Maximizing Human Capital: Talent Decision-Making Using Information Technology

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***Abstract*—In the current fiercely competitive landscape, an organization's ability to succeed depends on its ability to leverage information technology to support personnel decisions that optimise the use of its people resources. This research examines five different strategies for optimising human capital through the use of information technology within the framework of multi-criteria decision-making (MCDM). Alternatively, you can leverage data-driven performance monitoring systems, artificial intelligence-driven talent acquisition platforms, virtual reality (VR) onboarding and training simulations, predictive analytics tools for succession planning and talent forecasting, and machine learning algorithms for skill assessment and development. Eight criteria—efficacy, efficiency, accuracy, accessibility, scalability, ethical concerns, influence on the organization's success, and trend adaptability—were developed to assess these options. We may determine the weights associated with each choice and rate them by applying the entropy weighted WASPAS (weighted aggregated sum product assessment) approach on top of the T-spherical fuzzy set (T-SFS) theory. This study adds to our understanding of how businesses could utilize information technology wisely to enhance human resource management in addition to providing guidance on how to assess various approaches based on how well they perform across a variety of metrics. Human resource specialists and organizational leaders may make use of the useful suggestions made by the study to improve personnel decision-making procedures and to make the most of their workforce's potential in the digital age.**

Keywords*—*WASPAS; information technology; virtual reality; entropy; machine learning; T-spherical fuzzy Sets

I. Introduction

The modern economy, which is marked by a quick pace and intense international competition, presents organizations with the difficult task of optimizing the use of their human resources more and more [1]. An organization's most significant resource is its human capital, which includes the professional abilities, expertise, experience, and inventiveness of its workforce. The degree to which this resource is successfully handled and exploited will determine its success in a highly competitive market [2]. Talent decision-making has emerged as a crucial facet of human resource management, facilitating the formulation of recruiting, development, and retention strategies that align with the organization's goals and objectives [3]. As stated by [4], subjective evaluations, intuition, and prior experience were often used in the traditional talent decision-making process. Conversely, firms are progressively utilising information technology to supplement and improve personnel management techniques in this data-driven decision-making era [5].

A wide range of resources that may be used to gather, evaluate, and apply data in order to make strategic decisions are included in the term "information technology" [6]. Zhang's [7] hybrid approach, which integrated rough set theory with deep learning, aimed to improve thermodynamic parameter estimation as well as provide more accurate and reliable predictions for a broad variety of engineering applications. These were the aims of the technique. The concept of human capital is essential to the decision-making process about talent. This theory holds that expenditures in human capital, such as education and training, provide observable benefits in the form of enhanced productivity, creativity, and organizational success [8]. Ramana et al. [9] developed a fuzzy-based method to assess potential sites for solar power plants. This method takes into account a wide range of factors, such as the influence on the environment, the economic viability, and the technical feasibility of the project.

By utilizing this theoretical framework, businesses may strategically allocate resources to recruit, develop, and retain elite talent, hence optimizing their human capital potential [10]. The use of automated decision-making that is based on fuzzy logic was examined by Berbiche et al. [11] in order to make supply chain operations more adaptive and robust in the face of uncertain conditions.

Organizations may make proactive, data-driven decisions about their talent pool and optimize their daily HR processes with the help of information technology. Human resource professionals may gain a better knowledge of the patterns, behaviors, and trends seen in the workforce by utilizing big data and advanced analytics. They are able to predict future talent demands and create plans to meet those expectations as a result. Predictive analytics may be used, for instance, to estimate employee turnover rates, spot potential flight hazards, and highlight impending talent shortages. This gives companies the capacity to take advantage of opportunities and manage dangers [12] when they present themselves. There are a few disadvantages to the broad use of information technology in hiring decisions in addition to the many advantages. For the purpose of determining the dependability of Internet of Things (IoT) systems, Singh et al. [13] presented parametric evaluation approaches. These methodologies drew attention to ways in which Internet of Things devices might be made more reliable and efficient. Concerns about bias, justice, and accountability in the decision-making process are also raised by the increasing use of algorithmic decision-making. This is a result of the possibility that AI-powered systems might inadvertently exacerbate prejudice or create new disparities. Consequently, businesses must use caution and make sure that the use of technology is guided by moral standards, transparency, and accountability [14].

A. Literature Review

An important development in the handling of imprecision in decision-making contexts was the introduction of the notion of "fuzzy sets" (FS) by Zadeh [14]. In spite of the inaccurate and confusing information being presented, Zadeh's mathematical method proven to be a useful tool for navigating the complexities of decision-making processes. Through the integration of the notion of "intuitionistic fuzzy sets" (IFS), Atanassov [15] expanded on earlier research and examined the attributes of membership and non-membership, thereby augmenting the potential of fuzzy sets to handle intricate decision-making situations [16]. For the purpose of optimizing hybrid heating systems, Altork and Alamayreh [17] conducted economic studies for the purpose of heating households in Jordan and selected optimal stations. The framework that they have developed allows for a comprehensive analysis and enhancement of the household heating solutions. A method to computational fluid dynamics modelling was developed and validated by Vasudevan et al. [18] by the use of wind tunnel measurements. This technique was applied to both urban and isolated street canyon situations. The key characteristics and operators in the system were emphasized by Cuong and Kreinovich [19]. Among the things they contributed were projection models [20], universal dice similarity measurements [21, 22]. Deva and Mohanaselvi [23] introduced geometric aggregation operations that were based on picture fuzzy Choquet integrals. Their goal was to enhance decision-making across a number of different qualities.

Singh's research on "correlation coefficients for picture fuzzy sets" [24] led to the creation of specialized metrics that are employed in the analysis of connections included within PFSs. Fuzzy techniques have a variety of practical applications; for instance, Abed and Rashid [25] evaluated the degree of advancement in Iraqi construction risk management by using a combination of fuzzy synthetic assessment and fuzzy analytical hierarchy process (AHP). To learn more about the basic properties of fuzzy connections in PFSs, Li et al. [26] carried out an enquiry. Li et al. [26] and Ashraf et al. [27-29], respectively, proposed an original distance metric for fuzzy sets of cubic PFSs and generalized simplified neutrosophic Einstein AOs. Ashraf et al. [29] Gundogdu and Kahraman [30] provided both of these contributions. The writers communicated both of these suggestions. PFSs were clearly subject to constraints, especially when the sum of the values exceeded one, leading to the construction of "spherical fuzzy sets" (SFS). Munir et al. [31] developed the T-SF Einstein hybrid aggregation techniques for decision-making. Several qualities are used in these procedures. In order to study the selection of photovoltaic cells, Zeng et al. [32] employed T-SF Einstein interactive aggregation operators [33]. Mani and Munusamy [34] developed a model for predicting cardiac issues that was based on fuzzy rules. This model was produced with the use of data lake technology. For the purpose of early diagnosis and treatment planning, this model is a reliable resource that makes use of fuzzy logic to account for ambiguities that may be present in medical data. A modified fuzzy method that was developed by Nanduri et al. [35] was able to improve the accuracy of harmful content identification, which in turn led to an improvement in the automatic classification of cyber hate speech on online social networks.

Using a T-SF DEMATEL approach, Sarkar et al. [36] assessed the potential for social banking systems throughout their research. The Sugeno-Weber triangular norm-based aggregation operators were studied by Sarkar et al. [36]. The framework of T-SF Hypersoft served as the backdrop for our enquiry. The best appropriate construction business was selected using the MCDM model with different attributes provided by Gurmani et al. [37]. The linguistic interval-valued T-SF TOPSIS approach is employed by this model for selection. These contributions underscore the usefulness of T-SFSs in complex decision-making scenarios by expanding our understanding and facilitating the use of these systems across several domains. These contributions have been advantageous to several fields.

Entropy-based methodological approaches have been integrated into MCDM research recently, with the goal of improving decision-making processes across a range of areas. An entropy-based MCDM approach for material selection was presented and proven to be successful by the authors Hussain and Mandal [38]. To address the variety and ambiguity that come with choosing criteria, this approach was created. The potential uses of entropy-based approaches in many fields, including the assessment of the placement of facilities and the sustainability of road transportation, have been further explored in more recent studies by El-Araby et al. [39] and Wang et al. [40]. In instances when decision-making is difficult and unexpected, these studies emphasize the need of using entropy-based objective weighing processes to provide better and more trustworthy conclusions.

Research has also concentrated on the properties of objective techniques for weighing the relative significance of criteria in MCDM situations. When choosing weighing processes that are appropriate for choice concerns, researchers and practitioners may benefit greatly from the insights offered by Mukhametzyanov [41] regarding the benefits and drawbacks of entropy, CRITIC, and SD methodologies. Additionally, studies by Zafar et al. [42] and Yadav et al. [43] have shown that entropy-based MCDM strategies work well for a variety of evaluation tasks. These duties entail the selection of biological materials and the use of blockchain technology, respectively. These results highlight the importance of using entropy-based methods to solve a broad range of choice issues and to support better decision-making in a broad range of applications [44].

The use of MCDM approaches—along with other techniques like WASPAS—has increased significantly in a number of areas. Khotimah et al. [45] created a hybrid decision support system that integrates clustering techniques with AHP and TOPSIS. This system was designed to provide assistance to small and medium-sized businesses (SMEs). This framework enhances the performance of the organization as well as the strategic decision-making process. Eghbali-Zarch et al. [46] illustrated the useful application of the VIKOR-WASPAS-entropy approach within the framework of their study on silent Genset selection. Moghrani et al. [47] introduced a hybrid technique to failure mode and effects analysis (FMEA) that used MCDM and a belt conveyor system in a mining scenario. The purpose of this method was to improve risk prioritisation and maintenance strategies. Al-Barakati et al. [48] offered a strategy for choosing foreign payment methods that makes use of spherical fuzzy WASPAS entropy goal weighting. This example highlighted the flexibility of WASPAS in the finance domain. Using MCDM approaches in combination with the G4 framework developed by the Global Reporting Initiative (GRI), Kumar et al. [49] graded Indian businesses according to their performance in terms of sustainability and evaluated the disclosures they made about sustainability.

In the context of supply chains for renewable energy, Bathrinath et al. [50] investigated the issue of strategic supplier selection using a fuzzy BWM-WASPAS-COPRAS model. Using fuzzy AHP-WASPAS techniques, Bathrinath et al. [50], the study's authors, looked at the aspects that affect building sites' long-term performance. A deeper comprehension of sustainability in the construction industry has been attained as a result of the research findings. More precisely, to explore the use of solar energy to guarantee Vietnam's long-term sustainability, Thanh and Lan [51] employed a hybrid SWOC-FAHP-WASPAS model. They provided an extensive analysis of the potential and limitations that solar energy presents in the framework of sustainable development. Handayani et al. [52] state that the WASPAS method was applied for choosing online English courses. WASPAS showed its adaptability in choosing educational possibilities through the use of this software. The process of assessing and prioritizing the various public transportation systems has involved the use of many MCDM models and methodologies.

B. *Motivation and Contribution*

This study is being conducted to look at this phenomena since human capital is becoming more widely acknowledged as being essential to how firms operate in the modern knowledge-based economy. Businesses have discovered that the efficient management and use of people has become more crucial to preserving their innovativeness and competitiveness.

- It is possible for traditional methods of staff management, training, and recruiting to result in poor outcomes, which in turn restricts the amount of creativity and efficiency that may be achieved on the job.
- Considering that contemporary contexts for managing people are notoriously difficult to understand and riddled with ambiguity, it is imperative that sophisticated decision-making frameworks be implemented immediately.
- Due to the fact that academic studies do not often have much to do with the organizational contexts that exist in the real world, it is vital to do research that can integrate theory with practice.
- For the purpose of ensuring the credibility and reliability of the results, it is essential to carry out exhaustive validation and robustness tests in decision-making research.

This paper makes several contributions to the existing literature and practice of human capital management:

- The idea of using T-SFS theory in combination with the Entropy Weighted WASPAS technique to assess various IT-based talent decision-making policies is covered in this paper
- The aim of this presentation is to offer HR professionals and executives practical suggestions on enhancing talent decision-making via information technology utilization.
- This paper offers long-term advice on how businesses can be ready to maximize their information technology investments in order to improve their human resource management procedures. Consequently, this will help companies achieve their objectives, maintain their competitive advantage, and promote development and innovation, in that order.
- The domains of information technology, human resource management, and MCDM have advanced theoretical understanding through the integration of concepts from fuzzy set theory, entropy, and decision-making techniques.
- It provides a thorough framework for directing decision-making processes related to talent management, bridging the gap between theoretical ideas and practical applications. This aids in our comprehension of the difficulties involved in hiring decisions in the digital age.

A brief summary of the contributions your article which applies these key principles has made to the domains of information technology integration, decision-making procedures, and human resource management.

C. *Structure of the Paper*

In Section II, the foundational ideas of T-SFS theory are examined, providing the framework for the suggested approach. The methodology for the proposed work is outlined in Section III, which compares many methods of talent decision-making utilizing T-SFSs and the Entropy Weighted WASPAS technique. This section explains how to use entropy to create weights and the WASPAS approach to rank alternatives. In Section IV, the practical applications of the suggested model are examined, showing how the approach might be applied to resolve HRM problems in the real world. Case studies and examples demonstrate the effectiveness and applicability of the proposed information technology-based talent decision-making process optimization strategy. Section V provides a summary of the study's key findings, a discussion of its theoretical and practical contributions, and recommendations for further research [53].

II. PRELIMINARIES

Definition 2.1 [54] A T-SFS in U is defined as:

$$\psi = \{\langle h, A(h), B(h), C(h) | h \in U \rangle\}, \tag{1}$$

where $A(h), B(h), C(h) \in [0,1]$, so that, for every $h \in U$, $0 \leq D^t(h) + B^t(h) + C^t(h) \leq 1$. For some $h \in U$, the symbols $A(h), B(h), and C(h)$ stand for membership degree (MD), abstinence degree (AD), and non-membership degree (N-MD), respectively. This pair is represented as $L = (D_L, B_L, G_L)$.

It is referred to as T-SFN throughout this paper and has the following conditions: $D_L^t + B_L^t + C_L^t \leq 1; D_L, B_L, G_L \in [0,1]$.

Definition 2.2 [54] It is essential to classify T-spherical fuzzy numbers (T-SFNs) before applying them to real-world scenarios. T-SFN is the equivalent of "score function" (SF) in this case. Let $L = (D_L, B_L, G_L)$ be described as follows:

$$S(L) = D_L^t - C_L^t \tag{2}$$

It is challenging to determine which is superior, nevertheless, because the previously mentioned function is insufficient for classifying T-SFNs in different contexts. One way to achieve this is to define an accuracy function H of L as follows:

$$\hbar^{\wp}(L) = D_L^t + B_L^t + C_L^t. \tag{3}$$

We will offer guidelines for aggregating T-SFNs in an operational manner.

Definition 2.3 *[34] Let* $L_1 = \langle D_1, B_1, G_1 \rangle$ *and* $L_2 = \langle D_2, B_2, G_2 \rangle$ *be two T-SFNs, then:*

$$L_1^G = \langle G_1, B_1, D_1 \rangle, \tag{4}$$

$$L_1 \vee L_2 = \langle max\{D_1, D_2\}, min\{B_1, B_2\}, min\{G_1, G_2\} \rangle, \tag{5}$$

$$L_1 \wedge L_2 = \langle min\{D_1, D_2\}, max\{B_1, B_2\}, max\{G_1, G_2\} \rangle, \tag{6}$$

$$L_1 \oplus L_2 = \langle \sqrt[t]{D_1^t + D_2^t - D_1^t D_2^t}, B_1 B_2, G_1 G_2 \rangle, \tag{7}$$

$$L_1 \otimes L_2 = \langle D_1 D_2, \sqrt[t]{B_1^t + B_2^t - B_1^t B_2^t}, \sqrt[t]{C_1^t + C_2^t - C_1^t C_2^t} \rangle, \tag{8}$$

$$\sigma L_1 = \langle \sqrt[t]{1 - (1 - D_1^t)^\sigma}, B_1^\sigma, G_1^\sigma \rangle, \tag{9}$$

$$L_1^\sigma = \langle D_1^\sigma, \sqrt[t]{1 - (1 - B_1^t)^\sigma}, \sqrt[t]{1 - (1 - C_1^t)^\sigma} \rangle. \tag{10}$$

Definition 2.4 Let $L_1 = \langle D_1, B_1, G_1 \rangle$ and $L_2 = \langle D_2, B_2, G_2 \rangle$ be two T-SFNs and $\mathbb{E}, \mathbb{E}_1, \mathbb{E}_2 > 0$ be the real numbers, then we have:

1) $L_1 \oplus L_2 = L_2 \oplus L_1$
2) $L_1 \otimes L_2 = L_2 \otimes L_1$
3) $\mathbb{E}(L_1 \oplus L_2) = (\mathbb{E}L_1) \oplus (\mathbb{E}L_2)$
4) $(L_1 \otimes L_2)^{\mathbb{E}} = L_1^{\mathbb{E}} \otimes L_2^{\mathbb{E}}$
5) $(\mathbb{E}_1 + \mathbb{E}_2)L_1 = (\mathbb{E}_1 L_1) \oplus (\mathbb{E}_2 L_2)$
6) $.L_1^{\mathbb{E}_1 + \mathbb{E}_2} = L_1^{\mathbb{E}_1} \otimes L_2^{\mathbb{E}_2}$

Definition 2.5 The T-spherical fuzzy weighted geometric (T-SFWG) operator for T-SFNs $T_j = (j = 1,2,3, \dots, s)$ is defined as

$$T - SFWG(S_1, TS_2, \dots, S_s) = \prod_{j=1}^{s} S_j^{O_j},$$

where $w = (w_1, w_2, \dots, w_s)^T$ is the weighted vector of $G_j = (j = 1,2,3, \dots, s)$, $O_j > 0$, and $\sum_{j=1}^{s} O_j = 1$. As a consequence, the result given in Theorem 2.6 may be obtained based on Definition 2.5.

Theorem 2.6 The aggregated value of a collection of $T - SFNsG_j (j = 1,2,3, \dots, s)$ using the T-SFWG operator is also a $T - SFN$, and

$$T - SFWG(S_1, S_2, \dots, S_s) = \left(\prod_{j=1}^{s} (D_j^D + \varrho_j^D)^{O_j^D} - \prod_{j=1}^{s} \varrho_j^{aO_j^D}, \prod_{j=1}^{s} \varrho_j^{aO_j^D}, \sqrt[n]{1 - \prod_{j=1}^{s} (1 -_j^{aO_j^D})} \right). \tag{11}$$

III. T-Spherical Fuzzy Entropy-WASPAS Method

Assume that $D = \{D_1, \dots, D_i, \dots, D_n\}$, a set of n alternatives, exist and that n is greater than or equal to 2.G represents a finite collection of criteria and may be expressed as follows: G is equal to $G = \{G1, \dots, Gj, \dots, Gm\} (m \geq 2)$. Assume that $D = \{D_1, \dots, D_e, \dots, D_z\} (z \geq 2)$ represents the group of invited DMs. The T-Spherical fuzzy Entropy-WASPAS method methodology may be explained by going through the following steps.

Algorithm

Step 1: Table I lists the eight linguistic terms that characterize each alternative. Linguistic idioms associated with knowledge complement these notions, as Table II illustrates. A complete depiction of the information assessment process is made feasible by the wide range of linguistic terminology available. Enter the T-SPFNs data set and compare it to the appropriate options $D_p; (p = 1,2, \dots, n)$ and the impact of different criteria $G_q; (q = 1,2, \dots, m)$.

TABLE I. LINGUISTIC TERMS FOR EVALUATION IN IT-BASED TALENT DECISION-MAKING

Linguistic Term	Description	T-SFN
Very High ($\boldsymbol{VH}$)	*Represents exceptional performance where the alternative meets all criteria with minimal issues and exceeds expectations in all aspects.*	$(\langle \mathbf{0.90}, \mathbf{0.05}, \mathbf{0.10} \rangle)$
High ($\boldsymbol{H}$)	*Represents strong performance where the alternative effectively meets criteria with minor, easily manageable issues.*	$(\langle \mathbf{0.85}, \mathbf{0.10}, \mathbf{0.15} \rangle)$
Moderate ($\boldsymbol{M}$)	*Represents satisfactory performance where the alternative meets criteria with occasional, manageable challenges.*	$(\langle \mathbf{0.80}, \mathbf{0.15}, \mathbf{0.20} \rangle)$
Adequate ($\boldsymbol{AD}$)	*Represents acceptable performance where the alternative maintains consistency in meeting criteria but may encounter occasional, manageable issues.*	$(\langle \mathbf{0.75}, \mathbf{0.20}, \mathbf{0.25} \rangle)$
Acceptable ($\boldsymbol{AC}$)	*Represents acceptable but not outstanding performance where the alternative can handle criteria with occasional challenges under specific conditions.*	$(\langle \mathbf{0.65}, \mathbf{0.25}, \mathbf{0.30} \rangle)$
Limited ($\boldsymbol{L}$)	*Represents performance with limitations where the alternative may face moderate challenges under certain circumstances.*	$(\langle \mathbf{0.60}, \mathbf{0.30}, \mathbf{0.35} \rangle)$
Poor ($\boldsymbol{P}$)	*Represents poor performance where the alternative experiences frequent challenges but remains stable overall.*	$(\langle \mathbf{0.50}, \mathbf{0.35}, \mathbf{0.40} \rangle)$

TABLE II. DECISION MAKERS

Profession	Role	Responsibility	Experience & Qualifications
Operations	*Operations Manager*	*Ensuring alignment of talent strategy with operational goals*	*12+ years in operations, MBA in Operations Management*
Finance	*CFO*	*Allocating resources for talent management initiatives*	*10+ years in finance, CPA qualification*
Diversity, Equity & Inclusion	*DEI Manager*	*Fostering an inclusive workplace culture and diversity initiatives*	*5+ years in DEI, Certification in Diversity Management*

Step 2: As Table I provides the LTs, determine the ratings of DMs based on the significance of T-SFNs. Assume that $L_k = \langle D_{L_k}, B_{L_k}, G_{L_k} \rangle$ is the T-SFN for the k-th DM's significance. The weight h_k of the k-th DM may therefore be calculated using the formula given in Eq. 12 shown below:

$$h_k = \frac{L_k}{\sum_{k=1}^{p} L_k}, k = 1,2,3, \quad (12)$$

where $L_k = D_{L_K}^t - C_{L_k}^t$ and clearly $\sum_{k=1}^{p} h_k = 1$.

Step 3: Utilising Eq. 11, compute the aggregated decision matrix (ADM) $M = [M_{ij}]_{r \times s}$.

Entropy Method

By employing Eq. 11, it is possible to calculate the aggregated decision matrix (ADM) $M = (M_{ij})$. The entropy approach is a methodology that is utilised in MCDM for the purpose of calculating the weights of criteria based on their respective entropy values. It does this by determining the degree of uncertainty or unpredictability associated with each criterion and then assigning weights in accordance with that degree.

Step 4.1:

Find the aggregated matrix's score matrix using Eq. 13.

$$T_{i,j} = D_{i,j}^t - C_{i,j}^t. \quad i = 1,2,\ldots,m; \; j = 1,2,\ldots,n; \quad (13)$$

Step 4.2:

Data normalization is the process of transforming the input data into a decision-making matrix with a range of 0 to 1. A vital simplification strategy when the requirements ask for a range of numerical values is normalization. Eq. 14 was used to normalize the entropy method for the benefit type criterion, while Eq. 15 was used for the cost type criterion.

$$O_{ij} = \frac{E_{ij} - \min(E_{ij})}{\max(E_{ij}) - \min(E_{ij})} \quad i = 1,2,\ldots,m; \; j = 1,2,\ldots,n; \; (14)$$

$$O_{ij} = \frac{\max_i(E_{ij}) - E_{ij}}{\max_i(E_{ij}) - \min(E_{ij})} \quad i = 1,2,\ldots,q; \; j = 1,2,\ldots,p; \; (15)$$

Step 4.3:

The standardized value is found in this phase by using Eq. 16.

$$V_{ij} = \frac{O_{ij}}{\sum_{i=1}^{m}(O_{ij})} \quad i = 1,2,\ldots,m; \; j = 1,2,\ldots,n; \quad (16)$$

Step 4.4:

Eq. 17 illustrates how the standardized value may be used to find the entropy value.

$$Z_j = -h \sum_{i=1}^{m} \left(V_{ij} \ln(V_{ij}) \right) \quad j = 1,2,\ldots,n; \quad (17)$$

where $h = \frac{1}{\ln(m)}$.

Step 4.5:

Eq. 18 is used to determine the degree of divergence J_j for each criterion before determining the weights of the j th criteria.

$$J_j = 1 - Z_j \quad j = 1,2,\ldots,n; \quad (18)$$

Step 4.6:

To determine weights, use Eq. 19.

$$W_{v_j} = \frac{J_j}{\sum_{j=1}^{n}(J_j)} \quad j = 1,2,\ldots,n; \quad (19)$$

such that, $W_{v_j} \in [0,1]$ and $\sum_{i=1}^{n} W_{v_j} = 1$. There are a lot of zeros in the measured data set V_{ij}. Consequently, we have to apply the constraint $V_{ij}\ln(V_{ij}) = 0$. for $V_{ij} = 0$ in the Z_j computation. This causes the entropy value to drop for such values, increasing the weight [55]. The modified standardisation method initially presented in Equation 16 is shown in Eq. 20 to avoid zero values in the normalised data set.

$$V_{ij} = \frac{O_{ij} + C}{\sum_{i=1}^{m}(O_{ij} + C)} \quad i = 1,2,\ldots,m; \; j = 1,2,\ldots,n; \quad (20)$$

where G is a constant satisfying the condition,

$$O_{ij} + C > 0$$

Step 5: WASPAS method.

Step 5.1: Apply Eq. 21 to normalize the cost and benefit criterion.

$$Y_{ij} = \begin{cases} \dfrac{F_{(ij)}}{\max_i F_{(ij)}}, & i = 1,2,\ldots,m; \; j = 1,2,\ldots,n; \\ \dfrac{\max_i F_{(ij)}}{F_{(ij)}}, & \end{cases} \quad (21)$$

Step 5.2: To get the additive relative significance in the weighted normalized data for each option, use Eq. (22):

$$X^1{}_i = \sum_{j=1}^{n} Y_{ij} \cdot O_j \quad i = 1,2,\ldots,n; \quad (22)$$

where $X^1{}_i$ indicates the additive relative importance of each alternative.

Step 5.3: To get the multiplicative relative relevance of the weighted normalized data for each option, use Eq. (23):

$$X^2{}_i = \prod_{j=1}^{n} Y_{ij}^{O_j} \quad i = 1,2,\ldots,n; \quad (23)$$

Step 5.4: Describe the joint generalized criteria (X), which was developed to integrate and generalise multiplicative and additive approaches.

$$Q_i = \frac{1}{2}\left(\sum_{j=1}^{n} Y_{ij} \cdot O_j + \prod_{j=1}^{n} Y_{ij}^{O_j} \right) \quad i = 1,2,\ldots,r; \quad (24)$$

Moreover, as $H \in [0,1]$, apply Eq. (25) to improve ranking accuracy:

$$Q_i = H \sum_{j=1}^{n} Y_{ij} \cdot O_j + (1-H) \prod_{j=1}^{n} Y_{ij}^{O_j} \quad i = 1,2,\ldots,r; \quad (25)$$

The method's step-by-step reasoning and decision-making process are visually shown in a Fig. 1.

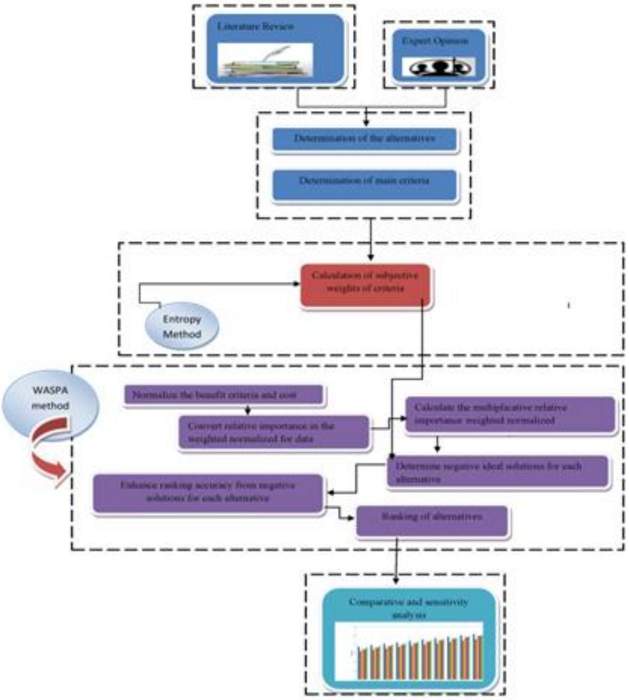

Fig. 1. The procedure of algorithm

IV. Statement of the Problem

The problem description states that information technology solutions can improve the processes used by firms to choose talent. More precisely, the challenge is figuring out which of the many workable options will enhance talent forecasting, succession planning, talent acquisition, performance management, and skill assessment and development. In order to make a selection, a number of options must be compared according to a number of criteria, such as how well they function, how accurate they are, how easy they are to use, how scalable they are, how they affect business performance, and how well they can adjust to emerging trends. Achieving top performance in terms of luring, nurturing, and keeping exceptional employees while also conforming to strategic objectives and adjusting to evolving business and technological environments is the ultimate objective.

A. Definition of Alternatives

- Implementation of AI-driven talent acquisition platforms $\boldsymbol{D_1}$:

Objective Illustration: Using modern facilities artificial intelligence technologies to expedite the recruiting of outstanding personnel. With the use of machine learning algorithms, artificial intelligence-powered systems may evaluate application data, match candidates to job requirements, and automate several steps in the hiring process.

Practical Example: For the purpose of determining whether or not an applicant is a suitable match for a job, platforms such as HireVue use artificial intelligence to analyses video interviews and assess whether or not the applicant's tone, word choice, and facial expressions are appropriate. Because of this, the process of hiring is streamlined, and businesses are able to locate excellent individuals more quickly.

- Adoption of data-driven performance management systems $\boldsymbol{D_2}$:

Objective Illustration: The output of workers is monitored and evaluated by performance management systems that are driven by data. This allows for the identification of strengths, weaknesses, and the overall efficacy of the team.

Practical Example: One example of a platform that combines data analytics is Workday, which is used for the administration of employee performance. Through the establishment of performance objectives, the provision of continual feedback, and the examination of performance patterns, managers have the ability to utilize it to make informed decisions about the needs for advancement, training, and developments.

- Integration of machine learning algorithms for employee skill assessment and development $\boldsymbol{D_3}$:

Objective Illustration: By analyzing performance records, identifying areas of weakness, and developing tailored methods for professional development, algorithms that have been taught using machine learning have the potential to execute these tasks.

Practical Example: Through the use of machine learning, systems like as LinkedIn Learning are able to personalize course suggestions for each individual by taking into consideration the individual's current skill set, job function, and career objectives. Individuals are able to acquire new skills and advance more quickly in their jobs if they concentrate their efforts on certain segments of the workforce.

- Utilization of VR simulations for training and onboarding $\boldsymbol{D_4}$:

Objective Illustration: VR simulations provide workers the opportunity to engage in immersive training experiences, allowing them to perfect their skills in an environment that is both safe and realistic.

Practical Example: VR is used by Walmart in order to better prepare its staff for real-life circumstances, such as the overwhelming amount of purchasing that occurs on Black Friday. This is beneficial to workers because it provides them with experience working under pressure, which enables them to be better prepared for and perform better in situations that are more similar to real world circumstances.

- Deployment of predictive analytics tools for succession planning and talent forecasting $\boldsymbol{D_5}$:

Objective Illustration: It is possible for predictive analytics systems to anticipate the organization's future people needs and identify potential future leaders by examining data from both the past and the present related to the workforce.

Practical Example: Watson Talent, a software developed by IBM, is able to estimate future staffing needs and discover employees who have significant potential for leadership by studying corporate patterns and people data. This information may be used by businesses in order to make preparations for the future and to ensure that they have the appropriate individuals to lead their development.

Definition of criteria

- Effectiveness $\boldsymbol{G_1}$: The extent to which the alternative achieves its objectives and contributes to the enhancement of the organization's processes for making decisions on talent.
- Efficiency $\boldsymbol{G_2}$: The degree to which the alternative maximizes benefits, minimizes costs, and makes the best use of available resources while installing and maintaining the solution.
- Accuracy $\boldsymbol{G_3}$: The accuracy and dependability of the alternative's projections, insights, and recommendations derived by data and algorithms are taken into account.
- User-friendliness $\boldsymbol{G_4}$: The alternative's usability, accessibility, and intuitiveness for all parties involved in the talent decision-making process and the usage of technology—HR specialists, managers, and staff members—are noteworthy.
- Scalability $\boldsymbol{G_5}$: When choosing a substitute, one should take into account characteristics like scalability, adaptability, and the capacity to respond to evolving, complicated, and expanding talent management demands inside the organization.
- Ethical considerations $\boldsymbol{G_6}$: The absence of bias in decision-making is one of the ethical issues raised by the alternative, along with worries about equality, transparency, and the protection of personal data.
- Impact on organizational performance $\boldsymbol{G_7}$: To what degree does the substitute contribute to the enhancement of critical performance metrics (KPIs) including employee productivity, contentment, and retention, along with the organization's overall effectiveness.
- Adaptability to future trends $\boldsymbol{G_8}$: Future developments in technology, shifts in the workforce's demographics, and organizational needs will determine how well the alternative adapts and remains relevant.

B. Experimental Results

The T-SF-based Entropy-WASPAS application procedure can be divided into the stages that follow:

Step 1: The DMs employed the T-SFNs dataset and several criteria (including language phrases from Table I) as listed in Table III for each alternative.

TABLE III. EVALUATIONS OF EACH ALTERNATIVE

DMs	Alternative	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8
DM_1	D_1	H	M	L	AD	P	AC	VH	L
	D_2	M	L	P	VH	AD	AC	H	P
	D_3	L	VH	H	AC	P	AD	VH	AD
	D_4	P	VH	AC	M	L	H	VH	M
	D_5	AC	M	VH	P	H	AD	L	AC
DM_2	D_1	VH	L	AC	H	VH	M	AD	H
	D_2	AC	H	M	VH	P	L	AD	P
	D_3	P	VH	AD	M	AC	H	L	L
	D_4	L	VH	P	AD	H	AC	M	VH
	D_5	AD	M	VH	AC	P	L	H	VH
DM_3	D_1	H	AD	VH	AC	P	M	VH	AC
	D_2	VH	P	AC	M	L	AD	H	P
	D_3	M	VH	H	P	AD	L	AC	AD
	D_4	L	AC	VH	H	M	P	AD	H
	D_5	AD	VH	L	AC	H	M	P	AC

Step 2: The scoring function described in Eq. 2 was applied to determine the weights of the DMs. Table IV presents the obtained values.

TABLE IV. EVALUATIONS OF EACH ALTERNATIVE_WEIGHT

	Decision-maker	Role	Key responsibilities	Weight
DM 1	VH	AD	AC	0.5653
DM 2	H	P	AD	0.3013
DM 3	VH	H	AC	0.1334

Step 3: To construct the ADM $M = \left[M_{ij}\right]_{r\times s}$, utilise Equation (11). Table V presents the obtained outcomes.

TABLE V. DMS WEIGHTS FOR EVALUTION

G	D_1	D_2	D_3	D_4	D_5
G	⟨0.810, 0.124	⟨0.853, 0.125	⟨0.832, 0.114	⟨0.813, 0.120,	⟨0.801, 0.116
G	⟨0.830, 0.113	⟨0.800, 0.150	⟨0.781, 0.209	⟨0.790, 0.220,	⟨0.761, 0.219
G	⟨0.761, 0.256	⟨0.751, 0.218	⟨0.690, 0.267	⟨0.880, 0.269,	⟨0.750, 0.231
G	⟨0.640, 0.234	⟨0.690, 0.332	⟨0.730, 0.290	⟨0.750, 0.303,	⟨0.640, 0.364
G	⟨0.641, 0.340	⟨0.761, 0.418	⟨0.690, 0.430	⟨0.530, 0.0.38	⟨0.530, 0.365
G	⟨0.601, 0.475	⟨0.630, 0.450	⟨0.531, 0.491	⟨0.430, 0.526,	⟨0.800, 0.230
G	⟨0.520, 0.403	⟨0.600, 0.460	⟨0.570, 0.501	⟨0.615, 0.470,	⟨0.611, 0.120
G	⟨0.450, 0.404	⟨0.510, 0.430	⟨0.611, 0.400	⟨0.570, 0.404,	⟨0.621, 0.409

Step 4: Entropy Method

Step 4.1: Eq. 13 is used to calculate an aggregate matrix's scoring matrix.

$$\begin{bmatrix} 0.4437 & 0.2366 & 0.5898 & 0.1157 & 0.0276 & 0.3273 & 0.5904 & 0.0758 \\ 0.5903 & 0.0290 & 0.1134 & 0.3277 & 0.0756 & 0.2362 & 0.4436 & 0.5905 \\ 0.3256 & 0.5905 & 0.4436 & 0.0297 & 0.2349 & 0.0771 & 0.1151 & 0.5905 \\ 0.0740 & 0.1159 & 0.5896 & 0.4436 & 0.3267 & 0.0300 & 0.2372 & 0.5904 \\ 0.2367 & 0.5905 & 0.0773 & 0.1131 & 0.4428 & 0.3270 & 0.0290 & 0.5905 \end{bmatrix}$$

Step 4.2: Utilizing Eq. 14 and 15, normalize the data.

$$\begin{bmatrix} 0.7160 & 0.3697 & 1.0000 & 0.2076 & 0.0000 & 0.4320 & 0.6430 & 0.0000 \\ 1.0000 & 0.0000 & 0.0703 & 0.7199 & 0.1155 & 0.3064 & 0.2615 & 1.0000 \\ 0.4873 & 1.0000 & 0.7148 & 0.0000 & 0.4992 & 0.8414 & 0.8466 & 0.3647 \\ 0.0000 & 0.1547 & 0.9996 & 1.0000 & 0.7205 & 1.0000 & 0.0000 & 0.9998 \\ 0.3151 & 0.9999 & 0.0000 & 0.2014 & 1.0000 & 0.0000 & 1.0000 & 0.3567 \end{bmatrix}$$

Step 4.3: For non-zero inputs, compute standardized values U_{ij} using Eq. 20.

$$\begin{bmatrix} 0.2423 & 0.1731 & 0.2838 & 0.1529 & 0.1034 & 0.1076 & 0.0955 & 0.0769 \\ 0.2989 & 0.0995 & 0.1079 & 0.2635 & 0.1273 & 0.1735 & 0.1454 & 0.2308 \\ 0.1967 & 0.2985 & 0.2299 & 0.1080 & 0.2066 & 0.2886 & 0.2571 & 0.2308 \\ 0.0996 & 0.1303 & 0.2838 & 0.3241 & 0.2524 & 0.3227 & 0.2156 & 0.2308 \\ 0.1624 & 0.2985 & 0.0946 & 0.1515 & 0.3102 & 0.1078 & 0.2864 & 0.2308 \end{bmatrix}$$

Step 4.4: Determine entropy values. Applying Eq. 17 to Z_j.

$$\begin{bmatrix} 0.9626 & 0.9447 & 0.9420 & 0.9506 & 0.9527 & 0.9365 & 0.9585 & 0.9636 \end{bmatrix}$$

Step 4.5: Utilizing Eq. 18, determine the degree of divergence X_j for every criteria.

$$\begin{bmatrix} 0.0373 & 0.0552 & 0.0579 & 0.0493 & 0.0472 & 0.0634 & 0.0414 & 0.0364 \end{bmatrix}$$

Step 4.6: Utilizing Eq. 19, compute weights W_{v_j}.

$$\begin{bmatrix} 0.0962 & 0.1422 & 0.1492 & 0.1271 & 0.1216 & 0.1633 & 0.1067 & 0.0937 \end{bmatrix}$$

Step 5.1: The two benefit and cost criteria might be normalized with the application of Eq. (21). Table VI presents the calculated values.

TABLE VI. NORMALIZED DECISION MATRIX

Alternative	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8
D_1	0.7515	0.4007	0.9989	0.1959	0.0468	0.5543	1.0000	0.1284
D_2	0.9997	0.0491	0.1920	0.5549	0.1280	0.4000	0.7513	1.0000
D_3	0.5514	1.0000	0.7513	0.0504	0.3977	0.1306	0.1950	0.9999
D_4	0.1253	0.1962	0.9986	0.7514	0.5534	0.0508	0.4018	1.0000
D_5	0.4009	0.9999	0.1310	0.1915	0.7498	0.5537	0.0491	1.0000

Steps 5.2-5.4: The weighted normalized data were subjected to the following equations to determine the relative relevance of each alternative: (X^1 for additive evaluation, (X^2 for multiplicative evaluation, and (X) for joint evaluation. These equations are based on the data. For a depiction of the findings, see Table VII.

TABLE VII. NORMALISED MATRIX

Alternative	X^1	X^2	Q	Ranking
D_1	0.5181	0.3584	0.4383	0.4383
D_2	0.4571	0.3074	0.3822	0.3822
D_3	0.4980	0.3334	0.4157	0.4157
D_4	0.4966	0.3250	0.4108	0.4108
D_5	0.5052	0.3485	0.4268	0.4268

The above table provides an overview of the findings from a meticulous investigation of several options, denoted as D_i. The overall ranking of each alternative is influenced by the normalised scores obtained for each of these categories.

Thorough analyses of $D_1 \succ D_5 \succ D_3 \succ D_4 \succ D_2$ are provided in order to provide a thorough grasp of their relative performances across various criteria and aid in well-informed decision-making.

C. Sensitivity Analysis

The influence of parameter H on several alternatives (D_1 to D_5) and their decision outcomes are sensitivity analysed and shown in Table VIII. With $D_1 \succ D_5 \succ D_3 \succ D_4 \succ D_2$, the corresponding rankings of alternatives remain constant as $lambda$ varies between 0.1 and 0.8. The decision-making model's stability and robustness are shown over a range of H values. Fig. 2 variations illustrate how different H values affect the framework's decision-making process.

TABLE VIII. INFLUENCE OF PARAMETER H ON SEVERAL ALTERNATIVES

Authors	Methodologies	Rankings	Best alternative
Chen [55]	*VIKOR*	$D_1 \succ D_5 \succ D_4 \succ D_2 \succ D_3$	D_1
Ali [60]	*CRITIC-MARCOS*	$D_1 \succ D_5 \succ D_2 \succ D_4 \succ D_3$	D_1
Fan et al. [57]	*COPRAS*	$D_1 \succ D_5 \succ D_2 \succ D_4 \succ D_3$	D_1
Ju et al. [56]	*TODIM*	$D_1 \succ D_5 \succ D_3 \succ D_2 \succ D_4$	D_1
Zhang and Wei [58]	*D-CRITIC and CPT–CoCoSo*	$D_1 \succ D_5 \succ D_3 \succ D_2 \succ D_4$	D_1
Proposed	$\boldsymbol{Entropy - WASPAS}$	$D_1 \succ D_5 \succ D_3 \succ D_4 \succ D_2$	D_1

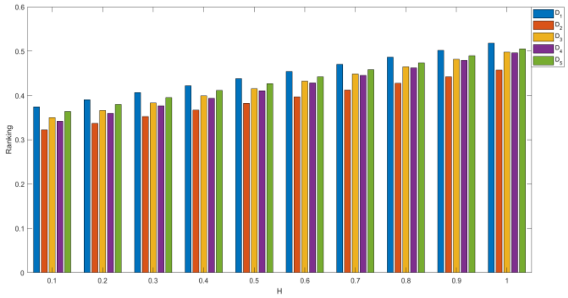

Fig. 2. Visualizing variations with changing parameter (H)

D. Comparative Analysis

TABLE IX. THE INFLUENCE OF THE PARAMETER H ON THE OUTCOME OF THE DECISION

H	D_1	D_2	D_3	D_4	D_5	Ranking
$H = 0.1$	0.3744	0.3223	0.3498	0.3422	0.3641	$D_1 > D_5 > D_3 > D_4 > D_2$
$H = 0.2$	0.3904	0.3373	0.3663	0.3594	0.3798	$D_1 > D_5 > D_3 > D_4 > D_2$
$H = 0.3$	0.4064	0.3523	0.3828	0.3765	0.3955	$D_1 > D_5 > D_3 > D_4 > D_2$
$H = 0.4$	0.4223	0.3673	0.3992	0.3937	0.4112	$D_1 > D_5 > D_3 > D_4 > D_2$
$H = 0.5$	0.4383	0.3822	0.4157	0.4108	0.4268	$D_1 > D_5 > D_3 > D_4 > D_2$
$H = 0.6$	0.4543	0.3972	0.4321	0.4280	0.4425	$D_1 > D_5 > D_3 > D_4 > D_2$
$H = 0.7$	0.4702	0.4122	0.4486	0.4451	0.4582	$D_1 > D_5 > D_3 > D_4 > D_2$
$H = 0.8$	0.4862	0.4272	0.4651	0.4623	0.4739	$D_1 > D_5 > D_3 > D_4 > D_2$
$H = 0.7$	0.4702	0.4122	0.4486	0.4451	0.4582	$D_1 > D_5 > D_3 > D_4 > D_2$
$H = 0.9$	0.4862	0.4272	0.4651	0.4623	0.4739	$D_1 > D_5 > D_3 > D_4 > D_2$

Emphasizing the significance of validation measures and conducting thorough comparisons with existing related work holds paramount importance. In our thorough comparison study, we looked closely at the practicality and effectiveness of several decision-making techniques inside the newly introduced T-SFS framework. Due to our thorough investigations, rigors validation, and significant use of robustness checks throughout the study, the results were more dependable and consistent. Table IX offers a compelling summary of the primary findings from our research. A comprehensive understanding of the benefits and drawbacks of alternate decision-making approaches is attained by looking closely at each element, which when taken as a whole yields nuanced revelations. In summary, this research advances our knowledge of decision-making in the context of T-SFSs by offering trustworthy insights for strategically integrating T-SFSs. In a thorough comparison combining several approaches, the Entropy-WASPAS methodology consistently performs better than the state-of-the-art methods CRITIC-MARCOS, VIKOR, COPRAS, TODIM, D-CRITIC and CPT–CoCoSo. D_1 is constantly shown to be the best option by Entropy-WASPAS, proving its effectiveness [59].

E. Discussion

Organisations all around the globe are always struggling to figure out how to enhance their methods of selecting candidates for open positions. When we keep to the tried-and-true methods of managing, developing, and acquiring persons, we limit ourselves to the innovative ideas and opportunities for growth that are available to us. In addition, because of the inherent inefficiencies that these systems now possess, it is often not possible to scale them up [60]. In order to address these issues, technological advancements are leading to the development of new platforms and methods that assist individuals in making critical choices. According to research, talent management methods that make use of information technology are much more effective and efficient. One example is the use of talent acquisition systems that are driven by artificial intelligence. These systems automate duties such as screening resumes and matching prospects in order to make the process of recruitment more effective [61]. Performance management systems that are powered by data provide useful insights for the growth of staff members by enhancing the monitoring and evaluation of performance [62]. Managing the complexity of IT talent decision-making may be accomplished by the use of the Entropy Weighted WASPAS approach, which is suggested by the study in addition to the T-SFS theory. The entropy approach helps in assessing the relative worth of each decision, which helps to reduce the subjective biases that are present in the process of assigning weights [39, 40]. The WASPAS system enhances the accuracy and reliability of judgements by providing a robust framework for grading possibilities in accordance with a number of criteria [15]. The T-SFS theory offers a more sophisticated approach to decision-making via the incorporation of ambiguity and vagueness [56]. This is particularly useful in the context of talent management.

It has been determined that D_1, which consists of talent acquisition platforms that are driven by artificial intelligence, is the most suitable solution for maximising the utilisation of human resources within the proposed paradigm. Additionally, this new research lends credence to the notion that artificial intelligence and machine learning have the potential to significantly enhance the precision and effectiveness of the recruitment process. Learning retention and skill transfer are both improved with the use of virtual reality (VR) simulations (D_4) because they provide learning experiences that are both immersive and engaging. To ensure the growth of the personnel, this is essential.

As part of our extensive comparative study, we looked at the practicability and effectiveness of a number of different decision-making approaches that were implemented inside the T-SFS framework. Because we evaluated everything in great detail and made full use of robustness testing, the results are more dependable and consistent than they would have been otherwise. In a side-by-side comparison with other approaches that are considered to be state-of-the-art, the Entropy-WASPAS methodology was shown to be the better option [56-59]. This consistent performance demonstrates that the Entropy-WASPAS approach is effective when applied to scenarios involving decision-making procedures. Table IX provides a summary that is both appealing and complete of our most important findings. When it comes to conventional decision-making processes, uncertainty and ambiguity are two of the most typical challenges that arise. The T-SFS model provides a state-of-the-art method to modelling uncertainty thanks to its enhanced accuracy and versatility in portraying the nuances of human judgment. When dealing with complex issues involving human management, having superior modelling ability is very necessary in order to make informed decisions.

By including ethical considerations into the decision-making process, one may ensure that it is both fair and transparent. This provides a solution to the problem of privacy and bias, which is becoming more urgent in this era of big data and artificial intelligence. In order for the proposed solutions to be effective in the long term, they need to be able to adjust to the shifting trends in both technology and operations inside the company.

Why the Proposed Work is better than Previous Approaches

- The proposed research combines the Entropy-WASPAS method with T-SFS to provide a more reliable decision-making framework. In terms of handling ambiguity and uncertainty, T-SFS outperforms traditional fuzzy sets, leading to more precise predictions.
- As part of the work that is planned, there will be a significant number of sensitivity studies and robustness testing. Through the use of these validation procedures, which may have been lacking in older methodologies, the results are assured to be trustworthy and consistent.
- In a comprehensive comparison with the following approaches: CPT-CoCoSo, D-CRITIC, TODIM, VIKOR, COPRAS, and CRITIC-MARCOS, the Entropy-WASPAS approach often outperforms the methods that are considered to be state-of-the-art. The fact that this is the case demonstrates how effective it is in decision-making situations.

How the Proposed Work Solves the Issues of Previous Approaches?

- Traditional methods to decision-making are often unsuccessful because they are characterized by ambiguity and uncertainty. T-SFS is an enhanced way of modelling uncertainty that is capable of capturing the nuances of human judgment with more precision and adaptability than other methods.
- Both entropy and WASPAS are used in the process of weight calculation and ranking, respectively, in order to guarantee that the framework for decision-making is both robust and well-balanced. The entropy method performs a decent job of resolving the subjective biases that are present in weight assignment, but the WASPAS method offers a grading system that is comprehensive.
- One of the ways in which the work that has been proposed is distinct from previous approaches is that it clearly identifies ethical considerations as a criteria. Through this method, we are able to have the assurance that privacy, transparency, and equality are all taken into consideration throughout the whole process of decision-making.
- These examples illustrate how the techniques that have been provided may be applied to situations that occur in the actual world. One example is the use of artificial intelligence (AI) for the purpose of talent acquisition, virtual reality (VR) for the purpose of training, and predictive analytics for the purpose of succession planning. Through the use of this pragmatic strategy, companies are certain that they will reap the benefits of theoretical advancements.

V. Conclusions and Implications

This study has highlighted the need of optimizing human capital by investigating the manner in which talent decision-making and information technology are combining. It was demonstrated that D_1 is the best option for maximizing human capital by carrying out a thorough examination of several rival strategies and using the Entropy Weighted WASPAS approach to T-SFS theory. Employee engagement, retention, and skill development are all optimized as a consequence of D_1 's immersive learning experiences. An essential addition of the study is that it provides decision-makers with a concrete platform by demonstrating the effectiveness and applicability of the suggested strategy in assessing talent decision-making scenarios. The study's practical consequences for human resources professionals and company leaders underscore the transformative potential of information technology in talent management. To determine the long-term effects that training in D_1 has on an organization's operation, researchers may conduct longitudinal studies and make more improvements in the future. Overall, the results of this research add to the growing corpus of information about the optimization of human resources and underscore the critical role that technology will play in determining the future direction of talent management.

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