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A Behavioral Fuzzy Decision Support Framework for Optimizing Sectoral Work Models in the Life 3.0 Era

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ABSTRACT

In the context of the Life 3.0 paradigm, where digitalization is accelerating, determining the most appropriate innovative working model for different sectors has become a strategic imperative. However, the literature lacks integrated multi-criteria approaches for evaluating the effectiveness of alternative working models, such as freelance, hybrid, remote, and metaverse-based models, within a sectoral context. This study aims to determine the most appropriate working model based on the structural, digital, and operational characteristics of different sectors and to identify the criteria that should be prioritized in this decision-making process. The Information and Technology, Education and Consulting, Marketing and E-Commerce, and Finance and Insurance sectors are analyzed. First, 17 criteria affecting the selection of working models are identified. Publications indexed in the Web of Science (WoS) database are scanned using a Robotic Process Automation (RPA) approach, and the eight most frequent and relevant criteria are selected using text mining techniques. Data obtained from interviews with five experts are then weighted according to the experts' demographic characteristics using a dimensionality reduction method. The criteria weights are determined using the SITDE method, while the alternatives are ranked using the RATGOS algorithm. In addition, a novel fuzzy set system, Behavioral Leadership Fuzzy Sets (BLFSs), is developed and integrated into the model to analyze the impact of decision-maker behaviors on managerial reflexes. The proposed framework integrates artificial intelligence and multi-criteria decision-making techniques, reduces subjectivity through data-driven criteria selection and expert weighting, and incorporates behavioral leadership characteristics into the decision process. The findings indicate that the hybrid model is the most appropriate working model across all four sectors. However, sectoral priorities differ: career and development opportunities are the most important criterion in the IT sector, whereas market access and ethical responsibilities are prioritized in the finance sector.

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1. Introduction

The Life 3.0 paradigm represents a transformation in which humans extend cognitive and physical capacities through technologies such as artificial intelligence, augmented reality, biotechnology, the Internet of Things (IoT), and quantum computing. This evolution reshapes not only technology but also social and organizational structures, leading traditional working models toward flexible and digital forms [1]. Freelance and hybrid models enable autonomy and balance between remote and on-site work, while metaverse-based environments dissolve spatial limits through virtual offices and avatars [2]. Yet, the effectiveness of these new-generation models differs across sectors depending on business structures, regulations, and human resource dynamics [3]. For instance, flexible and remote work yield higher efficiency in technology sectors, whereas hybrid models are more suitable for regulated areas such as finance and insurance. Metaverse applications, on the other hand, remain in the prototype stage within technology-oriented creative industries [4]. A holistic approach is necessary to determine the effectiveness of alternative working models (freelance, hybrid, remote, metaverse-based, etc.) on a sectoral basis [5]. Economic conditions, social dynamics, legal regulations, and environmental factors also directly influence the selection of the right working model [6]. However, despite all these variables, the lack of a commonly accepted framework for determining the most appropriate working model across sectors leads to various problems, such as uncertainty, implementation errors, and productivity losses in corporate decision-making processes [7]. The number of studies in the existing literature that conduct prioritization analyses is quite limited [8]. This limitation constitutes a significant "missing gap" in the literature, hindering the deepening of academic discussions and making it difficult for policymakers and managers to develop scientifically based strategies.

Accordingly, the objective of this study is to develop and demonstrate an integrated decision support framework for evaluating alternative future work models through a proof-of-concept application rather than to establish universally generalizable empirical rankings. The study proposes a new decision-making model based on sectoral comparisons, encompassing the Information and Technology, Education and Consulting, Marketing and E-Commerce, and Finance and Insurance sectors. First, 17 decision criteria and four alternative working models are identified. Publications on the subject are analyzed using the Robotic Process Automation (RPA) approach in the Web of Science (WoS) database. Following RPA, text mining and content analysis highlight the eight most significant and recurring criteria from these 17 criteria. Then, in-depth interviews are conducted with five experts selected from different sectors. The weighting process is carried out using the dimensionality reduction method based on the experts' demographic and professional characteristics. The criteria weights are calculated using the SITDE method, and the alternatives are ranked using the RATGOS algorithm. Furthermore, to model the impact of decision-maker behaviors on managerial reflexes, the newly developed Behavioral Leadership Fuzzy Sets (BLFSs) approach is integrated into the model, introducing uncertainty, intuition, and behavioral variability into the decision-making process. The main research questions sought to be answered within the scope of the study are as follows: (1) Which is the most appropriate and sustainable innovative working model in the context of Life 3.0 for different sectors? (2) What are the most important key criteria at the sectoral level in this decision-making process, and how do the relative weights of these criteria change?

This study contributes to the literature by developing an original methodology that incorporates integrated artificial intelligence and multi-criteria decision-making techniques to identify innovative working models based on sectoral suitability in the context of Life 3.0. The decision-making model proposed in this study demonstrates numerous advantages over previously developed models in the literature. (1) First, instead of the subjective selection based on expert priorities frequently encountered in traditional methods, the Robotic Process Automation (RPA) approach was used in the decision-making criteria determination process, and content mining was conducted using recent publications in the Web of Science (WoS) database. This enabled objective prioritization of only the eight most influential criteria out of the 17 initially identified criteria. This allowed for the multi-criteria decision-making (MCDM) analysis to be freed from excessive criteria load and achieve a more focused structure. Furthermore, artificial intelligence-based classification and pattern recognition algorithms were used in this process to enhance the model's methodological originality. (2) In weighting expert opinions, we went beyond traditional assumptions of equal weights and objectively calculated the importance levels of experts based on their demographic and professional characteristics using the dimensionality reduction technique. While many models in the literature assume fixed expert weights, this model analyzes expert contributions more precisely through a machine learning-based data processing process. (3) Another significant innovation contributing to the literature is the development of a new fuzzy set system called Behavioral Leadership Fuzzy Sets (BLFSs). This unique structure allows us to evaluate expert opinions not only in terms of content but also based on leadership profiles (e.g., authoritarian, innovative, collaborative, etc.), providing an important solution to the frequently criticized subjectivity problem. The BLFS approach can model expert behavior more flexibly and realistically compared to classical fuzzy sets, thereby increasing the reliability of the decision-making system.

Despite the growing literature on digital transformation, hybrid work, algorithmic management, and Life 3.0, existing studies generally examine these issues separately, focus on a single sector, or rely on conventional evaluation approaches that overlook behavioral uncertainty and sector-specific priorities. Consequently, decision-makers still lack an integrated framework capable of objectively identifying the most appropriate work model while simultaneously incorporating behavioral leadership characteristics, data-driven criterion extraction, differentiated expert importance, and robust multi-criteria evaluation. This methodological gap also creates a practical challenge for organizations attempting to design sustainable work policies under rapidly evolving technological environments. The proposed framework directly addresses this need by integrating artificial intelligence, behavioral fuzzy modeling, machine learning-based expert weighting, and advanced MCDM techniques into a unified decision support architecture that can assist managers and policymakers in selecting context-sensitive work models across different sectors.

The methodological design of this study is grounded in the growing body of literature emphasizing the importance of integrating behavioral factors into multi criteria decision making environments characterized by uncertainty and complex human interactions. Recent studies have highlighted that conventional fuzzy and MCDM approaches often focus primarily on numerical assessments while providing limited capability to explicitly represent leadership-driven behavioral influences on expert judgments. In parallel, advances in entropy-based weighting techniques and ranking methodologies have demonstrated the value of improving objectivity, robustness, and interpretability in complex decision systems. Building upon these developments, the proposed BLFS, SITDE, and RATGOS framework seeks to extend existing methodological foundations by incorporating behavioral leadership effects, dynamic information-based weighting mechanisms, and transparent ranking procedures within a unified decision architecture.

Today's world is on the verge of a new evolutionary phase driven by artificial intelligence (AI) capable of designing both its hardware and software, conceptualized by Tegmark as "Life 3.0". This new era represents the technological evolution of life [9]. This process, triggered by the fourth industrial revolution, also known as Industry 4.0, is described as a major change and transformation that will affect the lives of people, societies, organizations, and states. Successfully managing this transformation necessitates a major organizational transformation in economic, social, technological, political, and legal spheres. However, discussions have already moved beyond Industry

4.0 to the "Employment 5.0" paradigm, which prioritizes collaboration between humans and machines, sustainability, and employee well-being [10]. This study examines this transformation from this broad perspective and examines its technological, economic, social, ethical-legal, and environmental dimensions in depth, considering the current literature.

The impacts of digital transformation on working life have influenced the business world and decision-makers, as well as shaping the literature. Among the studies examining the impacts of digital transformation, systematic literature reviews addressing paradigms such as Industry 4.0 [11], Industry 5.0, and Employment 5.0 [12] emphasize the need for a holistic and human-centered approach to managing the transformation. Studies on the impacts of remote and hybrid work on transformation have largely emphasized the complex nature of these working models [13] and focused on the impacts on work-life balance [14]. The gig economy, which has been frequently studied due to the impact of this transformation, has been discussed from the perspectives of revealing the dilemma of workers' autonomy [15] and insecurity [16], positioning workers [17], privacy and data security, social problems, power asymmetries [18] and legal issues [19]. Along with this change, algorithmic management has been frequently discussed with both its positive and negative effects.

The technological transformation is fundamentally changing the economic structure. This process has proliferated the “gig economy” model, which offers flexibility [20] but also carries the risk of depriving workers of rights such as social protection and job security [21]. On the other hand, artificial intelligence [22] and digital transformation [23], expected to enable new business models and trillions of dollars in productivity gains, are also emerging as a new economic frontier in the metaverse [24]. However, this transformation also brings with it serious challenges such as increasing income inequality [25] and technological unemployment [26]. As a response to this situation, alternative models such as the sustainability-oriented “regenerative economy”, which aims to minimize resource use, are being proposed. This model aims to minimize resource flow through processes such as reuse and recycling, and to develop “human technologies” that produce less waste by responding to people’s basic needs [27]. The technological transformation of working life brings with it serious ethical and legal challenges, with “Algorithmic Management (AM)” [28] at its core. While AM offers increased productivity, it also carries risks such as reducing worker autonomy [29], reinforcing racial biases [30], and increasing burnout [31]. The gig economy, on the other hand, is characterized by fundamental problems such as the legal “misclassification” of workers [32] and the exclusion of social protection [33], as well as the opaque control of platforms [34]. The technological revolution is reshaping the social fabric of working life, presenting a complex structure that offers opportunities such as flexibility [35] and challenges such as social isolation [36]. Hybrid and distributed working models [37], which have become the norm after the pandemic, on the one hand, highlight the concept of "work-life flow", while on the other, they undermine traditional organizational culture [38] and can lead to employee isolation [39].

In summary, recent studies have extensively explored the impacts of digital transformation, algorithmic management, and new work models such as hybrid and gig work on organizational and employee outcomes. However, the majority of these works address the topic either conceptually or within a single-sector context, lacking an integrated and comparative perspective. Moreover, few studies combine artificial intelligence tools with multi-criteria decision-making techniques to objectively determine the most suitable work model for different sectors. The existing research mainly focuses on specific implications, such as flexibility, well-being, or digitalization, without quantitatively linking these to sectoral differences or behavioral aspects of decision-making. Addressing this gap, the present study introduces a comprehensive model that integrates Robotic Process Automation (RPA), dimensionality reduction, and Behavioral Leadership Fuzzy Sets (BLFSs) to evaluate innovative working models in the context of the Life 3.0 paradigm. This methodological integration provides a novel, data-driven, and behavior-sensitive framework for optimizing sectoral work models.

A comparative examination of the existing literature reveals three major limitations. First, most studies investigate hybrid work, digital transformation, or algorithmic management independently rather than providing a unified evaluation framework across multiple sectors. Second, previous research predominantly relies on conceptual discussions, surveys, or conventional decision-making techniques without integrating behavioral uncertainty into expert evaluations. Third, objective mechanisms for literature-driven criterion extraction and differentiated expert weighting remain largely unexplored. The present study addresses these limitations by integrating RPA, dimensionality reduction, BLFS, SITDE, and RATGOS into a unified framework that enables objective, behavior-sensitive, and sector-specific decision support.

2. Methodology

This study adopts a mixed conceptual–analytical research design. Conceptually, it develops a theoretical framework based on the Life 3.0 paradigm to interpret the transformation of work models in digitalized societies. Analytically, it employs a hybrid fuzzy multi-criteria decision-making (MCDM) approach integrated with Robotic Process Automation (RPA) and Behavioral Leadership Fuzzy Sets (BLFSs) to evaluate sector-specific work model preferences. This dual structure ensures that both theoretical insight and analytical rigor are achieved. The conceptual dimension allows for the identification of key constructs and relationships, while the analytical framework quantifies expert evaluations under uncertainty. Together, these layers constitute the methodological framework of the study, ensuring the correctness and consistency of the chosen approach.

Each methodological layer in the proposed architecture was selected to address a specific limitation that cannot be adequately handled by simpler or single-stage approaches. RPA-driven extraction reduces subjective bias in criteria selection by grounding the process in large-scale empirical evidence. BLFS provides behavioral modulation that captures leadership-driven variability in expert judgments, a dimension that conventional fuzzy sets cannot model. Dimensionality reduction objectively differentiates expert influence rather than assuming equal weights, improving representational fidelity. SITDE contributes distribution-sensitive weighting through skewness, offering a more precise reflection of criteria variability compared with traditional entropy-based methods. RATGOS enhances ranking stability by using geometric similarity ratios instead of linear distance measures prone to distortion in fuzzy environments. Together, these components create a complementary system where each layer resolves a specific methodological gap, collectively improving the transparency, reliability, and decision quality of the final model.

The present study employs a hybrid fuzzy multi-criteria decision-making framework integrated with Robotic Process Automation and Behavioral Leadership Fuzzy Sets. This method was chosen because it allows for the systematic evaluation of qualitative and quantitative factors under uncertainty, which is critical in analyzing complex and human-centered processes such as sectoral work model selection. Traditional statistical or regression-based approaches are limited in capturing the vagueness of expert judgments and the behavioral dynamics of decision-makers. In contrast, the proposed fuzzy–behavioral approach provides higher flexibility, robustness, and interpretability by combining human expertise with algorithmic precision. This hybrid integration ensures more reliable, context-sensitive, and data-driven results, thereby validating the methodological appropriateness of the study.

To improve the transparency of the proposed decision support framework, the interaction among the methodological components should be interpreted as a sequential information processing architecture rather than as independent analytical modules. The process begins with RPA-based literature mining, which identifies and filters candidate decision criteria from the Web of Science database. These criteria are subsequently evaluated by domain experts whose relative importance is objectively estimated through dimensionality reduction. Expert assessments are then transformed into Behavioral Leadership Fuzzy Sets to incorporate leadership-driven behavioral uncertainty. The aggregated behavioral evaluations are processed by the SITDE method to determine criterion weights, which are finally integrated into the RATGOS algorithm to obtain the sector-specific ranking of alternative work models. Consequently, the output generated at each stage serves as the direct input for the following module, creating a unified and logically connected decision support architecture. This process is visualized in Figure 1.

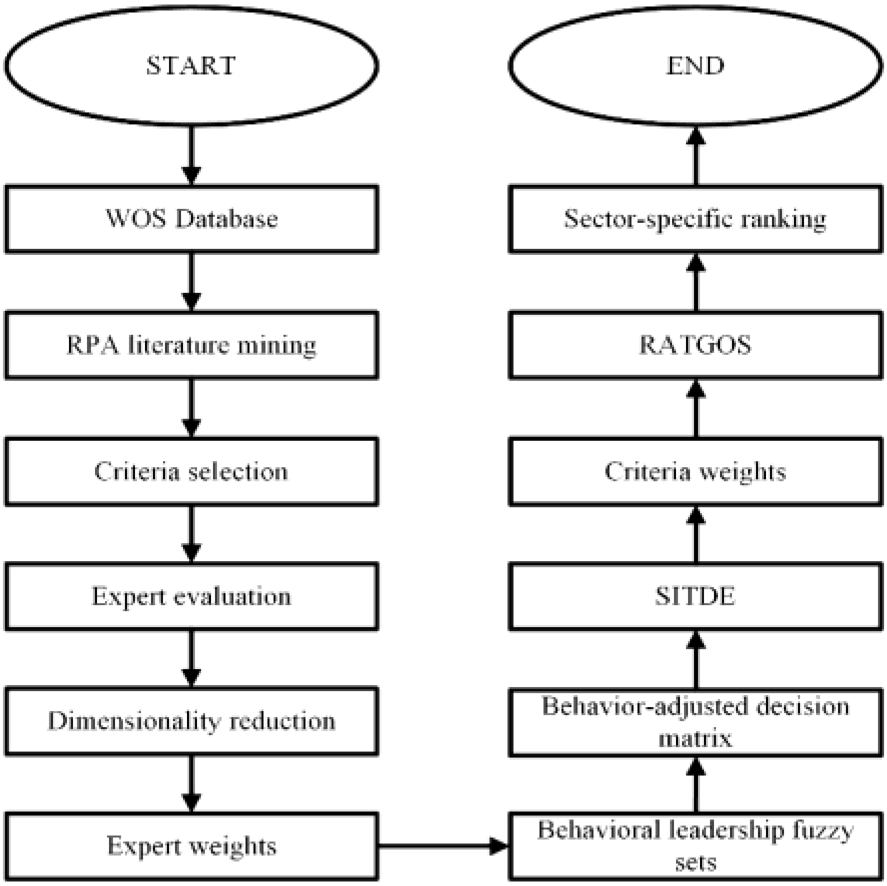

Fig. 1. Proposed Decision Support Framework

Although numerous well-established MCDM techniques such as AHP, TOPSIS, and VIKOR are widely used in the literature, they are limited in capturing distributional characteristics and nonlinear behavioral patterns of expert evaluations. The SITDE method was preferred because it incorporates skewness-based statistical weighting, which provides a more objective representation of criteria variability under uncertainty. Likewise, RATGOS was selected due to its ability to integrate geometric similarity ratios, enabling a more stable and discrimination-enhancing ranking structure compared with classical distance-based approaches. These two methods therefore offer superior robustness and sensitivity for a decision environment shaped by fuzzy behavioral assessments.

The methodological novelty of the proposed framework should be distinguished at two levels. First, BLFS constitutes the principal methodological development of the study by extending conventional fuzzy representations beyond uncertainty modeling to explicitly incorporate leadership-driven behavioral variability into expert assessments. This enables the decision process to represent not only what experts evaluate but also how behavioral characteristics may influence their judgments. Second, at the framework level, the contribution arises from constructing a sequential decision architecture in which literature-driven criterion identification, differentiated expert weighting, behavioral adjustment of expert evaluations, distribution-sensitive criterion weighting, and geometric similarity-based ranking are directly connected. In contrast to conventional MCDM applications that typically begin with predetermined criteria, assume equal expert importance, and represent uncertainty without an explicit behavioral layer, the proposed framework addresses these sources of subjectivity at different stages of the decision process. Its advantage therefore lies not merely in combining existing techniques but in integrating a newly developed behavioral fuzzy representation with complementary procedures that systematically control criterion-selection bias, expert heterogeneity, behavioral uncertainty, criterion variability, and ranking stability within a single decision-support architecture. The sensitivity and ablation analyses further demonstrate that these components collectively contribute to the stability of the resulting rankings.

2.1. Agentic Automation Pipeline Architecture

The abstract categorization process was implemented using UiPath's Agentic Automation platform (Maestro), representing the integration of RPA with AI agents. The Maestro platform was selected for its ability to combine rule-based automation with AI-powered decision-making capabilities. It allows seamless integration with bots, agents and humans within the same business process [40].

The automation pipeline consisted of three sequential stages. Each stage was designed for specific functionality within the overall workflow:

Stage 1: Data Extraction and Queue Management

RPA bots were programmed to extract abstracts from the WoS dataset. The extraction stage included several key features to ensure robust and efficient data processing. The RPA bots created login and session management for WoS access, and dynamically collected data from academic studies into Excel sheets. During this process, real-time data validation was performed and the RPA bots created structured data for uniform downstream processing through UiPath's queue management system to optimize the overall flow.

Stage 2: AI-Powered Content Analysis and Categorization

GPT-4.1-based agents served as the analytical components of the system, managing advanced NLP capabilities for semantic analysis. Each agent was configured with detailed prompts for classification and contextual understanding to ensure consistent and accurate categorization decisions.

The AI agents incorporated following analytical capabilities:

Semantic Analysis: Deep understanding of abstract content through transformer-based language modeling

Contextual Evaluation: Assessment of research context, methodology, and implications

Multi-criteria Decision Making: Evaluation against multiple category criteria with weighted scoring

Confidence Scoring: Generation of classification confidence metrics for quality assurance

Stage 3: Automated Results Consolidation and Output Generation

A specialized RPA bot collected categorization results from the AI agents and consolidated them into structured output formats. This stage incorporated comprehensive data validation, statistical analysis, and report generation capabilities to provide immediate insights into categorization outcomes.

The consolidation stage utilized comprehensive features to ensure complete data integration and analysis. The system performed automated data aggregation and statistical calculations while conducting quality assurance validation and error detection throughout the process. Results were generated in Excel format with multiple worksheets for organized data presentation, and all outputs were formatted to be visualization-ready for immediate analysis. Additionally, the system generated detailed audit trails to maintain process transparency and produced summary statistics along with distribution analysis to provide immediate insights into the categorization outcomes.

Although RPA is presented as part of the analytical pipeline, its primary contribution lies in automating the large-scale extraction and structuring of literature data rather than introducing a methodological enhancement to the decision model itself. The use of RPA reduces manual selection bias and ensures that the initial pool of criteria is grounded in a reproducible and systematic scan of the WoS database; however, the extent to which this automation improves objectivity beyond efficiency gains remains limited. For this reason, the RPA component should be viewed as a procedural facilitator rather than a standalone methodological innovation. Future studies may further strengthen this step by integrating validation mechanisms that measure the impact of automated extraction on criteria quality.

2.2. BLFSs

Let $\mathfrak{D}$ be a universe of discourse. Then, a BLFS ($\mathcal{B}$) is described as Eq. (1). Wherein $\mu(\mathscr{s})$ is the base membership of expert's assessment. The other five components are derived from this base membership regarding characteristics of behaviour leadership styles. First function, the membership of authoritarian, is calculated by Eq. (2) [41]. Wherein $\mathfrak{b}_1$ is the crisis/stress rate. This parameter is between 0 and 1. Authoritarian leaders tend to make more confident and clear decisions during times of stress and crisis. A high level of decision acuity, or $\mathfrak{b}_1$, indicates the expert's sensitivity to stress. The function that best mathematically models this situation is the exponential function.

The behavioral membership functions adopted in the proposed BLFS model are theoretically grounded in the premise that expert judgments are influenced not only by uncertainty but also by leadership related behavioral tendencies, including confidence, adaptability, consistency, and decision orientation. Unlike conventional fuzzy membership functions that primarily represent vagueness, the proposed behavioral structure explicitly incorporates variations arising from individual decision behavior. From an empirical perspective, the applicability of these membership functions is supported by the use of expert assessments collected from experienced professionals representing different sectors, allowing the behavioral parameters to reflect realistic variations encountered in practical decision making environments. Consequently, the BLFS framework provides a more behavior sensitive representation of expert knowledge while preserving the mathematical consistency required for fuzzy multi criteria decision making. The boundary of authoritarian membership is shown with Eq.s (3) – (6) and Figure 2. For $\forall\mu(\mathscr{s}) \in [0,1]$ and $\mathfrak{b}_1 \in [0,1]$.

The second function of BLFSs, the membership of democratic, is computed with the help of Eq. (7). Wherein $\mathfrak{b}_2$ is the rate of participation to decisions. This parameter is between 0 and 10. Democratic leaders' influence on decisions is gradual. The extent to which democratic leaders consider others' opinions is determined by the $\mathfrak{b}_2$ parameter. The function that best mathematically models this situation is the sigmoid function. The boundary of democratic membership is given with Eqs. (8) – (13) and Figure 3. For $\forall\mu(\mathscr{s}) \in [0,1]$ and $\mathfrak{b}_2 \in [0,10]$.

Third function, the membership of transformational, is obtained by Eq. (14). Wherein $\mathfrak{b}_3$ the rate of assessment/situation. This parameter is between 0 and 1. Transformational leaders tend to influence decisions optimally in the overall decision-making process, while making more reserved decisions in extreme situations. This characteristic allows this membership function to be modelled using a Gaussian curve. The boundary of transformational membership is defined with Eq.s (15) – (19) and Figure 4. For $\forall \mu(\mathcal{s}) \in [0,1]$ and $\mathfrak{b}_3 \in [0,1]$,

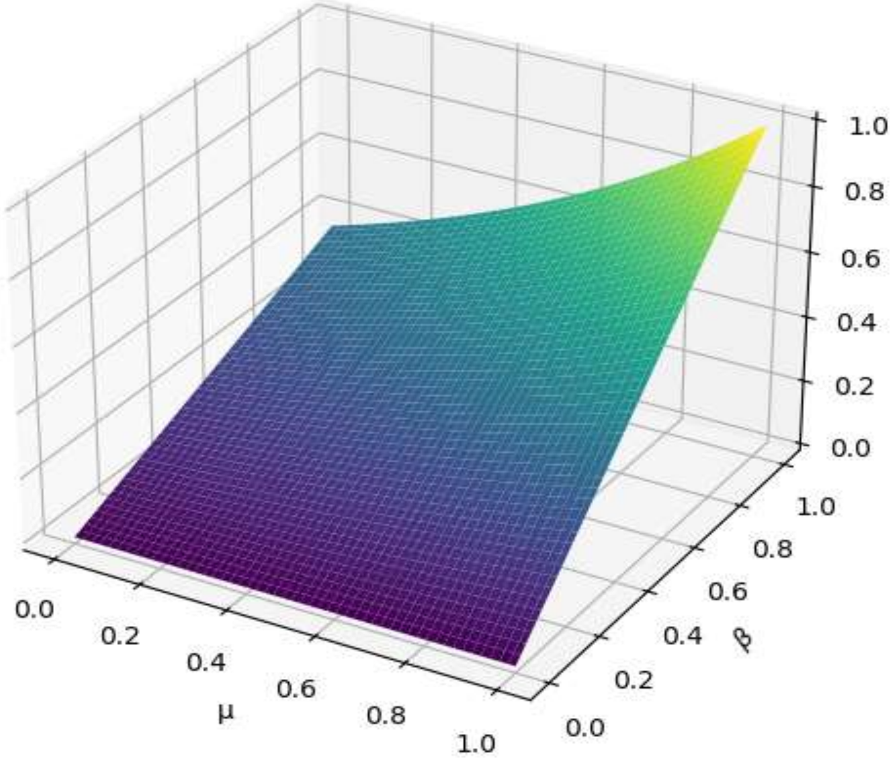

Fig. 2. The Membership of Authoritarian

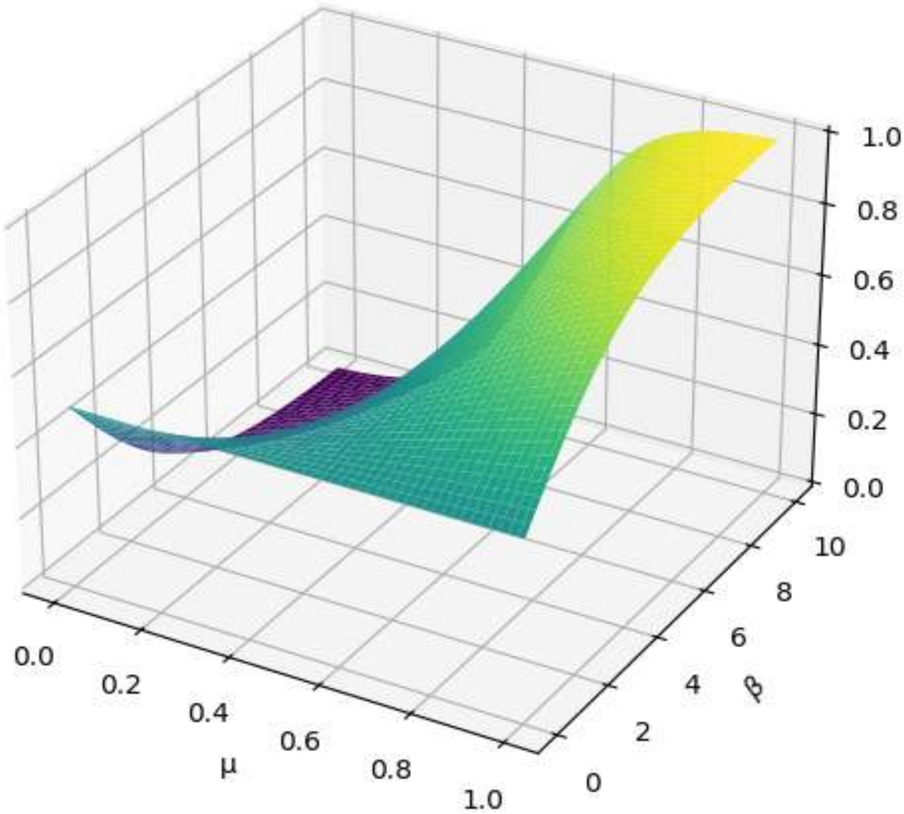

Fig. 3. The Membership of Democratic

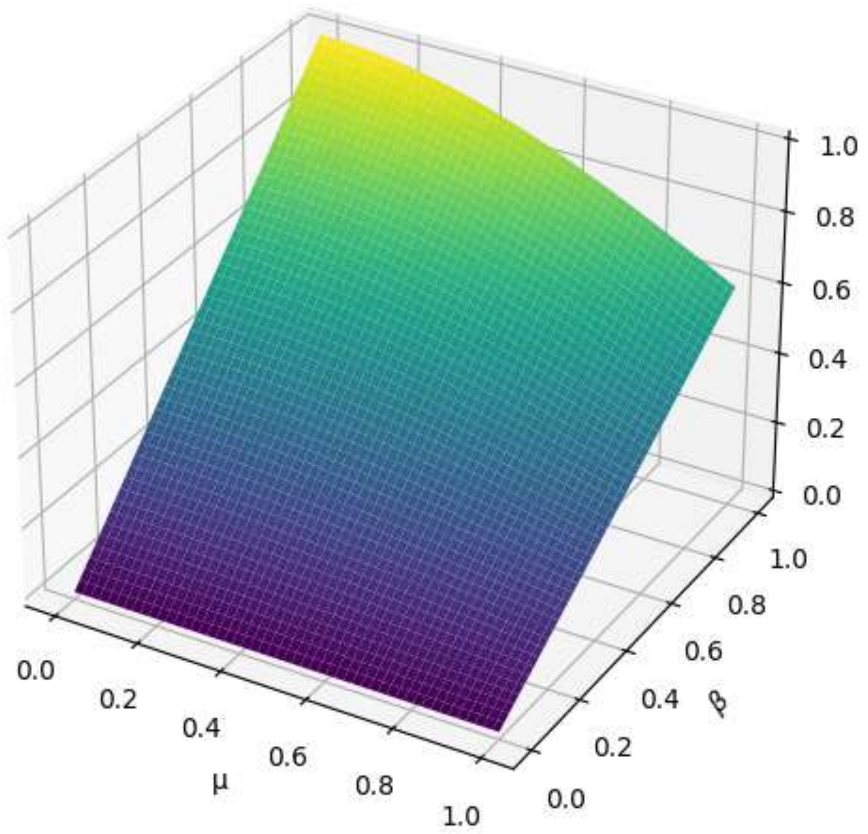

Fig. 4. Membership of Transformational

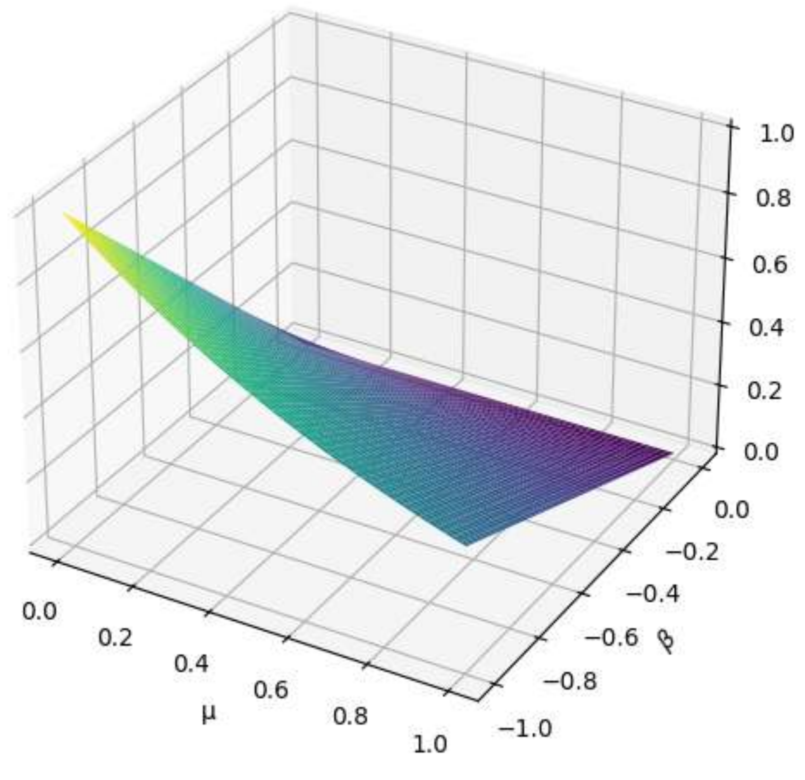

Fig. 5. Membership of Laissez-Faire

Fourth function, the membership of Laissez-Faire, is estimated using Eq. (20). Wherein $\mathfrak{b}_4$ parameter is between -1 and 0. Laissez-Faire leaders tend to abstract themselves from decisions in routine situations. In this respect, they are formulated with the inverse exponential function. The boundary of Laissez-Faire membership is determined via Eq.s (21) – (24) and Figure 5. For $\forall \mu(\mathscr{s}) \in [0,1]$ and $\mathfrak{b}_4 \in [-1,0]$.

The final function, the membership of servant, is identified with the help of Eq. (25). Wherein $\mathfrak{b}_5$ relates to the state of instability. This parameter is between 0 and 1. Servant leaders tend to avoid making decisions when situations are stable. That is, servant leaders increase their influence when stability is disrupted. Because of this structure, this leadership style is characterized by an inverse Gaussian curve. The boundary of servant membership is described using Eq.s (26) – (30) and Figure 6. For $\forall \mu(\mathscr{s}) \in [0,1]$ and $\mathfrak{b}_5 \in [0,1]$,

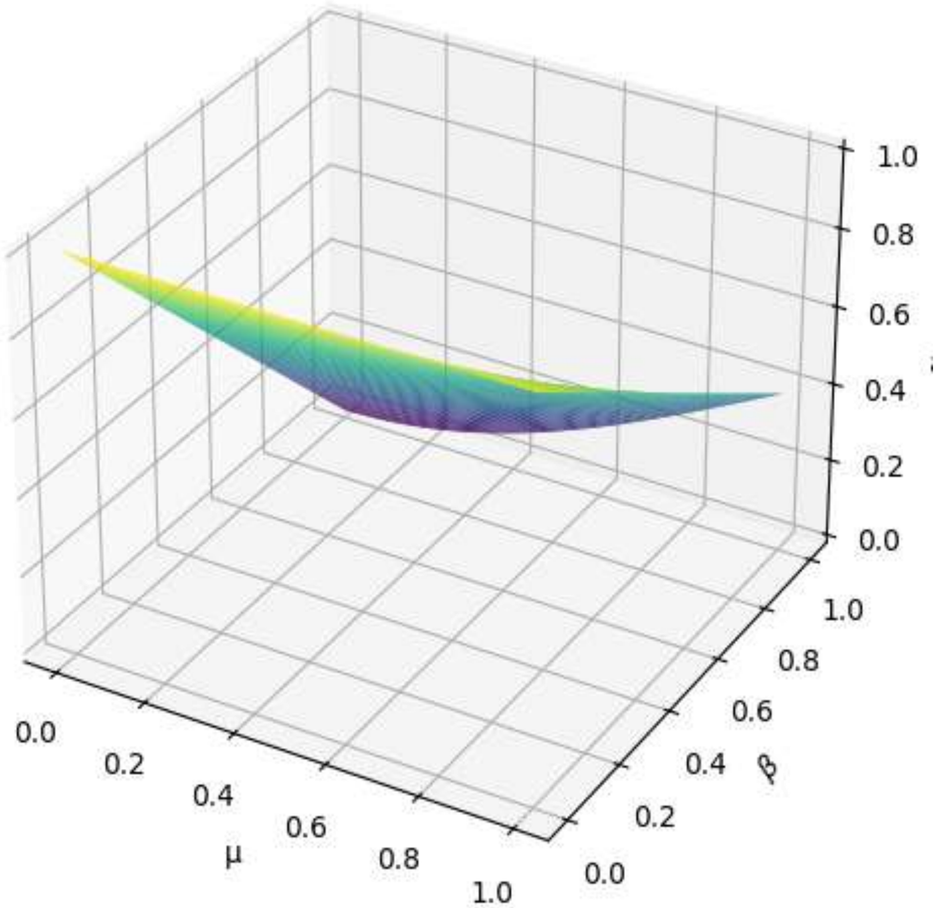

Fig. 6. Membership of Servant

In this situation, the generalized BLFS is defined as Equation (31). Assume that A and B be two BLFSs. Then, some operators are described with the help of .s (32) and (33). Consider that A and B be two BLFNs. The arithmetic operations are identified by Eq.s (34) – (37). Moreover, the score and accuracy of A are determined using Eq.s (38) and (39), respectively. To enhance interpretability, an essential strength of fuzzy systems, we clarify how BLFS operates in practice through a simplified illustrative rule structure. In the behavioral layer, each expert's linguistic evaluation is modulated by leadership-style parameters that follow mathematically defined membership functions. For example, when an expert exhibits a high authoritarian score under elevated stress conditions, the base fuzzy membership is amplified according to the exponential function in Eq. (2), producing a stronger decision signal. Conversely, a high democratic participation value results in a smoother gradation of influence as defined by the sigmoid-based function in Eq. (7). Through this structure, each leadership style generates a transparent and traceable transformation path from an expert's raw assessment to its behavior-adjusted membership value. This rule-like mapping demonstrates how the BLFS mechanism preserves interpretability by providing explicit behavioral modulation trajectories, allowing readers and practitioners to understand not only the final aggregated fuzzy values but also the behavioral reasoning embedded in each transformation step.

The behavioral membership functions used in the BLFS framework are theoretically specified representations of leadership-driven decision tendencies rather than empirically calibrated psychological functions. Their functional forms were selected to reflect the qualitative behavioral patterns associated with the corresponding leadership styles in the organizational behavior literature. Specifically, the exponential form used for authoritarian leadership represents an accelerating increase in decisional influence as stress or crisis intensity rises. The sigmoid form for democratic leadership reflects a gradual increase in participation-based influence followed by saturation at higher participation levels. The Gaussian structure assigned to transformational leadership represents stronger influence around balanced or moderate decision conditions and lower influence under extreme conditions. The inverse exponential formulation for laissez-faire leadership captures the declining involvement of the decision-maker as routine conditions become more dominant, whereas the inverse Gaussian structure for servant leadership represents increasing behavioral influence when organizational stability is disrupted. The associated behavioral parameters and their admissible ranges were therefore defined as theoretical control parameters that operationalize these leadership characteristics within the fuzzy decision environment; they were not estimated from psychometric, observational, or experimental datasets. Validation of the current BLFS formulation is consequently methodological rather than psychological or predictive. Mathematical boundary conditions, internal consistency of the membership functions, sensitivity analysis, and ablation analysis provide evidence that the framework operates coherently within the proposed decision architecture. However, these procedures do not constitute external empirical validation of the behavioral functions. Future studies should calibrate the BLFS parameters using validated leadership scales, observational managerial data, experimental decision settings, or longitudinal organizational datasets and compare theoretically generated memberships with empirically observed behavioral responses.

2.3. Dimensionality Reduction

The dimensionality reduction algorithm is used in the process of transforming the matrix in Eq. (40), which is constructed with t features of k experts, into a kx1 dimensional matrix. The elements of this one-dimensional matrix are used as coefficients of experts' assessments. Since the value range and unitary size of the columns of this matrix are not the same, the values are standardized. Standardization process is identified with Eq.s (41) – (43). In the end of standardization process, standardized matrix is obtained as Eq. (44). Afterwards, each column of standardized matrix is defined as standardized vector. Standardized vector is formed as Eq. (45). Covariance coefficient across ηv_j and ηv_k is estimated with the help of Eq.s (46) and (47). Thus, covariance matrix is formed as Eq. (48). After forming covariance matrix, the eigenvalues are estimated by solving Eq. (49). While creating the new matrix, the maximum of the eigenvalues is selected with Eq. (50) to preserve the maximum variance or minimize the information loss. Eigenvector for maximum eigenvalue is created by solving Eq. (51). Finally, one-dimensional matrix is obtained with Eq. (52). So, kxt dimensional matrix is multiplied by eigenvector. Next, new one-dimensional matrix's elements are normalized by Eq. (53). Thus, normalized elements are defined as coefficients of experts' assessments. Wherein $Q^{(i)}$ is the i^{th} element of Q.

2.4. SITDE

SITDE is a method that involves calculating criterion weights using the skewness parameter, a statistical calculation. SITDE offers an objective criterion weighting approach and its calculation procedure is as follows [42]. Firstly, the p-alternatives and q-criteria are defined. Next, assessments are collected, and evaluations are transformed into BLFNs. The assessment matrices of experts are developed as Eq. (54). Afterwards, BLFNs are multiplied by coefficients of experts' assessments using Eq. (55). Wherein the multiplication operator is defined in Eq. (36). Then multiplied BLFNs are summed with Eq. (56). Wherein aggregated operator is defined in Eq. (34). Then, the aggregated values are defuzzified by Eq. (57). Wherein score function is defined in Eq. (38). y_{ij} is positive value. Next, normalization of benefit criteria is defined in Eq. (58) and normalization of cost criteria is obtained in Eq. (59). At the same time, the standard deviation values for normalized scores are estimated with the help of Eq.s (60) and (61). Next, the skewness values of criteria are computed using Eq. (62). Eq. (63) is used for normalizing skewness values. Finally, the weight vector is defined with the help of Eq. (64).

2.5. RATGOS

RATGOS is an innovative approach that ranks alternatives using the geometric mean of weighted similarity ratios. This approach is based on the similarity ratio of evaluations to optimal values. The calculation procedure is as follows [43]. The decision matrix is obtained using Eqs (54) - (57) in the SITDE method. Next, optimal values are selected. Eq. (65) is used for benefit criteria and Eq. (66) is used for cost criteria. Afterwards, the similarity matrix is created. The values of similarity matrix are computed for benefit criteria by Eq. (67). Similarly, the values of similarity matrix are calculated for cost criteria by Eq. (68). Although this normalization process is similar to that of SITDE, it should be noted that it is reversed depending on the criteria type. Later, the normalized values are multiplied by the weights via Eq. (69). Finally, the geometric mean of the weighted values is estimated. Alternatives are ranked according to this geometric mean. Geometric mean is calculated with Eq. (70).

2.6. Ethics Statement

All methods were carried out in accordance with relevant guidelines and regulations. The study was based solely on voluntary expert opinions and did not involve clinical interventions, medical procedures, biological sample collection, patients, or vulnerable populations. An official review was obtained from the Ethics Committee of Istanbul Medipol University, which determined that the study was not contrary to research ethics principles and did not require formal ethical approval (Reference No: E-43037191-604.01-41898; Date: 01/06/2026). Informed consent was obtained from all participants prior to data collection, and participation was entirely voluntary.

3. Result

This part covers the results of the analysis for the Transformation of Working Life in Life 3.0. The process of analysis is visualized in Figure 7.

3.1. Evaluating the Criteria with RPA

The analysis of 924 academic abstracts revealed significant variations in research focus across the 17 predefined categories. The distribution demonstrates a clear concentration of research effort in specific areas, with a pronounced long-tail pattern indicating both dominant themes and underexplored research domains. To ensure transparency and reproducibility, literature retrieval was conducted via the Web of Science (WoS) Core Collection using keyword-based search strings, strictly limiting the scope to peer-reviewed journal articles while excluding books and conference proceedings. The filtered publication corpus was processed using GPT-4.1 for classification and criteria reduction. Through an RPA/AI-assisted and expert-driven workflow, the initial 17 criteria were systematically reduced to 8 core criteria by eliminating redundancies and filtering based on contextual relevance and corpus frequency. Furthermore, to validate the AI-generated classifications, a 10% random sample of the articles was independently audited and verified by human domain experts, the high consensus observed during this audit confirmed the robustness of the automated procedure. Table 1 shows category distribution results.

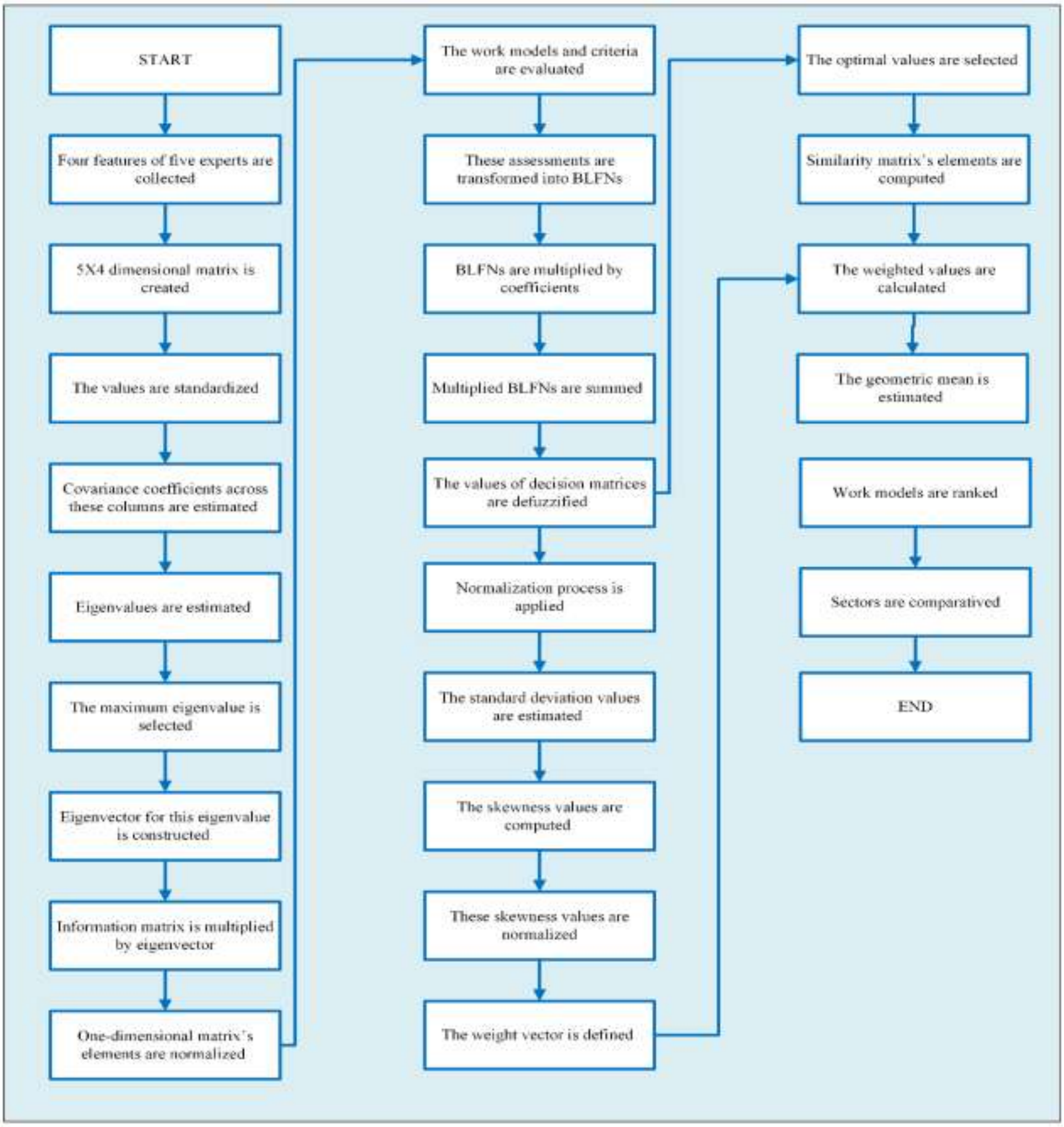

Fig. 7. Process of Analysis

The concentration of research around innovation, collaboration, career development, and sustainability suggests strong alignment with global research and policy priorities. Meanwhile, the limited coverage of cybersecurity, cost effectiveness, and environmental footprint points to possible gaps or emerging frontiers in academic inquiry. Mid-level attention is given to Ethical Responsibilities (8.0%) and Market Access (7.7%). In contrast, other categories are far less represented: Job Security (3.4%), Income Stability (2.7%), Technological Adaptation (2.1%), Legal Compliance (2.5%), and Cybersecurity (1.1%). The long tail includes Infrastructure Requirements, Cost Effectiveness, and Carbon Footprint, the latter represented by only a single abstract.

Table 1
Results summary of category distribution

Category	Count	Percent
Innovation Potential	168	18.2%
Collaboration and Networking	139	15.0%
Career and Growth Opportunities	112	12.1%
Sustainability Potential	107	11.6%
Inequality and Access Justice	88	9.5%
Ethical Responsibilities	74	8.0%
Market Access	71	7.7%
Social Contribution	44	4.8%
Job Security and Social Rights	31	3.4%
Income Stability	25	2.7%
Legal Compliance	23	2.5%
Technological Adaptation Requirement	19	2.1%
Cybersecurity and Data Protection	10	1.1%
Infrastructure Requirements	7	0.8%
Cost Effectiveness	5	0.5%
Carbon Footprint	1	0.1%
Total	924	100%

The use of the WoS database provides a structured, transparent, and reproducible basis for identifying literature-supported decision criteria; however, it does not eliminate all sources of selection bias. Relevant studies indexed in other databases, such as Scopus or discipline-specific repositories, may emphasize different dimensions of future work models. Therefore, the objectivity of the criteria-selection process should be understood as procedural objectivity within the defined WoS-based literature sample rather than as universal representativeness. Similarly, the robustness demonstrated by the sensitivity and ablation analyses refers to the internal stability of the proposed decision framework under the examined scenarios and should not be interpreted as evidence of external empirical generalizability. Accordingly, the present application is positioned as a proof of concept demonstrating the feasibility and analytical value of the proposed integrated framework. Future research should validate the framework using multiple bibliographic databases, larger and more diverse expert panels, additional sectors, and empirical organizational data before broader generalizations are made.

3.2. Calculating the Coefficients of Experts' Assessments

For transparency, the numerical results presented in the following tables are directly linked to the mathematical expressions provided in the Appendix. Table 2 represents the initial information matrix defined in Eq. (40); Table 3 is generated through Eqs. (41)–(44); Table 4 through Eqs. (45)–(48); Tables 5 and 6 through Eqs. (49)–(51); and Table 7 through Eqs. (52) and (53). The expert assessment and aggregated decision matrices are subsequently constructed using Eqs. (54)–(57). The normalized matrices, standard deviations, skewness values, and criterion weights reported in Tables 15, 16 and 17 are obtained through Eqs. (58)–(64). Finally, the optimal values, similarity matrices, weighted matrices, and geometric mean scores reported in Tables 18, 19, 20 and 21 are generated using Eqs. (65)–(70), respectively. Thus, each numerical output in the Results section corresponds directly to a defined mathematical operation in the Appendix.

The expert panel was formed through purposive selection, with emphasis on professional and sectoral experience rather than statistical representativeness. The expert-based component of the study is intended to provide structured domain judgments for demonstrating the operation of the proposed decision framework, rather than to estimate population-level parameters or establish statistically generalizable relationships. The five experts possess substantial professional experience, and their heterogeneity is further represented through age, total professional experience, sector-specific experience, and the number of firms in which they have worked. These characteristics are incorporated into the dimensionality-reduction procedure to differentiate their relative influence instead of assigning equal weights. Nevertheless, this weighting mechanism should not be interpreted as compensating for the limited panel size. Accordingly, the five-expert design is considered appropriate for the proof-of-concept implementation of the framework, while broader empirical validation requires a substantially larger and more heterogeneous expert sample.

The calculation of expert coefficients begins with the raw demographic and professional information presented in Table 2. Four features are considered for each of the five experts: age, total professional experience, sector-specific experience, and number of firms worked. These observations form the 5 × 4 information matrix defined in Eq. (40). Since these variables have different scales, the raw values are standardized using Eqs. (41)–(43), producing the standardized matrix in Table 3 as defined by Eq. (44). Each column of this matrix is then represented as a standardized vector according to Eq. (45), and the pairwise covariance coefficients are calculated using Eqs. (46) and (47) to construct the covariance matrix in Table 4 through Eq. (48). The eigenvalues of this covariance matrix are subsequently obtained using Eq. (49), as reported in Table 5. The largest eigenvalue is selected according to Eq. (50) because it represents the component preserving the greatest proportion of information, and its corresponding eigenvector is calculated using Eq. (51) and presented in Table 6. Finally, the original information matrix is projected onto this eigenvector using Eq. (52), generating a one-dimensional representation for each expert. These values are normalized using Eq. (53) to obtain the expert coefficients reported in Table 7. The resulting coefficients represent the relative contribution of each expert and are subsequently used in Eq. (55) to weight the Behavioral Leadership Fuzzy Number evaluations before expert assessments are aggregated.The information matrix is shown in Table 2.

Table 2
Information Matrix

	Age	Total	Sector	Firms
EXPR1	44	20	18	2
EXPR2	42	18	10	3
EXPR3	36	13	7	3
EXPR4	44	19	7	3
EXPR5	34	16	14	4

To establish a direct numerical link between the equations presented in the Appendix and the empirical results, the generation of Table 3 can be illustrated using the age variable for EXPR1 as a representative calculation. According to Table 2, the age values of the five experts are 44, 42, 36, 44, and 34, giving an arithmetic mean of 40 as calculated in Eq. (41). The centered value for EXPR1 is therefore 44 − 40 = 4 according to Eq. (42). The normalization term defined in Eq. (43) is obtained from the Euclidean magnitude of the centered age vector as $\sqrt{[(44-40)^2 + (42-40)^2 + (36-40)^2 + (44-40)^2 + (34-40)^2]} = \sqrt{88} = 9.3808$. Consequently, the standardized age value for EXPR1 is 4/9.3808

= 0.426, which corresponds to the value reported in the first cell of Table 3. The same procedure is applied to all expert characteristics to construct the complete standardized matrix in Table 3 according to Eq. (44). The standardized vectors are then used in Eqs. (45)–(48) to generate the covariance matrix in Table 4, after which Eqs. (49)–(51) produce the eigenvalues and the eigenvector reported in Tables 5 and 6. Finally, Eqs. (52) and (53) transform and normalize these results to obtain the expert coefficients in Table 7, which are subsequently incorporated into Eq. (55) when weighting the expert evaluations. Thus, standardized matrix formed in Eq. (44) is obtained and given in Table 3.

Table 3
Standardized Matrix

	Age	Total	Sector	Firms
EXPR1	0.426	0.505	0.714	-0.707
EXPR2	0.213	0.144	-0.126	0.000
EXPR3	-0.426	-0.757	-0.441	0.000
EXPR4	0.426	0.324	-0.441	0.000
EXPR5	-0.640	-0.216	0.294	0.707

Afterwards, each column of Table 3 is defined as standardized vector as Eq. (45). Next, covariance coefficients across these columns are estimated with the help of Eq.s (46) and (47). Thus, covariance matrix formed in Eq. (48) is created and shared in Table 4.

Table 4
Covariance Matrix

	Age	Total	Sector	Firms
Age	0.200	0.169	0.018	-0.151
Total	0.169	0.200	0.094	-0.102
Sector	0.018	0.094	0.200	-0.059
Firms	-0.151	-0.102	-0.059	0.200

After constructing the covariance matrix presented in Table 4, its eigenvalues are calculated using Eq. (49), and the corresponding explained-variance ratios are subsequently determined. In addition, explained variances are determined. The results are summarized in Table 5.

Table 5
Eigenvalues and Explained Variances

Eigenvalue	Explained Variance
0.5132	64.15%
0.0002	0.03%
0.1894	23.68%
0.0972	12.15%

As can be seen from eigenvalues or explained variances in Table 5, the maximum eigenvalue is selected with Eq. (50) and equals to .5132. Then, eigenvector for this eigenvalue is constructed by solving Eq. (51). The eigenvector is illustrated in Table 6.

Table 6
Eigenvector

Eigenvector
0.57028
0.56525
0.29957
-0.5153

Finally, the expert-information matrix is projected onto the eigenvector associated with the largest eigenvalue using Eq. (52), resulting in a one-dimensional representation of the experts. This matrix is shared in Table 7.

Table 7
One-dimensional Matrix and Coefficients

	One-dimensional
EXPR1	40.759
EXPR2	35.576
EXPR3	28.429
EXPR4	36.383
EXPR5	30.566

Next, this one-dimensional matrix's elements are normalized by Eq. (53). The coefficients of experts' assessments are displayed in Figure 8.

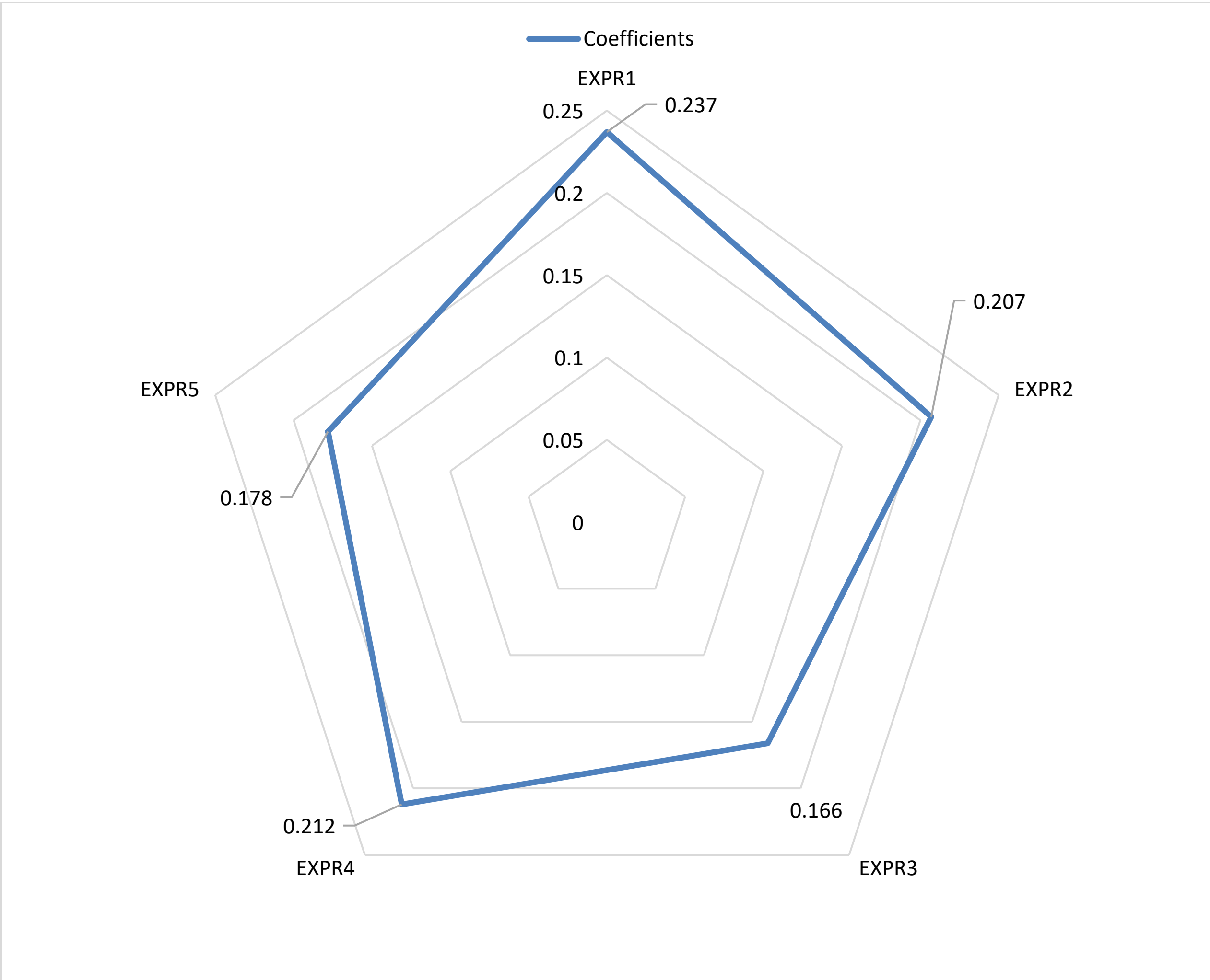

Fig. 8. Coefficients of Experts

3.3. Weights of Criteria

Firstly, 4-work models and 8-criteria are defined. 4-work models are freelance work model (FLNC), platform economy (gig economy) (GIBEC), metaverse workspaces (METAVR), and hybrid work model (HBRT). 8-criteria are presented in Table 8.

Table 8
Criteria

Criteria	Codes
Innovation Potential	INPTN
Collaboration and Networking	CLBNW
Career and Growth Opportunities	CGROP
Sustainability Potential	STBPN
Inequality and Access Justice	INAJS
Ethical Responsibilities	ETRPN
Market Access	MRACS
Social Contribution	SCNTR

These work models and criteria are evaluated according to four sectors: Information and Technology, Education and Consulting, Marketing and E-Commerce, and Finance and Insurance. The assessments for Information and Technology are exhibited in Table 9.

Table 9
Assessments for IT

EXPR1	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	9	9	8	8	9	9	7	4
GIBEC	7	6	8	8	8	9	6	3
METAVR	8	9	7	8	5	9	9	6
HBRT	8	6	7	6	7	6	6	8
EXPR2	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	8	7	8	9	9	5	6
GIBEC	8	7	6	9	7	9	8	7
METAVR	6	7	8	6	8	6	8	7
HBRT	6	8	7	8	9	9	8	7
EXPR3	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	3	3	3	2	5	3	4	3
GIBEC	4	4	4	4	5	5	4	4
METAVR	4	4	5	5	6	5	6	4
HBRT	5	6	7	7	7	7	7	6
EXPR4	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	8	7	8	9	9	5	4
GIBEC	7	6	6	8	7	9	6	4
METAVR	6	7	7	6	6	6	8	6
HBRT	6	6	7	7	7	7	7	7
EXPR5	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	7	6	7	8	8	5	4
GIBEC	7	6	6	7	7	8	6	5
METAVR	6	7	7	6	6	7	8	6
HBRT	6	7	7	7	8	7	7	7

The assessments for Education and Consulting are shown in Table 10.

These assessments are transformed into BLFNs. Next, BLFNs are multiplied by coefficients in Table 6 using Eq. (55). Then, multiplied BLFNs are summed with Eq. (56). The decision matrices by sectors are expressed in Table 13.

After determining the expert coefficients, the numerical calculation proceeds to the evaluation of the four work-model alternatives with respect to the eight selected criteria. Tables 9, 10, 11 and 12 report the raw assessments provided by the five experts for the Information and Technology, Education and Consulting, Marketing and E-Commerce, and Finance and Insurance sectors, respectively. These values constitute the initial expert evaluation matrices represented by Eq. (54).

Each assessment is first transformed into a Behavioral Leadership Fuzzy Number according to the BLFS formulation described in Section 2.2. The resulting fuzzy evaluations are then multiplied by the corresponding expert coefficients from Table 7 using Eq. (55), with the multiplication operation defined in Eq. (36). The weighted expert evaluations are subsequently aggregated using Eq. (56), based on the aggregation operator in Eq. (34). This procedure converts the individual expert assessments into a single behavior-adjusted collective evaluation for each alternative–criterion combination. The resulting sector-specific aggregated Behavioral Leadership Fuzzy Number matrices are presented in Table 13. These matrices constitute the direct input to the next calculation stage, where they are defuzzified using Eq. (57) and subsequently processed by SITDE to determine criterion weights and by RATGOS to rank the work-model alternatives.

Table 10
Assessments for EC

EXPR1	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	7	8	6	7	6	8	6	8
GIBEC	8	8	7	8	9	9	9	8
METAVR	7	6	5	8	7	8	5	3
HBRT	6	8	8	9	8	7	6	8
EXPR2	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	5	8	7	9	8	7	8	9
GIBEC	8	7	6	9	8	7	9	5
METAVR	7	7	8	6	7	9	6	8
HBRT	9	9	8	8	9	6	8	8
EXPR3	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	5	5	6	6	5	5	5
GIBEC	5	5	5	5	6	6	7	7
METAVR	5	5	5	5	5	4	5	4
HBRT	7	8	8	8	8	8	7	8
EXPR4	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	8	6	7	6	7	6	8
GIBEC	8	7	6	8	8	7	9	7
METAVR	7	6	5	6	7	8	5	4
HBRT	7	8	8	8	8	7	7	8
EXPR5	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	7	6	7	7	7	6	8
GIBEC	7	7	6	8	8	7	9	7
METAVR	7	6	6	6	7	7	5	5
HBRT	7	8	8	8	8	7	7	8

The assessments for Marketing and E-Commerce are given in Table 11.

Table 11
Assessments for ME

EXPR1	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	7	8	8	5	8	8	7
GIBEC	6	9	9	9	8	7	6	8
METAVR	8	7	7	8	7	9	9	5
HBRT	9	8	9	8	7	6	7	6
EXPR2	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	7	6	9	9	8	7	7	6
GIBEC	8	7	6	7	9	8	7	8
METAVR	7	9	8	7	9	9	9	7
HBRT	7	6	8	8	7	7	8	8
EXPR3	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	5	5	6	4	4	5	5	5

Table 11
Continued

EXPR1	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
GIBEC	6	6	5	5	6	5	5	5
METAVR	6	5	5	5	6	6	6	5
HBRT	6	6	7	8	7	7	7	7
EXPR4	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	6	8	8	5	7	7	6
GIBEC	6	7	6	7	8	7	6	8
METAVR	7	7	7	7	7	9	9	5
HBRT	7	6	8	8	7	7	7	7
EXPR5	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	6	8	7	6	7	7	6
GIBEC	7	7	7	7	8	7	6	7
METAVR	7	7	7	7	7	8	8	6
HBRT	7	7	8	8	7	7	7	7

The assessments for Finance and Insurance are given in Table 12.

Table 12
Assessments for FI

EXPR1	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	9	9	7	8	7	6	8	7
GIBEC	6	5	8	7	4	7		6
METAVR	8	9	8	8	8	8	8	7
HBRT	8	7	9	8	8	6	6	6
EXPR2	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	7	6	8	9	8	7	9	8
GIBEC	7	6	9	8	7	8	7	8
METAVR	7	9	8	7	8	7	8	6
HBRT	9	8	7	6	8	7	8	7
EXPR3	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	1	2	3	1	1	1	2	1
GIBEC	4	4	5	5	5	4	5	5
METAVR	5	4	4	4	4	3	3	4
HBRT	7	7	8	8	8	8	7	8
EXPR4	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	7	6	7	8	7	6	8	7
GIBEC	6	5	8	7	5	7	6	6
METAVR	7	9	8	7	8	7	8	6
HBRT	8	7	8	8	8	7	7	7
EXPR5	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	6	6	6	7	6	5	7	6
GIBEC	6	5	8	7	5	7	6	6
METAVR	7	8	7	7	7	6	7	6
HBRT	8	7	8	8	8	7	7	7

Table 13 therefore represents the aggregated output of the expert-evaluation stage after BLFS transformation, expert weighting, and fuzzy aggregation. To make these fuzzy evaluations suitable for the subsequent numerical weighting and ranking procedures, each Behavioral Leadership Fuzzy Number is converted into a crisp score using the score function defined in Eq. (38) and applied through Eq. (57). The resulting defuzzified sector-specific decision matrices are presented in Table 14. These crisp values form the common numerical basis for the subsequent SITDE criterion-weighting procedure and RATGOS alternative-ranking procedure. Afterwards, the values of decision matrices are defuzzified by Eq. (57). The defuzzified decision matrices are shown in Table 14.

Table 13
Decision Matrices

IT	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.9,1,0,0.4,1)	(0.9,1,0,0.5,1)	(0.6,0.6,0,0.6,1)	(0.6,0.4,0,0.7,1)
GIBEC	(0.7,0.9,0,0.5,1)	(0.7,0.7,0,0.6,1)	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.9,1,0,0.4,1)	(0.7,0.8,0,0.5,1)	(0.6,0.5,0,0.6,1)
METAVR	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.7,0,0.6,1)
HBRT	(0.7,0.8,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)
EC	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	(0.7,0.7,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.7,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)
GIBEC	(0.8,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.9,1,0,0.4,1)	(0.7,0.9,0,0.5,1)
METAVR	(0.7,0.8,0,0.5,1)	(0.7,0.7,0,0.5,1)	(0.7,0.7,0,0.6,1)	(0.7,0.8,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.6,0.6,0,0.6,1)	(0.6,0.6,0,0.6,1)
HBRT	(0.8,0.9,0,0.5,1)	(0.8,1,0,0.4,1)	(0.8,1,0,0.4,1)	(0.8,1,0,0.4,1)	(0.8,1,0,0.4,1)	(0.7,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.8,1,0,0.4,1)
ME	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	(0.7,0.7,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.7,0,0.6,1)	(0.7,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)
GIBEC	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.7,0.7,0,0.5,1)	(0.8,0.9,0,0.5,1)
METAVR	(0.8,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.9,1,0,0.4,1)	(0.9,1,0,0.4,1)	(0.7,0.7,0,0.6,1)
HBRT	(0.8,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.8,1,0,0.4,1)	(0.8,1,0,0.4,1)	(0.7,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)
FI	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	(0.8,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.6,0.7,0,0.6,1)	(0.8,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)
GIBEC	(0.7,0.7,0,0.6,1)	(0.6,0.5,0,0.6,1)	(0.8,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.6,0.6,0,0.6,1)	(0.7,0.9,0,0.5,1)	(0.6,0.7,0,0.6,1)	(0.7,0.8,0,0.5,1)
METAVR	(0.7,0.9,0,0.5,1)	(0.9,1,0,0.4,1)	(0.8,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.8,0,0.5,1)	(0.8,0.9,0,0.5,1)	(0.7,0.7,0,0.6,1)
HBRT	(0.8,1,0,0.4,1)	(0.8,0.9,0,0.5,1)	(0.8,1,0,0.4,1)	(0.8,0.9,0,0.5,1)	(0.8,1,0,0.4,1)	(0.7,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)	(0.7,0.9,0,0.5,1)

Table 14
Defuzzified Matrices

IT	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	3.027	3.246	3.041	3.171	3.386	3.362	2.669	2.303
GIBEC	3.092	2.846	2.947	3.253	3.122	3.386	2.927	2.473
METAVR	2.947	3.176	3.114	2.976	2.940	3.112	3.324	2.846
HBRT	2.976	3.041	3.125	3.128	3.266	3.191	3.128	3.150
EC	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	2.878	3.217	2.879	3.204	3.041	3.122	2.957	3.300
GIBEC	3.217	3.122	2.889	3.300	3.324	3.219	3.443	3.106
METAVR	3.058	2.879	2.841	2.976	3.058	3.253	2.587	2.600
HBRT	3.191	3.362	3.322	3.368	3.362	3.123	3.128	3.322
ME	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR

Table 14
Continued

IT	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	2.879	2.889	3.318	3.253	2.806	3.122	3.122	2.889
GIBEC	3.041	3.219	3.112	3.195	3.318	3.114	2.879	3.217
METAVR	3.150	3.180	3.114	3.122	3.204	3.400	3.400	2.746
HBRT	3.219	3.058	3.345	3.322	3.125	3.072	3.174	3.128
FI	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	3.098	3.012	3.032	3.216	3.004	2.734	3.227	3.004
GIBEC	2.846	2.540	3.300	3.114	2.625	3.092	2.650	2.957
METAVR	3.122	3.373	3.199	3.100	3.199	3.041	3.184	2.856
HBRT	3.339	3.174	3.339	3.259	3.322	3.117	3.128	3.117

Since all criteria are benefit, Eq. (58) is used for normalization process. The normalized matrices for SITDE are given in Table 15.

Table 15
Normalized Matrices for SITDE

IT	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.974	0.877	0.969	0.939	0.868	0.926	1.000	1.000
GIBEC	0.953	1.000	1.000	0.915	0.942	0.919	0.912	0.931
METAVR	1.000	0.896	0.946	1.000	1.000	1.000	0.803	0.809
HBRT	0.990	0.936	0.943	0.952	0.900	0.975	0.853	0.731
EC	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	1.000	0.895	0.987	0.929	1.000	1.000	0.875	0.788
GIBEC	0.895	0.922	0.983	0.902	0.915	0.970	0.751	0.837
METAVR	0.941	1.000	1.000	1.000	0.995	0.960	1.000	1.000
HBRT	0.902	0.856	0.855	0.884	0.904	1.000	0.827	0.783
ME	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	1.000	1.000	0.938	0.960	1.000	0.984	0.922	0.951
GIBEC	0.947	0.897	1.000	0.977	0.846	0.987	1.000	0.854
METAVR	0.914	0.909	0.999	1.000	0.876	0.904	0.847	1.000
HBRT	0.894	0.945	0.930	0.940	0.898	1.000	0.907	0.878
FI	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.919	0.843	1.000	0.964	0.874	1.000	0.821	0.951
GIBEC	1.000	1.000	0.919	0.995	1.000	0.884	1.000	0.966
METAVR	0.911	0.753	0.948	1.000	0.821	0.899	0.832	1.000
HBRT	0.852	0.800	0.908	0.951	0.790	0.877	0.847	0.916

Later, the standard deviation values are estimated with the help of Eq.s (60) and (61). The standard deviation values for normalized scores by sectors are shared in Table 16.

Next, the skewness values are computed using Eq. (62). Then, these skewness values are normalized by Eq. (63). The results are summarized in Table 17.

Finally, the weight vector is defined with the help of Eq. (64). These vectors according to sectors are presented in Figure 9.

When the values of the weight vector in Table 17 are examined, the most important criteria are CGROP and STBPN with .150 and .147 for information and technology sector, respectively. Similarly, the most important criteria are SCNTR and STBPN with .152 and .145 for education and consulting sector. The most important criteria are INAJS and CLBNW with .151 and .144 for marketing and E-commerce sector. Finally, the most important criteria are MRACS and ETRPN with .161 and .160 for finance and insurance sector.

Table 16
Standard Deviation Values

IT	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
St Dev	0.018	0.047	0.023	0.031	0.049	0.034	0.073	0.104
EC	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
St Dev	0.042	0.053	0.059	0.044	0.044	0.018	0.090	0.088
ME	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
St Dev	0.040	0.040	0.033	0.022	0.058	0.038	0.055	0.058
FI	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
St Dev	0.053	0.093	0.036	0.021	0.080	0.050	0.073	0.030

Table 17
Skewness, Normalized Skewness and Weight

IT	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
S	-0.916	1.456	1.588	1.465	0.870	0.488	0.853	-0.115
LS	0.301	0.641	0.654	0.642	0.578	0.532	0.576	0.447
EC	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
S	1.687	1.340	-2.973	1.959	-0.040	-0.316	0.996	2.584
LS	0.824	0.800	0.301	0.841	0.693	0.668	0.776	0.878
ME	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
S	1.335	1.587	-0.051	0.217	2.153	-2.839	0.630	0.515
LS	0.791	0.808	0.680	0.704	0.845	0.301	0.738	0.729
FI	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
S	0.834	2.032	1.741	-0.320	1.910	2.851	2.932	-0.042
LS	0.499	0.639	0.609	0.301	0.626	0.714	0.720	0.358

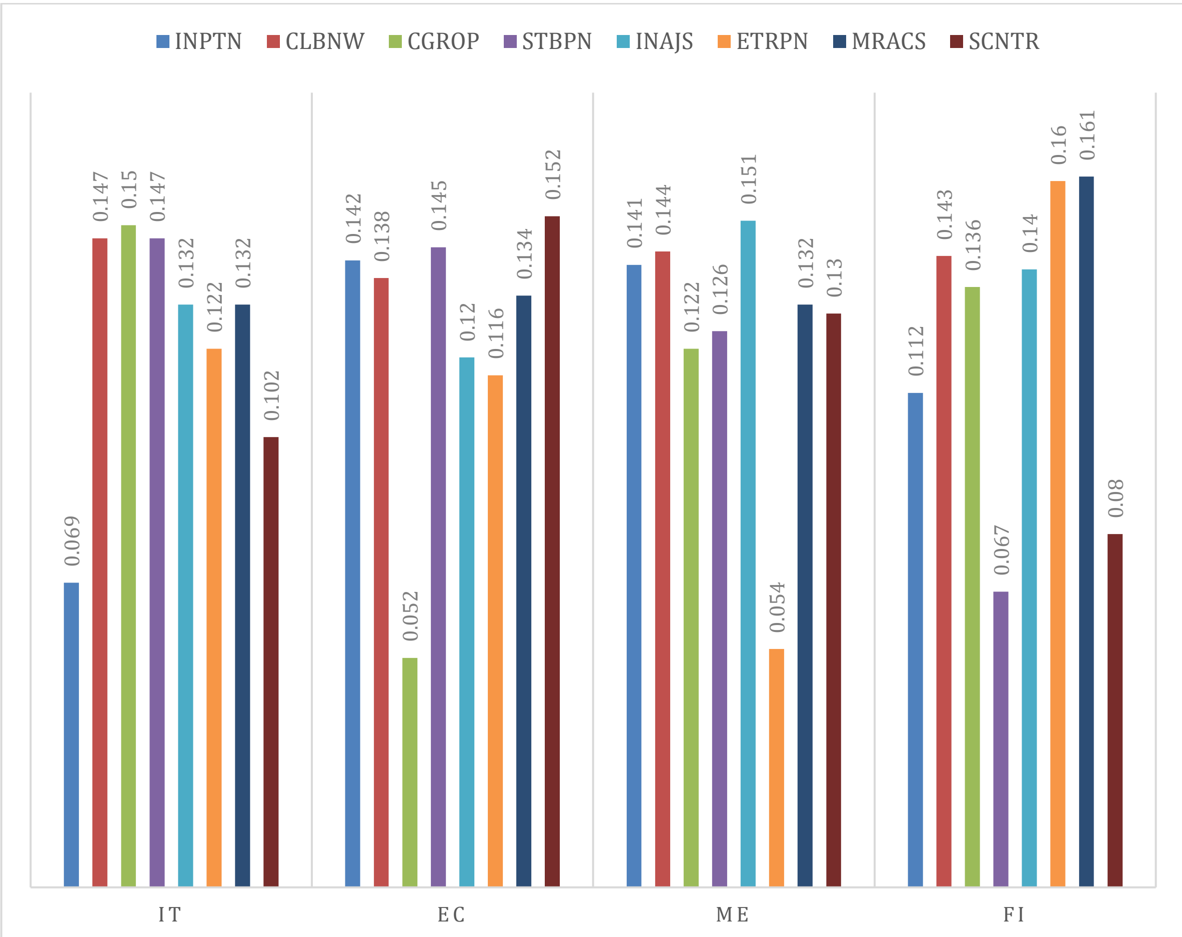

Fig. 9. Weight Vectors by Sectors

3.4. Ranking of 4-Work Models

The evaluation matrices are used for RATGOS. Accordingly, the optimal values are selected by Eq. (65). It should be noted that all criteria are benefit. The optimal values by sectors are displayed in Table 18.

Table 18
Optimal Values

IT	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
Optimal	3.092	3.246	3.125	3.253	3.386	3.386	3.324	3.150
EC	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
Optimal	3.217	3.362	3.322	3.368	3.362	3.253	3.443	3.322
ME	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
Optimal	3.219	3.219	3.345	3.322	3.318	3.400	3.400	3.217
FI	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
Optimal	3.339	3.373	3.339	3.259	3.322	3.117	3.227	3.117

Afterwards, similarity matrix's elements are computed using Eq. (67). Thus, the similarity matrices are created. The similarity matrices by sectors are illustrated in Table 19.

Table 19
Similarity Matrices

IT	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.979	1.000	0.973	0.975	1.000	0.993	0.803	0.731
GIBEC	1.000	0.877	0.943	1.000	0.922	1.000	0.881	0.785
METAVR	0.953	0.978	0.997	0.915	0.868	0.919	1.000	0.904
HBRT	0.962	0.937	1.000	0.962	0.965	0.943	0.941	1.000
EC	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.895	0.957	0.867	0.951	0.904	0.960	0.859	0.993
GIBEC	1.000	0.929	0.870	0.980	0.989	0.990	1.000	0.935
METAVR	0.950	0.856	0.855	0.884	0.909	1.000	0.751	0.783
HBRT	0.992	1.000	1.000	1.000	1.000	0.960	0.908	1.000
ME	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.894	0.897	0.992	0.979	0.846	0.918	0.918	0.898
GIBEC	0.945	1.000	0.930	0.962	1.000	0.916	0.847	1.000
METAVR	0.978	0.988	0.931	0.940	0.966	1.000	1.000	0.854
HBRT	1.000	0.950	1.000	1.000	0.942	0.904	0.934	0.972
FI	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.928	0.893	0.908	0.987	0.904	0.877	1.000	0.964
GIBEC	0.852	0.753	0.988	0.956	0.790	0.992	0.821	0.949
METAVR	0.935	1.000	0.958	0.951	0.963	0.976	0.987	0.916
HBRT	1.000	0.941	1.000	1.000	1.000	1.000	0.969	1.000

Using the weight vectors in Table 17, the weighted values are calculated with the help of Eq. (69). The weighted matrices by sectors are presented in Table 20.

Finally, the geometric mean is estimated with Eq. (70). Geometric means of 4-work models by sectors are summarized in Figure 10.

As can be seen from geometric mean values in Figure 10, the most optimal work model is HBRT with .117 for information and technology sector. Similarly, the most optimal work model is HBRT with .118 for education and consulting sector. The most optimal work model is HBRT with .116 for marketing and E-commerce sector. Finally, the most optimal work model is HBRT with .118 for finance and insurance sector.

Table 20
Weighted Matrices

IT	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.067	0.147	0.146	0.143	0.132	0.121	0.106	0.075
GIBEC	0.069	0.128	0.141	0.147	0.122	0.122	0.116	0.080
METAVR	0.066	0.143	0.149	0.134	0.115	0.112	0.132	0.092
HBRT	0.066	0.137	0.150	0.141	0.128	0.115	0.124	0.102
EC	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.127	0.132	0.045	0.138	0.108	0.111	0.115	0.151
GIBEC	0.142	0.129	0.045	0.143	0.119	0.114	0.134	0.142
METAVR	0.135	0.119	0.045	0.129	0.109	0.116	0.101	0.119
HBRT	0.141	0.138	0.052	0.145	0.120	0.111	0.122	0.152
ME	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.126	0.130	0.121	0.123	0.128	0.049	0.121	0.117
GIBEC	0.134	0.144	0.113	0.121	0.151	0.049	0.112	0.130
METAVR	0.138	0.143	0.113	0.118	0.146	0.054	0.132	0.111
HBRT	0.141	0.137	0.122	0.126	0.142	0.049	0.123	0.127
FI	INPTN	CLBNW	CGROP	STBPN	INAJS	ETRPN	MRACS	SCNTR
FLNC	0.104	0.128	0.124	0.067	0.127	0.140	0.161	0.077
GIBEC	0.095	0.108	0.135	0.064	0.111	0.159	0.132	0.076
METAVR	0.104	0.143	0.131	0.064	0.135	0.156	0.159	0.073
HBRT	0.112	0.135	0.136	0.067	0.140	0.160	0.156	0.080

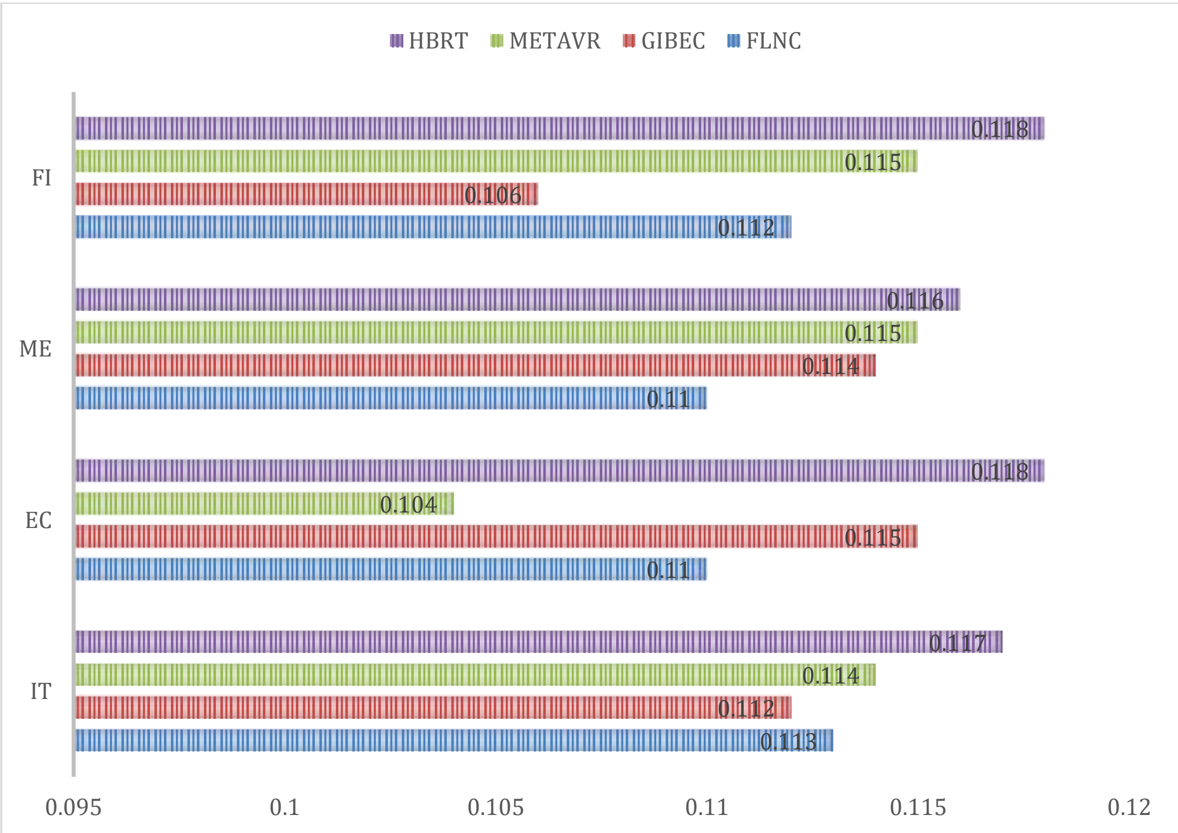

Fig. 10. Geometric Means

3.5. Sensitivity Analysis and Ablation Studies

Sensitivity analysis is a recommended approach for multi-criteria decision-making methods. This allows the robustness of the results to be tested. In other words, the effect of a minimal increase in input values on the results is examined. In this manuscript, a scenario is constructed with a minimal increase in each criterion. In other words, the weight of the first criterion is increased, and the weights of all criteria are normalized. This results in new scenario weights. Using these new weights, the alternatives are ranked, and the results of all scenarios are compared. The results of this scenario-based sensitivity analysis are presented in Table 21.

Table 21
Sensitivity Analysis

IT	SA1	SA2	SA3	SA4	SA5	SA6	SA7	SA8
FLNC	3	3	3	3	3	3	3	3
GIBEC	4	4	4	4	4	4	4	4
METAVR	2	2	2	2	2	2	2	2
HBRT	1	1	1	1	1	1	1	1
EC	SA1	SA2	SA3	SA4	SA5	SA6	SA7	SA8
FLNC	3	3	3	3	3	3	3	3
GIBEC	2	2	2	2	2	2	2	2
METAVR	4	4	4	4	4	4	4	4
HBRT	1	1	1	1	1	1	1	1
ME	SA1	SA2	SA3	SA4	SA5	SA6	SA7	SA8
FLNC	4	4	4	4	4	4	4	4
GIBEC	3	3	3	3	3	3	3	3
METAVR	2	2	2	2	2	2	2	2
HBRT	1	1	1	1	1	1	1	1
FI	SA1	SA2	SA3	SA4	SA5	SA6	SA7	SA8
FLNC	3	3	3	3	3	3	3	3
GIBEC	4	4	4	4	4	4	4	4
METAVR	2	2	2	2	2	2	2	2
HBRT	1	1	1	1	1	1	1	1

As can be seen from the results in Table 21, the rankings by sector are internally consistent, meaning that the ordering of the working models remains unchanged across all sensitivity scenarios. This robustness was tested by constructing each scenario through a controlled sensitivity procedure in which the weight of a single criterion was increased by 5 percent while the remaining criteria weights were proportionally re-normalized to preserve a constant total weight. The stability of the rankings under these targeted perturbations demonstrates that the results are not sensitive to marginal variations in individual criterion importance. In particular, the primary recommendation of the model—the hybrid work model—remains unchanged across all scenarios, even when the relative importance of criteria fluctuates. Such robustness is particularly valuable because it indicates that the proposed decision framework does not produce fragile or overly weight-dependent outcomes, thereby increasing confidence for practitioners and policymakers in applying the model to real-world decision-making contexts.

Additionally, ablation studies are performed. In this context, each component of the model is removed from the analysis process in each analysis. In other words, the expert weighting process is removed, and an analysis is performed by assuming equal importance coefficients for each expert. In another analysis, the criterion weights are assumed to be equal, and the analysis is removed. Thus, the SITDE analysis is obtained with a disqualified analysis. The results of all these situations are summarized in Table 22.

When Table 22 is examined, the ranking results have the same order in every case. This demonstrates the universality of the results. However, these results are for the assessment of experts only. The change in these results should be examined in case of changes in possible criterion weights. In this context, a sensitivity analysis of the possible combinations of the model is performed. The sensitivity analyses of the combinations are shared in Table 23.

Table 22
Results of Ablation Studies

IT	Our Model	BLFS+SITDE+RATGOS	DR+BLFS+RATGOS	DR+SITDE+RATGOS
FLNC	0.113	0.111	0.115	0.104
GIBEC	0.112	0.112	0.115	0.104
METAVR	0.114	0.114	0.117	0.107
HBRT	0.117	0.117	0.121	0.113
EC	Our Model	BLFS+SITDE+RATGOS	DR+BLFS+RATGOS	DR+SITDE+RATGOS
FLNC	0.110	0.110	0.115	0.101
GIBEC	0.115	0.115	0.120	0.110
METAVR	0.104	0.104	0.109	0.091
HBRT	0.118	0.118	0.123	0.116
ME	Our Model	BLFS+SITDE+RATGOS	DR+BLFS+RATGOS	DR+SITDE+RATGOS
FLNC	0.110	0.110	0.114	0.101
GIBEC	0.114	0.114	0.118	0.107
METAVR	0.115	0.115	0.120	0.109
HBRT	0.116	0.116	0.121	0.111
FI	Our Model	BLFS+SITDE+RATGOS	DR+BLFS+RATGOS	DR+SITDE+RATGOS
FLNC	0.112	0.109	0.115	0.097
GIBEC	0.106	0.105	0.110	0.093
METAVR	0.115	0.113	0.119	0.108
HBRT	0.118	0.118	0.124	0.116

Note: DR denotes the dimensionality reduction procedure used to determine expert weights based on demographic and experiential features.

Table 23
Sensitivity Analysis of Combinations

BLFS+SITDE+RATGOS		INPTN+5%	CLBNW+5%	CGROP+5%	STBPN+5%	INAJS+5%	ETRPN+5%	MRACS+5%	SCNTR+5%
IT	FLNC	4	4	4	4	4	4	4	4
	GIBEC	3	2	3	3	3	3	3	3
	METAVR	2	3	1	2	2	2	2	2
	HBRT	1	1	2	1	1	1	1	1
EC	FLNC	3	3	3	2	3	3	3	3
	GIBEC	2	2	2	3	2	2	2	2
	METAVR	4	4	4	4	4	4	4	4
	HBRT	1	1	1	1	1	1	1	2
ME	FLNC	4	4	4	4	4	4	3	4
	GIBEC	3	3	3	3	3	3	4	3
	METAVR	2	2	2	2	2	2	2	1
	HBRT	1	1	1	1	1	1	1	1
FI	FLNC	3	3	4	3	3	3	3	2
	GIBEC	4	4	3	4	4	4	4	4
	METAVR	2	2	2	1	2	1	2	3
	HBRT	1	1	1	2	1	2	1	1
ML+BLFS+RATGOS		INPTN+5%	CLBNW+5%	CGROP+5%	STBPN+5%	INAJS+5%	ETRPN+5%	MRACS+5%	SCNTR+5%
IT	FLNC	4	4	4	4	4	4	4	4
	GIBEC	3	3	3	3	3	3	3	3
	METAVR	2	2	1	2	2	2	2	2
	HBRT	1	1	2	1	1	1	1	1
EC	FLNC	3	3	3	2	3	3	3	3
	GIBEC	2	2	2	3	2	2	2	2
	METAVR	4	4	4	4	4	4	4	4
	HBRT	1	1	1	1	1	1	1	2

Table 23
Continued

BLFS+SITDE+RATGOS		INPTN+5%	CLBNW+5%	CGROP+5%	STBPN+5%	INAJS+5%	ETRPN+5%	MRACS+5%	SCNTR+5%
ME	FLNC	4	4	4	3	4	4	3	4
	GIBEC	2	3	3	4	3	3	4	3
	METAVR	3	2	2	2	2	2	2	1
	HBRT	1	1	1	1	1	1	1	1
FI	FLNC	3	3	4	3	3	3	3	2
	GIBEC	4	4	3	4	4	4	4	4
	METAVR	1	2	2	1	2	1	2	3
	HBRT	2	1	1	2	1	2	1	1
ML+SITDE+RATGOS		INPTN+5%	CLBNW+5%	CGROP+5%	STBPN+5%	INAJS+5%	ETRPN+5%	MRACS+5%	SCNTR+5%
IT	FLNC	3	4	3	4	4	3	4	4
	GIBEC	4	2	4	3	3	4	3	3
	METAVR	2	3	1	2	2	2	2	2
	HBRT	1	1	2	1	1	1	1	1
EC	FLNC	3	3	3	2	3	3	3	3
	GIBEC	2	2	2	3	2	2	2	2
	METAVR	4	4	4	4	4	4	4	4
	HBRT	1	1	1	1	1	1	1	2
ME	FLNC	4	4	4	4	4	4	3	4
	GIBEC	3	3	3	3	3	3	4	3
	METAVR	2	2	2	2	2	2	2	1
	HBRT	1	1	1	1	1	1	1	1
FI	FLNC	4	3	4	3	3	3	4	2
	GIBEC	3	4	3	4	4	4	3	4
	METAVR	2	2	2	1	2	1	2	3
	HBRT	1	1	1	2	1	2	1	1

Table 23 presents the sensitivity analysis results for different combinations of the model components, whileFigure 11 provides the corresponding comparative results. Therefore, it is concluded that all proposed components are significant. In other words, the ranking results are universal, but the model is significant in terms of robustness against possible scenarios. Moreover, comparative analysis is performed. The comparative results are summarized in Figure 11.

4. Conclusion

The finding that the hybrid work model ranks first across all four sectors is broadly consistent with the growing literature emphasizing the advantages of combining flexibility with continued organizational and social interaction. Previous studies have associated hybrid and distributed work with improved work-life balance, greater flexibility, and changing patterns of employee autonomy, while also emphasizing that fully remote arrangements may generate social isolation and weaken traditional organizational culture. The present findings extend this literature by suggesting that the attractiveness of hybrid work may not arise from superiority on a single criterion but from its ability to balance competing organizational requirements. Hybrid structures preserve important benefits of digital and remote work while maintaining physical interaction, organizational coordination, and institutional control. This balancing capacity may explain why the hybrid model remains the highest-ranked alternative even though the relative importance of the evaluation criteria differs substantially across the examined sectors.

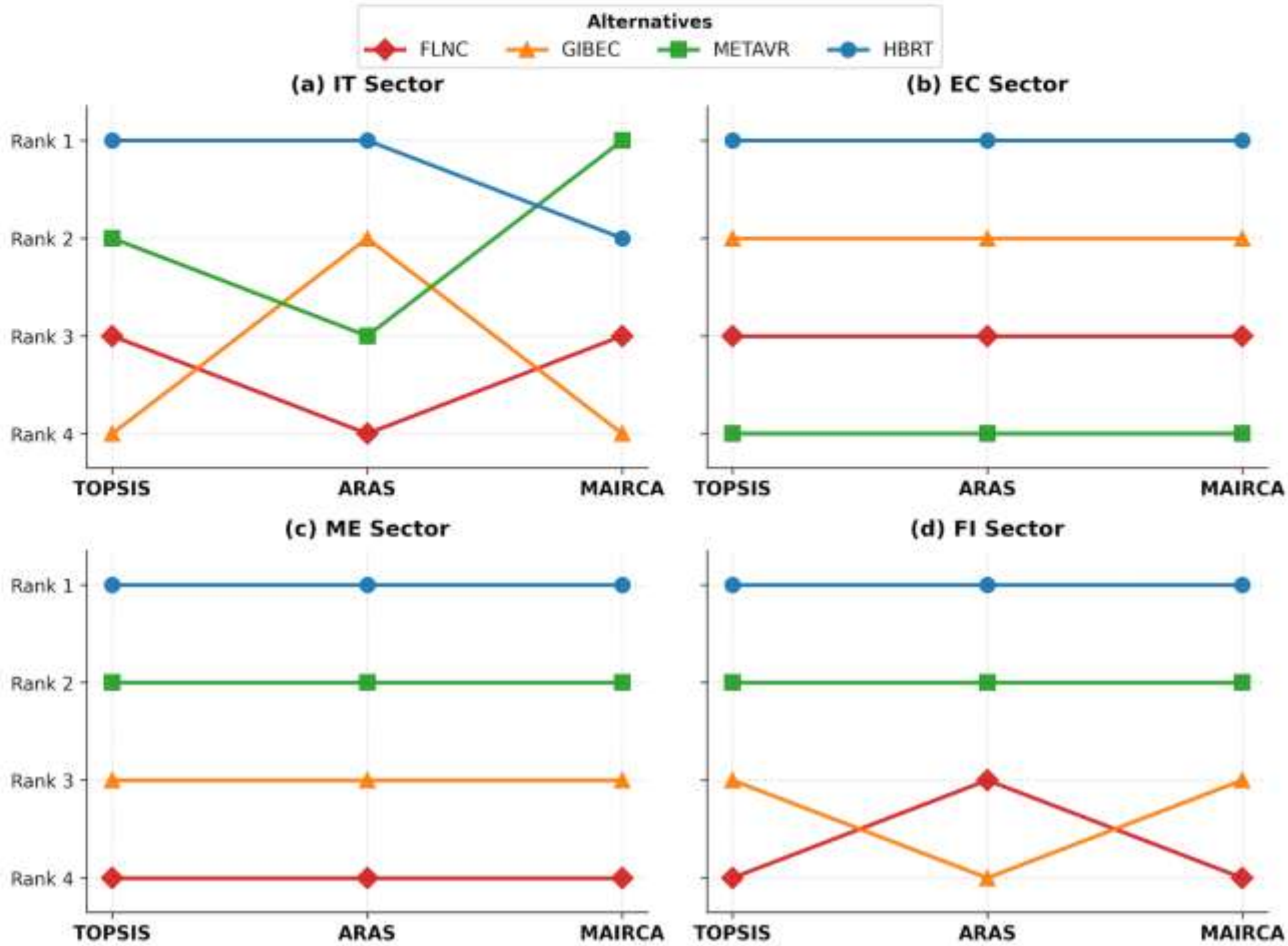

Fig. 11. Comparative Results

The result can also be interpreted by considering the limitations associated with the competing work models. The literature describes the gig economy as a source of flexibility and autonomy, but simultaneously identifies concerns regarding job insecurity, social protection, legal classification, privacy, and platform-based power asymmetries. These tensions may restrict the ability of gig-based arrangements to perform consistently across criteria related to sustainability, fairness, ethical responsibility, and social contribution. Similarly, metaverse-based working environments offer substantial potential for virtual collaboration and digitally mediated organizational processes, but their organizational adoption remains dependent on technological readiness, digital infrastructure, user acceptance, and the capacity to reproduce important dimensions of social interaction. Consequently, the current rankings do not imply that freelance, gig-based, or metaverse models lack value. Rather, they indicate that these models may provide stronger advantages under specific technological or organizational conditions, whereas the hybrid model offers a more immediately adaptable compromise across heterogeneous decision dimensions.

At the same time, the findings reveal an important tension between convergence in the preferred work model and divergence in the criteria explaining that preference. Career and growth opportunities are particularly influential in Information and Technology, social contribution is more prominent in Education and Consulting, inequality and access justice receives greater emphasis in Marketing and E-Commerce, and market access and ethical responsibilities are especially important in Finance and Insurance. This sectoral differentiation is consistent with previous research arguing that digital transformation cannot be understood as a purely technological process and that its outcomes depend on organizational capabilities, leadership, institutional conditions, and human-centered considerations. However, the present results add an important qualification to this literature: different sectors may arrive at the same general work-model preference for different reasons. Thus, similarity in final rankings should not be interpreted as evidence that sectoral requirements are homogeneous.

Some findings also qualify more technologically deterministic expectations concerning the future of work. The literature increasingly highlights the potential of artificial intelligence, the metaverse, algorithmic management, and digitally mediated employment structures to transform organizational life. Nevertheless, the present analysis does not place the most technologically intensive work model at the top of the ranking. Instead, hybrid work performs more consistently across the examined sectors. This suggests that technological intensity alone may be insufficient to determine the suitability of future work arrangements. Organizational viability appears to depend on the alignment of technological capabilities with human interaction, ethical considerations, career development, accessibility, and institutional requirements. In this respect, the findings are compatible with human-centered perspectives associated with Industry 5.0 and Employment 5.0, which emphasize complementarity between technological advancement, employee well-being, sustainability, and human-machine collaboration rather than technological substitution alone .

Theoretically, the findings support a contingency-oriented interpretation of future work design. Rather than assuming that a single technological trajectory determines the optimal form of employment, the results indicate that work-model suitability emerges from the interaction between sector-specific priorities and the capacity of each organizational configuration to accommodate multiple competing demands. The consistent position of the hybrid model can therefore be interpreted as evidence of adaptive fit within the analyzed decision context rather than universal superiority. Hybrid work appears to function as a bridging organizational form between traditional place-based employment and fully digitalized work arrangements, allowing organizations to adjust the relative intensity of physical presence, digital collaboration, autonomy, and managerial coordination according to sectoral needs. This interpretation also extends the Life 3.0 perspective by suggesting that the transformation of work is not simply a progression toward maximum digitalization. Instead, technological development and human organizational requirements are likely to co-evolve, making adaptable socio-technical configurations increasingly important.

The sector-specific criterion priorities further have managerial implications, but these should be interpreted in relation to the preceding theoretical findings. In Information and Technology, the importance of career and growth opportunities suggests that hybrid arrangements should be accompanied by continuous learning, skill development, and talent-retention mechanisms. In Education and Consulting, the prominence of social contribution highlights the importance of maintaining stakeholder interaction and broader societal value alongside digital flexibility. In Marketing and E-Commerce, the emphasis on inequality and access justice suggests that digital work structures should be designed to avoid exclusion arising from unequal technological access. In Finance and Insurance, the importance of market access and ethical responsibilities indicates that hybrid arrangements must remain compatible with regulatory requirements, transparency, client trust, and secure digital service delivery. Accordingly, the practical implication is not the adoption of a standardized hybrid model but the development of sector-specific hybrid configurations based on the dominant institutional and organizational priorities of each context.

The objective of this study is to identify the most appropriate innovative working model for different sectors, considering the digitalizing workforce dynamics within the framework of the Life 3.0 paradigm, and to analyze the criteria that should be prioritized in this decision-making process using a multidimensional approach. Four key sectors were evaluated for this purpose: Information and Technology, Education and Consulting, Marketing and E-Commerce, and Finance and Insurance.

To ensure objective decision-making, publications in the WoS database were scanned using the RPA approach, and eight of the most significant decision criteria were prioritized using content analysis and text mining. Expert opinions were weighted using the dimensionality reduction method, resulting in an objective assessment based on the experts' demographic and professional characteristics. Criteria weights were then determined using the SITDE method, and alternative working models were ranked using the RATGOS algorithm. Furthermore, the BLFSs approach, developed to model expert behavior based on leadership styles, adds a behavioral dimension to the study. The analysis results indicate that a hybrid working model stands out as the most suitable option across all sectors, while the priorities of decision criteria vary across sectors. For example, the most decisive criteria in the information technologies sector are "career and development opportunities," in the education sector, "social contribution," in the marketing sector, "fair access," and in the finance sector, "market access" and "ethical responsibilities." These findings highlight the criticality of a holistic decision-making process that takes sectoral differences into account. In terms of contributing to the literature, the study presents an innovative and original methodological framework, including objective criteria selection using AI-supported analyses, machine learning-based calculation of expert weights, the development of a new fuzzy set system, BLFS, and the context-specific application of the RATGOS method. The results of the hybrid fuzzy analysis indicate that the hybrid work model performs best in terms of adaptability, productivity, and organizational sustainability, followed by freelance and metaverse-based models. These findings emphasize that flexible but structured work systems provide optimal outcomes in most sectors analyzed. The study’s practical implication lies in guiding policymakers and organizations in designing sector-specific digital transformation strategies that balance human adaptability and technological capacity.

The primary contribution of this study should be interpreted as the development and demonstration of an integrated methodological framework rather than as the establishment of universally applicable rankings for future work models. Accordingly, the empirical application presented in this study serves as a proof of concept illustrating how artificial intelligence, behavioral fuzzy modeling, objective expert weighting, and advanced MCDM techniques can be successfully integrated within a unified decision support architecture. The resulting rankings should therefore be regarded as an illustrative application of the proposed methodology under the selected evaluation context, while broader empirical validation across different organizational settings remains an important direction for future research. While the unique methodological framework and findings of this study provide meaningful contributions to the literature, several theoretical and practical limitations warrant consideration. From a theoretical standpoint, the study focuses on a limited set of sectors and evaluation criteria; therefore, contextual factors such as cultural differences, organizational dynamics, and cross-sectoral interactions were beyond its scope. Moreover, the literature review was confined to the Web of Science database, which may have excluded some unique or emerging criteria discussed in alternative academic sources. A major limitation of the empirical application is the use of a five-member expert panel. Although the experts were purposively selected based on relevant professional and sectoral experience, such a small panel restricts the extent to which the resulting judgments can represent the broader population of managers, employees, organizations, or sectors. The dimensionality-reduction procedure improves the internal structuring of expert contributions by differentiating their influence according to demographic and experiential characteristics, but it does not eliminate sampling uncertainty or compensate for the limited number of evaluators. Therefore, reliability in the present study should primarily be interpreted in terms of the internal stability of the decision results, which is supported by the sensitivity and ablation analyses, rather than reproducibility across independent expert populations. Similarly, the current application provides methodological and contextual validity for demonstrating the functioning of the framework but does not establish broad external validity. The sectoral rankings should consequently be treated as proof-of-concept findings rather than population-level estimates. Future studies should replicate the framework with larger and more diverse expert panels, conduct independent panel replications, examine inter-expert agreement, and validate the resulting rankings across different countries, organizational settings, and sectoral contexts.

Additionally, as the behavioral leadership fuzzy sets framework is a relatively recent methodological innovation, further validation in different empirical contexts is necessary. Although the RATGOS algorithm enhances analytical robustness, its lack of comparative assessment with other ranking approaches may restrict methodological diversity. To advance this line of inquiry, future research could expand the model by incorporating larger and more diverse expert groups across different sectors, cultural contexts, and organizational settings. Empirical validation of the BLFS structure in these varied environments would enhance its generalizability and reliability. Furthermore, simulation-based comparative analyses between decision-making algorithms could provide valuable insights into their relative performance. Finally, developing sector-specific strategic frameworks in collaboration with policymakers would bridge current research gaps and strengthen both academic and practical applications.

Although the BLFS module represents a novel attempt to incorporate leadership-driven behavioral variability into fuzzy decision environments, its parameterization currently relies on theoretical formulations rather than empirical psychological measurements. The leadership styles and behavioral coefficients were derived from conceptual principles in the leadership literature but were not calibrated through observational or survey-based data. As a result, the behavioral layer should be interpreted as a theoretically grounded but preliminarily validated mechanism. Future research can strengthen this component by collecting empirical data on leaders’ decision patterns, estimating behavioral distributions statistically, and calibrating BLFS functions against actual psychological profiles. Such extensions would further enhance the realism and predictive accuracy of the behavioral module. The similarity of rankings across sectors indicates that certain criteria exert consistently strong influence regardless of contextual differences, which may lead to convergence in the final ordering of work models. This should not be interpreted as model failure but rather as evidence that hybrid work structures possess cross-sectoral advantages robust to variations in criteria weights. Nonetheless, the possibility of weight domination or structural rigidity cannot be fully ruled out. The findings should therefore be viewed with the understanding that the current model may be more sensitive to high-impact universal criteria than to subtle sector-specific nuances. Future research can address this by expanding the sectoral dataset, testing alternative weighting schemes, and conducting scenario-based simulations to more thoroughly examine model responsiveness.

Another limitation concerns the absence of direct benchmarking against widely used MCDM techniques such as AHP, ANP, TOPSIS, VIKOR, and PROMETHEE. The primary objective of this study was to introduce and validate the internal consistency of the proposed BLFS, SITDE, and RATGOS integrated framework rather than to establish superiority over existing approaches. Accordingly, robustness was evaluated through sensitivity and ablation analyses. Nevertheless, future studies may conduct comparative applications using established MCDM methods on the same dataset to provide additional evidence regarding the relative strengths, weaknesses, and practical advantages of the proposed framework. Although the BLFS framework provides a structured mechanism for incorporating leadership-related behavioral characteristics into decision-making processes, its current validation remains primarily methodological rather than organizational. The behavioral transformations embedded within BLFS were developed from established leadership theories and evaluated through computational analyses, sensitivity tests, and expert-based assessments.

However, the framework has not yet been validated through longitudinal leadership datasets, controlled field experiments, or large-scale organizational case studies. Consequently, the practical behavioral effects modeled by BLFS should be interpreted as theoretically informed representations rather than empirically confirmed organizational outcomes. Future research may extend the validation process by applying the framework within real organizational environments and comparing predicted decision patterns with observed managerial behaviors over time.

Although the proposed framework was evaluated using expert judgments obtained from experienced professionals with substantial domain knowledge, the size of the expert panel inevitably represents a limitation regarding the broader generalizability of the findings. The primary objective of this study was to demonstrate the applicability and methodological capability of the proposed integrated framework rather than to establish universally generalizable sectoral rankings. Future research may improve external validity by employing larger expert panels, involving participants from different countries and industries, and validating the proposed framework through multiple real-world case studies. Such extensions would provide additional evidence regarding the robustness, transferability, and practical applicability of the proposed decision support architecture.

Nomenclature

AI: Artificial Intelligence
BLFS: Behavioral Leadership Fuzzy Sets
DM: Decision Maker
DR: Dimensionality Reduction
IT: Information Technology
MCDM: Multi Criteria Decision Making
NLP: Natural Language Processing
RPA: Robotic Process Automation
RATGOS: Ranking Alternatives Through Geometric Ordinal Similarity
SITDE: Skewness Integrated Two-Dimensional Entropy
WoS: Web of Science
A_i: Alternative i
C_j: Criterion j
E_k: Expert k
w_j: Criterion weight
r_{ij}: Initial evaluation value
v_{ij}: Normalized evaluation value
S_i: Overall score of alternative i
M: Membership degree
ν: Non membership degree
π: Hesitation degree
m: Number of alternatives
n: Number of criteria

Appendix

Appendix A. Step-by-Step Computational Algorithm of the Proposed Framework

The complete computational procedure of the proposed decision support framework is organized below as a sequential algorithm. Each step identifies the required input, the corresponding mathematical expressions, and the output transferred to the subsequent stage. This structure is intended to improve transparency, reproducibility, and the traceability of the numerical analysis.

Step 1. Define the initial expert-information matrix. The demographic and professional characteristics of the experts, including age, total professional experience, sector-specific experience, and number of firms worked, are used as the initial inputs. These observations form the expert-information matrix defined in Eq. (40). The output of this step is the original $k \times t$ information matrix.

Step 2. Standardize the expert-information variables. Since the expert characteristics are measured on different scales, the variables are standardized using Eqs. (41)–(43). The standardized information matrix is then constructed according to Eq. (44). The output of this step is the scale-independent matrix used in the subsequent covariance analysis.

Step 3. Construct the standardized vectors and covariance matrix. Each column of the standardized matrix is represented as a standardized vector according to Eq. (45). Pairwise covariance coefficients between the expert-information variables are then calculated using Eqs. (46) and (47), and the complete covariance matrix is formed through Eq. (48). The output of this step is the covariance matrix representing the joint variation among the expert characteristics.

Step 4. Calculate eigenvalues and identify the dominant component. The eigenvalues of the covariance matrix are obtained using Eq. (49). The maximum eigenvalue is selected according to Eq. (50) to retain the component explaining the greatest proportion of variation. The output of this step is the dominant eigenvalue used to construct the corresponding eigenvector.

Step 5. Calculate the eigenvector and determine expert coefficients. The eigenvector associated with the maximum eigenvalue is calculated using Eq. (51). The original expert-information matrix is then projected onto this eigenvector using Eq. (52), producing a one-dimensional representation for each expert. These values are normalized using Eq. (53) to determine the expert coefficients. The output of this step is the normalized expert-weight vector used in the fuzzy aggregation process.

Step 6. Define the alternative–criterion assessment matrices. The work-model alternatives and decision criteria are evaluated by the experts, and the resulting assessment matrices are defined according to Eq. (54). The input at this stage consists of the expert judgments for each alternative–criterion combination. The output is the initial set of expert evaluation matrices.

Step 7. Transform expert assessments into Behavioral Leadership Fuzzy Numbers. The expert assessments are transformed into Behavioral Leadership Fuzzy Numbers using the BLFS membership functions and operators defined in Eqs. (1)–(39). The corresponding leadership-related behavioral parameters modify the original expert evaluations to represent behavioral uncertainty. The output of this step is the set of behavior-adjusted fuzzy evaluations.

Step 8. Weight and aggregate the expert evaluations. Each Behavioral Leadership Fuzzy Number is multiplied by the corresponding expert coefficient using Eq. (55), with the multiplication operator defined in Eq. (36). The weighted fuzzy evaluations are subsequently aggregated using Eq. (56), based on the aggregation operator defined in Eq. (34). The output is a single aggregated fuzzy decision matrix for each sector.

Step 9. Defuzzify the aggregated decision matrix. The aggregated Behavioral Leadership Fuzzy Numbers are converted into crisp values using Eq. (57), based on the score function defined in Eq. (38). The output of this step is the defuzzified decision matrix used in the criterion-weighting and ranking stages.

Step 10. Normalize the decision matrix for criterion weighting. The defuzzified values are normalized according to criterion type. Eq. (58) is used for benefit criteria, while Eq. (59) is used for cost criteria. The output is the normalized decision matrix required for the SITDE procedure.

Step 11. Calculate criterion variability and criterion weights. Standard deviation values are calculated using Eqs. (60) and (61). Criterion skewness values are then obtained using Eq. (62), normalized using Eq. (63), and converted into final criterion weights through Eq. (64). The output of this stage is the criterion-weight vector.

Step 12. Determine the optimal values for alternative ranking. The defuzzified decision matrix is transferred to the RATGOS procedure. Optimal values are identified using Eq. (65) for benefit criteria and Eq. (66) for cost criteria. The output is the criterion-specific optimal reference vector.

Step 13. Construct the similarity matrix. Similarity ratios between each alternative and the corresponding optimal values are calculated using Eq. (67) for benefit criteria and Eq. (68) for cost criteria. The output is the similarity matrix representing the relative proximity of each alternative to the optimal values.

Step 14. Calculate weighted similarity values. The similarity values are multiplied by the criterion weights using Eq. (69). The output is the weighted similarity matrix reflecting both alternative performance and criterion importance.

Step 15. Calculate final scores and rank the alternatives. The weighted similarity values are aggregated through the geometric mean defined in Eq. (70). The resulting score represents the overall performance of each alternative. Alternatives are ranked in descending order according to these scores, and the alternative with the highest score is identified as the most suitable work model.

Appendix B. Equations

$$\mathcal{B} = \{\mu(\mathscr{s}), \langle\mu_a(\mu(\mathscr{s})), \mu_d(\mu(\mathscr{s})), \mu_t(\mu(\mathscr{s})), \mu_l(\mu(\mathscr{s})), \mu_s(\mu(\mathscr{s}))\rangle | \mathscr{s} \in \mathfrak{D}\} \tag{1}$$

$$\mu_a(\mu(\mathscr{s})) = \mathfrak{b}_1 e^{\mu(\mathscr{s})-1} \tag{2}$$

$$-1 \leq \mu(\mathscr{s}) - 1 \leq 0 \tag{3}$$

$$\frac{1}{e} \leq e^{\mu(\mathscr{s})-1} \leq 1 \tag{4}$$

$$\frac{\mathfrak{b}_1}{e} \leq \mathfrak{b}_1 e^{\mu(\mathscr{s})-1} \leq \mathfrak{b}_1 \tag{5}$$

$$0 \leq \mu_a\big(\mu(\mathscr{s})\big) \leq 1 \tag{6}$$

$$\mu_d(\mu(\mathscr{s})) = \frac{1}{1+e^{-\mathfrak{b}_2(\mu(\mathscr{s})-0.5)}} \tag{7}$$

$$-0.5 \leq \mu(\mathscr{s}) - 0.5 \leq 0.5 \tag{8}$$

$$-0.5\mathfrak{b}_2 \leq -\mathfrak{b}_2(\mu(\mathscr{s}) - 0.5) \leq 0.5\mathfrak{b}_2 \tag{9}$$

$$e^{-0.5\mathfrak{b}_2} \leq e^{-\mathfrak{b}_2(\mu(\mathscr{s})-0.5)} \leq e^{0.5\mathfrak{b}_2} \tag{10}$$

$$1 + e^{-0.5\mathfrak{b}_2} \leq 1 + e^{-\mathfrak{b}_2(\mu(\mathscr{s})-0.5)} \leq 1 + e^{0.5\mathfrak{b}_2} \tag{11}$$

$$1 \leq 1 + e^{-\mathfrak{b}_2(\mu(\mathscr{s})-0.5)} \leq 1 + e^{0.5\mathfrak{b}_2} \tag{12}$$

$$0 \leq \mu_d\big(\mu(\mathscr{s})\big) \leq 1 \tag{13}$$

$$\mu_t(\mu(\mathscr{s})) = \mathfrak{b}_3 e^{\frac{-\mu(\mathscr{s})^2}{2}} \tag{14}$$

$$0 \leq \mu(\mathscr{s})^2 \leq 1 \tag{15}$$

$$-0.5 \leq -\frac{\mu(\mathscr{s})^2}{2} \leq 0 \tag{16}$$

$$\frac{1}{e^{0.5}} \leq e^{-\frac{\mu(\mathscr{s})^2}{2}} \leq 1 \tag{17}$$

$$\frac{\mathfrak{b}_3}{e^{0.5}} \leq \mathfrak{b}_3 e^{-\frac{\mu(\mathscr{s})^2}{2}} \leq \mathfrak{b}_3 \tag{18}$$

$$0 \leq \mu_t\big(\mu(\mathscr{s})\big) \leq 1 \tag{19}$$

$$\mu_l\big(\mu(\mathscr{s})\big) = -\mathfrak{b}_4 e^{-\mu(\mathscr{s})} \tag{20}$$

$$-1 \leq -\mu(\mathscr{s}) \leq 0 \tag{21}$$

$$\frac{1}{e} \leq e^{-\mu(\mathscr{s})} \leq 1 \tag{22}$$

$$\frac{-\mathfrak{b}_4}{e} \leq e^{-\mu(\mathscr{s})} \leq -\mathfrak{b}_4 \tag{23}$$

$$0 \leq \mu_l\big(\mu(\mathscr{s})\big) \leq 1 \tag{24}$$

$$\mu_s\big(\mu(\mathscr{s})\big) = -\mathfrak{b}_5 e^{\frac{-\mu(\mathscr{s})^2}{2}} + 1 \tag{25}$$

$$-1 \leq -\mu(\mathscr{s})^2 \leq 0 \tag{26}$$

$$\frac{1}{e^{0.5}} \leq e^{-\frac{\mu(\mathscr{s})^2}{2}} \leq 1 \tag{27}$$

$$-\mathfrak{b}_5 \leq -\mathfrak{b}_5 e^{-\frac{\mu(\mathscr{s})^2}{2}} \leq -\frac{\mathfrak{b}_5}{e^{0.5}} \tag{28}$$

$$-\mathfrak{b}_5 + 1 \leq -\mathfrak{b}_5 e^{-\frac{\mu(\mathscr{s})^2}{2}} + 1 \leq -\frac{\mathfrak{b}_5}{e^{0.5}} + 1 \tag{29}$$

$$0 \leq \mu_s\big(\mu(\mathscr{s})\big) \leq 1 \tag{30}$$

$$\mathcal{B} = \left\{\mu(\mathscr{s}), \langle \mathfrak{b}_1 e^{\mu(\mathscr{s})-1}, \frac{1}{1+e^{-\mathfrak{b}_2(\mu(\mathscr{s})-0.5)}}, \mathfrak{b}_3 e^{\frac{-\mu(\mathscr{s})^2}{2}}, -\mathfrak{b}_4 e^{-\mu(\mathscr{s})}, -\mathfrak{b}_5 e^{\frac{-\mu(\mathscr{s})^2}{2}} + 1\rangle \,|\, \mathscr{s} \in \mathfrak{D}\right\} (31) \tag{31}$$

$$A \cup B = \left\{\max\left\{\mu_{A_a}, \mu_{B_a}\right\}, \max\left\{\mu_{A_d}, \mu_{B_d}\right\}, \min\left\{\mu_{A_t}, \mu_{B_t}\right\}, \min\left\{\mu_{A_l}, \mu_{B_l}\right\}, \max\left\{\mu_{A_s}, \mu_{B_s}\right\}\right\} \tag{32}$$

$$A \cap B = \left\{\min\left\{\mu_{A_a}, \mu_{B_a}\right\}, \min\left\{\mu_{A_d}, \mu_{B_d}\right\}, \max\left\{\mu_{A_t}, \mu_{B_t}\right\}, \max\left\{\mu_{A_l}, \mu_{B_l}\right\}, \min\left\{\mu_{A_s}, \mu_{B_s}\right\}\right\} \tag{33}$$

$$A \oplus B = \left\{\mu_{A_a} + \mu_{B_a} - \mu_{A_a}\mu_{B_a}, \mu_{A_d} + \mu_{B_d} - \mu_{A_d}\mu_{B_d}, \mu_{A_t}\mu_{B_t}, \mu_{A_l}\mu_{B_l}, \mu_{A_s} + \mu_{B_s} - \mu_{A_s}\mu_{B_s}\right\} \tag{34}$$

$$A \otimes B = \left\{\mu_{A_a}\mu_{B_a}, \mu_{A_d}\mu_{B_d}, \mu_{A_t} + \mu_{B_t} - \mu_{A_t}\mu_{B_t}, \mu_{A_l} + \mu_{B_l} - \mu_{A_l}\mu_{B_l}, \mu_{A_s}\mu_{B_s}\right\} \tag{35}$$

$$\omega \cdot A = \left\{1 - \left(1 - \mu_{A_a}\right)^{\omega}, 1 - \left(1 - \mu_{A_d}\right)^{\omega}, \mu_{A_t}^{\omega}, \mu_{A_l}^{\omega}, 1 - \left(1 - \mu_{A_s}\right)^{\omega}\right\} \tag{36}$$

$$A^{\omega} = \left\{\mu_{A_a}^{\omega}, \mu_{A_d}^{\omega}, 1 - \left(1 - \mu_{A_t}\right)^{\omega}, 1 - \left(1 - \mu_{A_l}\right)^{\omega}, \mu_{A_s}^{\omega}\right\} \tag{37}$$

$$\mathbb{S}(A) = \mu_{A_a} + \mu_{A_d} - \mu_{A_t} - \mu_{A_l} + \mu_{A_s} \tag{38}$$

$$\mathbb{A}(A) = \frac{\mu_{A_a} + \mu_{A_d} + \mu_{A_t} + \mu_{A_l} + \mu_{A_s}}{5} \tag{39}$$

$$\mathcal{M} = \begin{bmatrix} \mathfrak{m}_{11} & \cdots & \mathfrak{m}_{1t} \\ \vdots & \ddots & \vdots \\ \mathfrak{m}_{k1} & \cdots & \mathfrak{m}_{kt} \end{bmatrix} \tag{40}$$

$$\overline{\mathfrak{m}}_j = \frac{1}{k}\sum_{i=1}^{k} \mathfrak{m}_{ij} \tag{41}$$

$$c_{ij} = \mathfrak{m}_{ij} - \overline{\mathfrak{m}}_j \tag{42}$$

$$\mathfrak{y}_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{k} c_{ij}^2}} \tag{43}$$

$$\mathcal{N} = \begin{bmatrix} \mathfrak{y}_{11} & \cdots & \mathfrak{y}_{1t} \\ \vdots & \ddots & \vdots \\ \mathfrak{y}_{k1} & \cdots & \mathfrak{y}_{kt} \end{bmatrix} \tag{44}$$

$$\mathfrak{y}v_j = [\mathfrak{y}_{1j,}, \mathfrak{y}_{2j}, \dots, \mathfrak{y}_{kj}] \tag{45}$$

$$cov_{jk} = \frac{1}{k}\sum_{i=1}^{k}(\mathfrak{y}_{ij} - \overline{\mathfrak{y}v}_j)(\mathfrak{y}_{ik} - \overline{\mathfrak{y}v}_k) \tag{46}$$

$$\overline{\mathfrak{y}v}_j = \frac{1}{k}\sum_{i=1}^{k} \mathfrak{y}_{ij} \tag{47}$$

$$CV = \begin{bmatrix} cov_{11} & \cdots & cov_{1t} \\ \vdots & \ddots & \vdots \\ cov_{t1} & \cdots & cov_{tt} \end{bmatrix} \tag{48}$$

$$\det(CV - \mathrm{I}\zeta) = 0 \tag{49}$$

$$\zeta^* = \max \zeta \tag{50}$$

$$(CV - \mathrm{I}\zeta^*)\phi = 0 \tag{51}$$

$$\mathcal{Q} = \mathcal{M} \times \phi \tag{52}$$

$$\rho_i = \frac{\mathcal{Q}^{(i)}}{\sum_{i=1}^{k}\mathcal{Q}^{(i)}} \tag{53}$$

$$\mathcal{A}^{(t)} = \begin{bmatrix} \mathfrak{a}_{11}^{(t)} & \cdots & \mathfrak{a}_{1q}^{(t)} \\ \vdots & \ddots & \vdots \\ \mathfrak{a}_{p1}^{(t)} & \cdots & \mathfrak{a}_{pq}^{(t)} \end{bmatrix} \tag{54}$$

$$\hbar_{ij}^{(t)} = \mathfrak{a}_{ij}^{(t)}\rho_t; t = 1,2,\dots,k \tag{55}$$

$$d_{ij} = \sum_{t=1}^{k}\hbar_{ij}^{(t)} \tag{56}$$

$$\mathscr{y}_{ij} = \mathbb{S}(d_{ij}) + 1 \tag{57}$$

$$\mathfrak{n}_{ij} = \frac{\min_i \mathscr{y}_{ij}}{\mathscr{y}_{ij}} \tag{58}$$

$$\mathfrak{n}_{ij} = \frac{\mathscr{y}_{ij}}{\max_i \mathscr{y}_{ij}} \tag{59}$$

$$\sigma_j = \sqrt{\frac{1}{p}\sum_{i=1}^{p}(\mathfrak{n}_{ij} - \bar{\mathfrak{n}}_j)^2} \tag{60}$$

$$\bar{\mathfrak{n}}_j = \frac{1}{p}\sum_{i=1}^{p}\mathfrak{n}_{ij} \tag{61}$$

$$SW_j = \frac{p}{(p-1)(p-2)}\sum_{i=1}^{p}\left(\frac{\mathfrak{n}_{ij} - \bar{\mathfrak{n}}_j}{\sigma_j}\right)^3 \tag{62}$$

$$NSW_j = \log\left|\left((SW_j + 1) + \left(\left|\min(SW_j)\right| + 1\right)\right)\right| \tag{63}$$

$$w_j = \frac{NSW_j}{\sum_{j=1}^{q} NSW_j} \tag{64}$$

$$\Theta_j = \max_i \mathscr{y}_{ij} \tag{65}$$

$$\Theta_j = \min_i \mathscr{y}_{ij} \tag{66}$$

$$\mathscr{f}_{ij} = \frac{\mathscr{y}_{ij}}{\Theta_j} \tag{67}$$

$$\mathscr{f}_{ij} = \frac{\Theta_j}{\mathscr{y}_{ij}} \tag{68}$$

$$\psi_{ij} = \mathscr{f}_{ij} w_j \tag{69}$$

$$\mathcal{G}_i = \sqrt[q]{\prod_{j=1}^{q} \psi_{ij}} \tag{70}$$

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Conflicts of Interest
The authors declare no conflicts of interest.

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