_{441} = 0.026$
	$w_{42} = 0.12$	$w_{442} = 0.013$
	$w_{43} = 0.64$	$w_{443} = 0.071$
$w_5 = 0.331$	$w_{51} = 0.33$	$w_{551} = 0.109$
	$w_{52} = 0.46$	$w_{552} = 0.152$
	$w_{53} = 0.21$	$w_{553} = 0.070$
$w_6 = 0.147$	$w_{61} = 0.59$	$w_{661} = 0.087$
	$w_{62} = 0.41$	$w_{662} = 0.060$
$w_7 = 0.047$	$w_{71} = 0.23$	$w_{771} = 0.011$
	$w_{72} = 0.77$	$w_{772} = 0.036$

Consistency Ratio (CR) $CR = \frac{CI}{RI} = \frac{0.129}{1.32} = 0.098 < 0.10$.

0.10 is the standard value, as AHP allows up to 10% inconsistency. If the inconsistency exceeds 10%, the pairwise comparison matrix must be reconsidered.

The pairwise comparison matrix is reasonably consistent. Now, we can continue the decision-making process for further calculations using the criteria weights 0.139, 0.149, 0.079, 0.111, 0.331, 0.147, and 0.047, respectively, for criteria C_1, C_2, C_3, C_4, C_5, C_6, and C_7.

Step 6: Sub-Criteria and Global Weights Calculations

In the same way, sub-criteria matrices are built, and respective weights are gained. Eventually, the global weights are acquired by combining the criteria weight with their respective sub-criteria weight.

Table 10 refers to the criteria, sub-criteria, and global weights necessary to rank the FOs in this study.

5.2. *PIVN-TOPSIS Method for Selection of the Best Alternative*

Proposed Methodology: In this approach, PIVN is utilised to rank the options and illustrate the numerical grading of the alternatives concerning the criteria. The decision-makers

Table 11
Linguistic variables in terms of PIVN for preferential rating of the FOs.

Linguistic Variable (LV)	PIVN
VP: Very Poor	$[1^{1-\tau}; 2^{\tau}]$
P: Poor	$[2^{1-\tau}, 3^{\tau}]$
F: Fair	$[3^{1-\tau}; 4^{\tau}]$
G: Good	$[4^{1-\tau}; 5^{\tau}]$
E: Excellent	$[5^{1-\tau}; 6^{\tau}]$

considered in this study are a group of 3 administrative officers $o = \{1, 2, \ldots, \gamma\}$ and 2 external experts $\upsilon = \{1, 2, \ldots, \rho\}$.

Each voter uses a numeric scale to rate their preferences, and the Arithmetic Mean Method is used to get the aggregated results. This approach is better because it gives decision-makers greater leeway in assigning weights to the various choices based on the criteria. The options are ranked using the weight assigned to each sub-criterion.

5.3. *Numerical Study*

The following Table 11 represents the linguistic preference of decision-makers in terms of PIVN.

Note 1. The different PIVN values for the TOPSIS methodology are obtained for different 'τ'. Decision-makers rate the alternatives concerning the sub-criteria. Their aggregation is used to determine the final decision matrix. The 'τ' chosen by the decision-makers is wholly based on their expertise.

5.4. *Calculations of PIVN-TOPSIS*

Step 1: Formation of the Decision Matrix (see Table 12)

Step 2: Calculation of Normalised Decision Matrix (see Table 13)

Step 3: Calculation of the Weighted Normalised Decision Matrix (see Table 14)

Step 4: Determination of the Ideal Best and Ideal Worst Value (see Table 15)

Step 5: Calculation of the Euclidean Distance from the Ideal Positive and Ideal Negative Solutions (see Table 16)

Step 6: Calculation of the Performance Score & Ranks (see Table 17)
The relative closeness value of FO F_2 is maximum at 0.774. Thus, F_2 ranks first followed by the F_1, F_3, F_5, F_6, F_4, F_7. Therefore, $F_2 \succ F_1 \succ F_3 \succ F_5 \succ F_6 \succ F_4 \succ F_7$ (see Fig. 3).

6. Comparative Analysis

There have been several attempts at comparative analysis using various MCDM approaches, such as SAW, WASPAS, and the WSM. There is a strong relationship between

Table 12
Decision matrix using PIVN.

Fs	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}
F_1	4.11	4.21	4.72	2.84	3.69	4.22	4.33	3.97	4.03
F_2	4.46	4.31	4.12	3.85	3.45	4.64	4.11	4.31	5.86
F_3	4.02	4.12	4.61	2.33	2.34	4.09	4.29	3.76	3.97
F_4	2.66	3.01	3.36	2.15	3.68	3.67	2.22	1.84	3.36
F_5	4.45	4.46	4.05	2.43	2.84	3.23	3.85	4.06	3.86
F_6	3.79	4.02	4.89	2.33	2.45	3.67	4.37	3.68	3.88
F_7	2.46	3.11	3.46	2.25	3.99	4.08	2.22	1.84	3.72
$\sqrt{x_{ij}^2}$	10.012	10.395	11.139	7.024	8.633	10.492	9.891	9.234	11.019

Fs	C_{41}	C_{42}	C_{43}	C_{51}	C_{52}	C_{53}	C_{61}	C_{62}	C_{71}	C_{72}
F_1	3.11	3.88	3.96	4.12	4.12	4.54	3.68	3.72	4.11	4.66
F_2	4.97	4.01	5.65	5.23	5.93	5.82	4.12	4.39	4.09	4.97
F_3	3.08	4.11	4.02	3.78	3.44	4.23	3.68	3.69	4.12	4.55
F_4	2.57	1.46	2.78	3.24	4.01	4.66	3.24	3.68	1.56	2.15
F_5	3.23	3.89	4.26	4.12	3.56	5.89	3.78	3.98	4.11	4.78
F_6	3.08	4.01	3.23	2.39	3.36	4.12	3.99	3.29	4.01	4.78
F_7	3.01	1.72	2.97	3.31	2.66	1.82	2.31	3.59	2.23	2.24
$\sqrt{x_{ij}^2}$	8.913	9.184	10.435	10.139	10.541	12.209	9.492	9.991	9.538	11.066

Table 13
Calculation of normalised decision matrix.

Fs	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}
F_1	0.4105	0.4050	0.4237	0.4043	0.4274	0.4022	0.4378	0.4299	0.3657
F_2	0.4455	0.4146	0.3699	0.5481	0.3996	0.4422	0.4156	0.4667	0.5318
F_3	0.4015	0.3963	0.4139	0.3317	0.2711	0.3898	0.4338	0.4072	0.3603
F_4	0.2657	0.2896	0.3016	0.3061	0.4263	0.3498	0.2245	0.1993	0.3049
F_5	0.4445	0.4291	0.3636	0.3459	0.3289	0.3079	0.3893	0.4397	0.3503
F_6	0.3786	0.3867	0.4389	0.3317	0.2838	0.3498	0.4418	0.3985	0.3521
F_7	0.2457	0.2992	0.3106	0.3203	0.4622	0.3889	0.2245	0.1993	0.3376

Fs	C_{41}	C_{42}	C_{43}	C_{51}	C_{52}	C_{53}	C_{61}	C_{62}	C_{71}	C_{72}
F_1	0.3489	0.4225	0.3795	0.4063	0.3909	0.3718	0.3877	0.3723	0.4309	0.4211
F_2	0.5576	0.4366	0.5414	0.5158	0.5626	0.4767	0.4340	0.4394	0.4288	0.4491
F_3	0.3456	0.4476	0.3852	0.3735	0.3264	0.3464	0.3877	0.3693	0.4319	0.4112
F_4	0.2883	0.1589	0.2664	0.3195	0.3805	0.3817	0.3413	0.3683	0.1636	0.1943
F_5	0.3624	0.4236	0.4082	0.4063	0.3378	0.4824	0.3982	0.3984	0.4309	0.4319
F_6	0.3456	0.4366	0.3095	0.2357	0.3188	0.3374	0.4208	0.3293	0.4204	0.4319
F_7	0.3377	0.1873	0.2846	0.32645	0.2524	0.1491	0.2434	0.3593	0.2338	0.2024

the various methods of ranking. Some of them have a perfect correlation, demonstrating the trustworthiness of the PIVN-based MCDM approach and its capacity to capture fine-grained information across various variables. The Simple Additive Weighting (SAW) method and the Weighted Sum Model (WSM) are the same at a fundamental level. Both rely on a linear additive function in which each criterion is multiplied by its respective weight and summed. The SAW weighted addition method is one of the simplest and most

Table 14
Calculation of weighted normalised matrix.

w_j	0.032	0.076	0.306	0.033	0.054	0.062	0.05	0.016	0.012
Fs	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}
F_1	0.0131	0.0308	0.1297	0.0133	0.0231	0.0249	0.0219	0.0069	0.0043
F_2	0.0143	0.0315	0.1132	0.0181	0.0216	0.0274	0.0208	0.0075	0.0064
F_3	0.0128	0.0301	0.1266	0.0109	0.0146	0.0242	0.0217	0.0065	0.0043
F_4	0.0085	0.0220	0.0923	0.0101	0.0230	0.0217	0.0112	0.0032	0.0037
F_5	0.0142	0.0326	0.1113	0.0114	0.0178	0.0191	0.0195	0.0070	0.0042
F_6	0.0121	0.0294	0.1343	0.0109	0.0153	0.0217	0.0221	0.0064	0.0042
F_7	0.0078	0.0227	0.0950	0.0106	0.0249	0.0250	0.0112	0.0032	0.0040

w_j	0.026	0.013	0.071	0.109	0.152	0.07	0.087	0.06	0.011	0.036
Fs	C_{41}	C_{42}	C_{43}	C_{51}	C_{52}	C_{53}	C_{61}	C_{62}	C_{71}	C_{72}
F_1	0.0091	0.0055	0.0269	0.0443	0.0594	0.0260	0.0337	0.0223	0.0047	0.0152
F_2	0.0145	0.0057	0.0384	0.0562	0.0855	0.0334	0.0378	0.0264	0.0047	0.0162
F_3	0.0090	0.0058	0.0274	0.0407	0.0496	0.0242	0.0337	0.0222	0.0048	0.0148
F_4	0.0075	0.0021	0.0189	0.0348	0.0578	0.0267	0.0297	0.0221	0.0018	0.0070
F_5	0.0094	0.0055	0.0290	0.0443	0.0513	0.0338	0.0346	0.0239	0.0047	0.0156
F_6	0.0090	0.0057	0.0220	0.0257	0.0485	0.0236	0.0366	0.0198	0.0046	0.0156
F_7	0.0088	0.0024	0.0202	0.0356	0.0384	0.0104	0.0212	0.0216	0.0026	0.0073

Table 15
Determination of the ideal best and ideal worst value.

Fs	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}
F_1	0.0131	0.0308	0.1297	0.0133	0.0231	0.0249	0.0219	0.0069	0.0044
F_2	0.0143	0.0315	0.1132	0.0181	0.0216	0.0274	0.0208	0.0075	0.0064
F_3	0.0128	0.0301	0.1266	0.0109	0.0147	0.0242	0.0217	0.0065	0.0043
F_4	0.0085	0.0220	0.0923	0.0101	0.0230	0.0217	0.0112	0.0032	0.0037
F_5	0.0142	0.0326	0.1113	0.0114	0.0178	0.0191	0.0195	0.0070	0.0042
F_6	0.0121	0.0294	0.1343	0.0109	0.0153	0.0217	0.0221	0.0064	0.0042
F_7	0.0079	0.0227	0.0951	0.0107	0.0250	0.0241	0.0112	0.0032	0.0041
P^+	0.0143	0.0326	0.1343	0.0181	0.0249	0.0274	0.0221	0.0075	0.0064
P^-	0.0079	0.0220	0.0923	0.0101	0.0146	0.0191	0.0112	0.0032	0.0037

Fs	C_{41}	C_{42}	C_{43}	C_{51}	C_{52}	C_{53}	C_{61}	C_{62}	C_{71}	C_{72}
F_1	0.0091	0.0065	0.0269	0.0443	0.0594	0.0260	0.0337	0.0223	0.0047	0.0152
F_2	0.0145	0.0057	0.0384	0.0552	0.0855	0.0334	0.0378	0.0264	0.0047	0.0162
F_3	0.0090	0.0058	0.0274	0.0407	0.0496	0.0242	0.0337	0.0222	0.0048	0.0148
F_4	0.0075	0.0021	0.0189	0.0348	0.0578	0.0267	0.0297	0.0221	0.0018	0.0070
F_5	0.0094	0.0055	0.0290	0.0443	0.0513	0.0338	0.0346	0.0239	0.0047	0.0156
F_6	0.0090	0.0058	0.0220	0.0257	0.0485	0.0236	0.0366	0.0198	0.0046	0.0156
F_7	0.0088	0.0024	0.0202	0.0356	0.0384	0.0104	0.0212	0.0216	0.0026	0.0073
P^+	0.0145	0.0058	0.0384	0.0562	0.0855	0.0338	0.0378	0.0264	0.0048	0.0162
P^-	0.0075	0.0021	0.0189	0.0257	0.0384	0.0104	0.0212	0.0198	0.0018	0.0070

widely used decision-making techniques. Its straightforward application and broad usability make it a preferred choice for decision-makers across various fields. The SAW method, emerging from decision theory, has been extensively applied since the mid-20th century, grounded in utility theory and linear weighting approaches. The principles of

Table 16
Calculation of the Euclidean distance from ideal positive and ideal negative solutions.

Fs	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}
F_1	0.013	0.031	0.129	0.013	0.023	0.025	0.022	0.007	0.004
F_2	0.014	0.032	0.113	0.018	0.022	0.027	0.021	0.008	0.006
F_3	0.013	0.030	0.127	0.011	0.015	0.024	0.022	0.006	0.004
F_4	0.008	0.022	0.092	0.010	0.023	0.022	0.011	0.003	0.003
F_5	0.014	0.033	0.111	0.011	0.018	0.019	0.019	0.007	0.004
F_6	0.012	0.029	0.134	0.011	0.015	0.022	0.022	0.006	0.004
F_7	0.008	0.023	0.095	0.011	0.025	0.024	0.011	0.003	0.004
P^+	0.014	0.033	0.134	0.018	0.025	0.027	0.022	0.008	0.006
P^-	0.008	0.022	0.092	0.010	0.015	0.019	0.011	0.003	0.004

Fs	C_{41}	C_{42}	C_{43}	C_{51}	C_{52}	C_{53}	C_{61}	C_{62}	C_{71}	C_{72}	S_i^+	S_i^-
F_1	0.009	0.006	0.027	0.044	0.059	0.026	0.034	0.022	0.005	0.015	0.034	0.056
F_2	0.014	0.006	0.038	0.056	0.085	0.033	0.038	0.026	0.004	0.016	0.021	0.074
F_3	0.009	0.006	0.027	0.041	0.049	0.024	0.034	0.022	0.005	0.015	0.045	0.048
F_4	0.008	0.002	0.019	0.035	0.058	0.027	0.030	0.022	0.002	0.007	0.063	0.030
F_5	0.009	0.005	0.029	0.044	0.051	0.034	0.035	0.024	0.005	0.016	0.046	0.045
F_6	0.009	0.006	0.022	0.026	0.048	0.024	0.037	0.020	0.005	0.016	0.054	0.051
F_7	0.009	0.002	0.020	0.036	0.038	0.010	0.021	0.022	0.003	0.007	0.076	0.016
P^+	0.014	0.006	0.038	0.056	0.086	0.034	0.038	0.026	0.005	0.016		
P^-	0.007	0.002	0.019	0.026	0.038	0.010	0.021	0.019	0.002	0.007		

Table 17
Calculation of the performance score & ranks.

F_s	D_i^+	D_i^-	$D_i^+ + D_i^-$	$K_i = D_i^- / (D_i^+ + D_i^-)$	Ranks
F_1	0.0337	0.0556	0.0894	0.6225	2
F_2	0.0215	0.0735	0.0950	0.7740	1
F_3	0.0452	0.0478	0.0930	0.5137	3
F_4	0.0628	0.0297	0.0925	0.3214	6
F_5	0.0464	0.0454	0.0918	0.4947	4
F_6	0.0542	0.0509	0.1052	0.4843	5
F_7	0.0758	0.0157	0.0915	0.1713	7

Fig. 3. Distance measure and ranking of individual FOs.

SAW are closely associated with weighted summation in decision theory, as discussed by early scholars such as Harsanyi (1955) and Churchman *et al.* (1957) in their examination of multi-criteria evaluations. Their work laid the foundation for basic decision-making approaches, including utility-based evaluation methods, from which SAW principles originate. The term “Simple Additive Weighting” does not have a definitive first publication explicitly using that title in the early days of decision theory. However, one of the earliest explicit references to the SAW method by name is often attributed to MacCrimmon (1968) in his report for RAND Corporation, which formalised the method’s structure as a weighted linear combination for multi-attribute problems. MacCrimmon’s (1968) contributions significantly shaped MADM methods, including SAW, by building upon pre-existing utility principles and linear weighting techniques. Similarly, the Weighted Sum Model (WSM) is among the earliest and most fundamental methods in Multi-Attribute Decision-Making (MADM). Like the SAW, the WSM basis is a linear additive function where an alternative’s performance is determined by summing the weighted attribute values. The origins of the WSM are utility theory and linear additive models used in early decision analysis. Fishburn (1967) formalised the additive utility model, a foundational WSM basis. However, the method was applied in operations research and economic decision-making even earlier. MacCrimmon (1968) provided one of the earliest formal discussions of WSM in decision analysis and consolidated this approach for MADM problems. Some scholars differentiate SAW and WSM based on the normalisation of criteria values. SAW typically requires normalisation, such as converting all values to a 0–1 scale or a standardised unit, while scholars often use the WSM in its raw form.

Consequently, WSM is more frequently utilised in operations research and optimisation, whereas SAW is in MADM studies. When normalisation is applied, scholars can see SAW as a specific case of WSM. Otherwise, the two methods are identical, differing only in terminology across research disciplines. Keeney and Raiffa (1976) elaborate on WSM and other MADM techniques. Triantaphyllou and Mann (1989) compare WSM with methods like AHP, ELECTRE, and TOPSIS, highlighting their strengths and weaknesses. Yoon and Hwang (1995) explore WSM applications in engineering and business decision-making. Triantaphyllou (2000) compares WSM with other MADM methods, including AHP, TOPSIS, and ELECTRE. Zavadskas *et al.* (2014) provide an overview of MADM techniques, including WSM, and offer practical recommendations for their selection. Zadeh (1963) developed WSM as a straightforward method for solving issues with numerous criteria. Alternatives may be compared using WSM’s scoring system, with the resulting scores used to choose which options are ultimately employed in the research. Zavadskas *et al.* (2012) developed the WASPAS technique. The WASPAS approach combines two MCDM techniques, the WSM and the Weighted Product Model (WPM). Table 18 presents the ranking of FOs using these MCDM techniques.

Figure 4 shows the clustered chart ranking of WASPAS, WSM and SAW methods.

7. Sensitivity Analysis

Examining the most sensitive criterion and switching the weights, the sensitivity analysis shown in Table 19 and Fig. 5 yields two more rankings. The research using this strategy

Table 18
Ranking of FOs by different MCDM methods.

Fs	SAW	WSM	WASPAS (0.5)
F_1	2	2	2
F_2	1	1	1
F_3	4	4	4
F_4	6	6	6
F_5	3	3	3
F_6	5	5	5
F_7	7	7	7

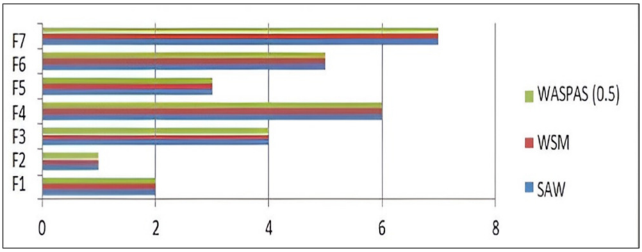

Fig. 4. Clustered chart representing the ranking of different MCDM methods.

Table 19
Representation of sensitivity analysis.

Fs	Ranking (PM)	Ranking (IW_1)	Ranking (IW_2)
F_1	2	2	2
F_2	1	1	1
F_3	3	4	4
F_4	6	6	7
F_5	4	3	3
F_6	5	5	5
F_7	7	7	6

discovered that "Accounts Knowledge" was given the most weight and, by extension, its subsidiary criterion. The research achieved a new ranking when decision-makers switched the global weights for the "Accounts Knowledge" and "Personality" criteria. The necessity of "PPT & FT software" for a finance officer became apparent during the COVID-19 epidemic. Working from home makes it easier to see how the "Technological Knowledge" criterion is crucial. Therefore, since "Problem Solving" had the most weight, we switched its weight with that of "FT software" in the second analysis. Simultaneously, the weight assigned to the "PPT" sub-criterion was switched with that assigned to the "Customer Management" sub-criterion.

Figure 5 shows different rankings obtained under sensitivity analysisn (see Table 20).

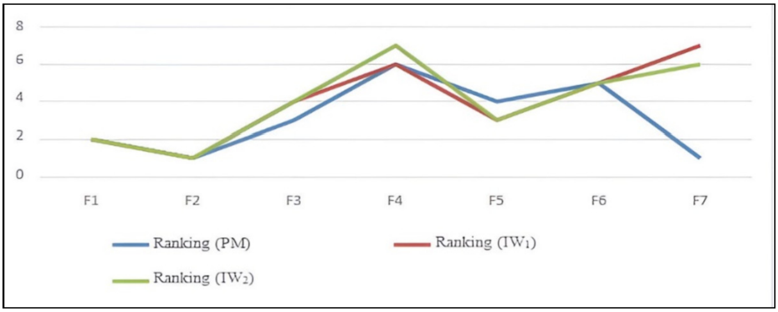

Fig. 5. Representation of different rankings obtained under sensitivity analysis.

Table 20
Correlations between ranks.

	SAW	WSM	WASPAS	PM	IW1	IW2
SAW	1	1.00**	1.00**	1.00**	0.90**	0.90**
WSM	1.00**	1	1.00**	1.00**	0.90**	0.90**
WASPAS	1.00**	1.00**	1	1.00**	0.90**	0.90**
PM	1.00**	1.00**	1.00**	1	0.90**	0.90**
IW1	0.90**	0.90**	0.90**	0.90**	1	0.81*
IW2	0.90**	0.90**	0.90**	0.90**	0.81*	1

** – Correlation is significant at the 0.01 level (2-tailed).
* – Correlation is significant at the 0.05 level (2-tailed).

8. Findings

A FO's evaluation should centre on several key criteria and sub-factors. The PIVN-AHP technique is used to calculate the weights. This demonstrates the significance of the "Accounts Knowledge" (C_5) criterion in selecting the most qualified FO. The "Growth of Customer" (CW_{31}) sub-criterion carries the most weight.

Sub-criteria were utilised to rank the options using the suggested technique. This method allows for highly granular requirements to be set for various specified FO characteristics. The most efficient finance officer was rated 'F_2' at 0.77, while the least efficient was rated 'F_7' at 0.17. This article focuses on the finer qualities of an FO, as there are more factors in the sub-criteria. The paper's authenticity and dependability are guaranteed by the exhaustive set of sub-criteria used to evaluate it. Using SAW, WSM, and WASPAS for comparison, all of the options performed similarly. The fact that the same ranking was achieved using a variety of procedures suggests that, despite their differences, decision-makers consistently favour the same alternatives. This study's sensitivity analysis revealed that altering the weights of the sensitive sub-criteria led to a different ranking. F_1 and F_2 rankings remained stable even when weights were switched around. It is more evidence that they excel in qualitative aspects, justifying their current position.

9. Limitations and Future Scopes

This study is limited to:

- FOs recruitment only.
- Application of Parametric Interval-Valued data.
- MCDM techniques: AHP and TOPSIS.

This framework can help assess FOs' performance in the future. Companies use client feedback to evaluate the performance of their FOs. Depending on the evaluation industry, decision-makers can rank FOs and recruit students or employees using several MCDM strategies, including the Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE) and the Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR). These methods incorporate hesitant and generalised hesitant fuzzy numbers along with MCDM tools. Since this is a branch of behavioural science, better methods may emerge to capture uncertainty more accurately.

Future research might involve students further analysing why teachers go to universities. This study's method of choosing a finance officer corresponds with the organisation's recruiting criteria. This method applies to situations of uncertain choice, such as choosing a family car, searching for EV charging stations, or choosing a site for buildings.

10. Conclusions

It is common knowledge that businesses benefit significantly from hiring competent finance officers and conducting regular performance reviews. The management of any given business is perpetually on the lookout for a qualified FO or officers who can improve the organisation's bottom line. Therefore, the selection and review process of a company's finance officer should be ongoing. This study presents a methodical framework that may be used universally to assess the effectiveness of an FO. A rigorous assessment mechanism has been developed to determine fair criteria and sub-criteria weights. Decision-makers can use this method to evaluate classroom instructors.

This study creates the AHP- TOPSIS approach for assessing FO performance, including a parametric Interval Numbers (PIVN) form. The parametric form of interval numbers aided in capturing the uncertainty that emerges in monetary attribute evaluation. In this article, we use the PIVN-AHP technique to determine the weights of the numerous criteria and sub-criteria involved in recruiting FOs and the PIVN-TOPSIS method to rank the candidates. Multiple businesses that rely on a combination of criteria to hire staff might benefit from this approach.

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