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Human-Centered Vibe Working Transformation: A Spherical Fuzzy Multi-Criteria Decision-Making Model

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Abstract

The rapid diffusion of artificial intelligence within knowledge-intensive work has given rise to vibe working, a transformative paradigm that reshapes organizational structures and career pathways. The fundamental problem associated with this transformation lies in balancing efficiency gains with the preservation of human roles, skill development, and long-term workforce sustainability. While numerous studies address AI-driven automation, limited attention has been paid to the systematic prioritization of transformation strategies and evaluation criteria in vibe working contexts. This gap creates uncertainty for organizations seeking effective and human-centered adaptation pathways. The primary aim of this study is to identify the most critical criteria and the most appropriate alternative strategies for minimizing vibe working-related risks. To address this gap, a novel fuzzy multi-criteria decision-making model is proposed, integrating distance-based expert weighting, the IDOCRIW method for criterion weighting, the RAM technique for alternative ranking, and spherical fuzzy sets for improved uncertainty modeling. The results indicate that potential for human-centered transformation is the most important criterion, followed by reduction in error rates and quality standardization. In terms of strategic alternatives, university–company–AI platform integration and the AI–human hybrid career ladder emerges as the most appropriate solutions. The study contributes to the literature by offering a structured prioritization framework and a robust methodological approach that accounts for expert heterogeneity and uncertainty. The findings suggest that integrated, human-centered, and collaborative strategies should be prioritized to ensure sustainable vibe working transformations.

Keywords: Vibe working; Human-centered transformation; Artificial intelligence; Fuzzy multi-criteria decision making; Workforce strategy

1. Introduction

Vibe working refers to an emerging work paradigm shaped by the increasing integration of artificial intelligence into everyday organizational processes, particularly in white collar occupations. It represents a structural transformation rather than a temporary technological adjustment, as work tasks are increasingly performed, supported, or coordinated by AI-driven systems. The primary aim of vibe working is to enhance efficiency, speed, and consistency in knowledge-intensive activities by relying on algorithmic assistance and automation. However, this transformation also produces significant labor market implications, especially at the entry level. As artificial intelligence increasingly substitutes routine cognitive tasks, many traditional junior positions lose their functional relevance (Kong et al., 2023). This situation creates a bottleneck for newly graduated employees who historically relied on these positions to acquire basic organizational skills and professional experience. The gradual erosion of entry-level roles weakens career ladders and disrupts conventional learning-by-doing mechanisms. In addition, early career workers face limited opportunities to develop contextual judgment, problem framing abilities, and informal organizational knowledge. These outcomes generate long-term risks for firms, as the absence of adequately trained future professionals may undermine institutional continuity (Neiroukh, 2025). From a broader perspective, vibe working should therefore be understood as a deep organizational transition that reshapes employment structures, alters skill formation processes, and raises critical questions regarding sustainable workforce development in AI-intensive environments.

The negative consequences generated by vibe working should not be treated as unavoidable outcomes of technological progress but rather as manageable risks that can be reduced through alternative transformation strategies. Several adaptive models have been proposed to preserve human involvement while benefiting from artificial intelligence. Human-in-the-loop entry jobs allow early career employees to work alongside AI systems, ensuring skill development through supervised interaction rather than full replacement (Saluja et al., 2024). Artificial internships and simulation-based career entry models provide structured learning environments where individuals gain experience without immediate exposure to high-risk tasks. Vibe working-based project pool models create flexible participation opportunities by assigning newcomers to short-term AI-supported projects. Protection zones for mid-level managerial development prevent the premature automation of coordination and leadership roles. Hybrid AI–human career ladders ensure gradual skill accumulation by combining automated support with progressive responsibility. University–company–AI platform integration strengthens alignment between education and labor market needs (Wang et al., 2025). Finally, full automation combined with reskilling models supports workforce transition by redirecting displaced employees into newly created roles. Collectively, these strategies mitigate employment shocks by maintaining learning channels, preserving institutional knowledge, and sustaining career continuity within vibe working ecosystems.

The selection of alternative transformation strategies in vibe working contexts requires careful evaluation based on multiple criteria. The intensity of human–AI collaboration determines whether intelligence is augmented or merely substituted. Organizational commitment and sense of belonging may decline if human contribution is perceived as secondary. Reductions in error rates and quality standardization reflect the operational benefits of AI integration but may also suppress creative variance (Rezaei, 2025). Cost efficiency considerations involve wages, training investments, and monitoring expenses. The devaluation risk of fundamental cognitive skills emerges when automation replaces basic analytical tasks. Income inequality and the narrowing of career paths represent broader socio-economic concerns linked to uneven access to advanced roles. Institutional knowledge loss becomes likely when experienced workers are displaced without proper transfer mechanisms. Ethical responsibility and accountability uncertainty arise when decision authority shifts to algorithms. The long-term preservation of strategic decision quality depends on retaining human judgment in complex contexts. Finally, the potential for human-centered transformation reflects whether vibe working supports inclusive development (Gerlich, 2025). These criteria jointly shape the effectiveness and sustainability of alternative strategies.

Identifying the most prioritized alternative transformation strategies is critical for addressing vibe working-related challenges in a timely and effective manner. Without clear prioritization, organizations may adopt fragmented solutions that fail to resolve core structural problems. The absence of prioritized strategies can intensify uncertainty, slow adaptation, and amplify employment risks. Determining

priority strategies also requires identifying the most influential evaluation criteria, as strategic effectiveness depends on contextual relevance. However, the existing literature provides limited guidance on systematically identifying both the most critical strategies and the most influential criteria in vibe working contexts. This limitation constitutes a significant research gap that generates ambiguity in decision-making and weakens policy design. The lack of structured prioritization frameworks leads to inconsistent applications and suboptimal outcomes across organizations. Therefore, a comprehensive priority analysis is needed to clarify strategic pathways and support evidence-based transformation. Addressing this gap is essential for advancing the vibe working literature and reducing uncertainty associated with AI-driven organizational change.

This study aims to identify the most prioritized alternative transformation strategies to minimize vibe working-induced challenges. To achieve this objective, a novel fuzzy multi-criteria decision-making model is developed. A comprehensive literature review is conducted, resulting in the identification of ten evaluation criteria and seven strategic alternatives. Expert opinions are collected from ten domain specialists. Experts' importance weights are determined using a distance-based weighting technique. The IDOCRIW method is employed for criterion weighting, while the RAM technique is used to rank strategies. Spherical fuzzy sets are integrated to manage uncertainty more effectively. The study seeks to answer the following research questions. (1) Which alternative transformation strategies are most effective in mitigating vibe working-related risks? (2) Which evaluation criteria play the most decisive role in prioritizing these strategies?

This study contributes to the vibe working literature by providing a structured prioritization framework grounded in fuzzy decision-making theory. It also introduces a methodological approach that integrates expert heterogeneity and uncertainty into strategic evaluation. The proposed model offers several advantages over existing decision-making models. (1) The use of distance-based expert weighting accounts for differences in expertise, addressing a common limitation of equal-weight assumptions. (2) The IDOCRIW technique is particularly suitable for vibe working contexts because it combines objective and subjective weighting mechanisms, allowing more balanced criterion evaluation. (3) The use of spherical fuzzy sets represents a methodological innovation, as these sets allow independent representation of membership, non-membership, and hesitancy degrees, offering greater flexibility than classical, intuitionistic, or Pythagorean fuzzy sets. This structure enables more accurate modeling of uncertainty in complex socio-technical systems.

The remainder of this paper is structured as follows. The second section reviews the relevant literature on vibe working, artificial intelligence, and transformation strategies. The third section presents the proposed methodology and explains the integrated fuzzy decision-making framework. The fourth section reports the analysis results obtained from the empirical application. The fifth section discusses the findings and their theoretical and practical implications. The final section concludes the study and outlines potential directions for future research.

2. Literature Review

The number of organizations incorporating and investing in artificial intelligence (AI) in their workflows to increase efficiency and improve quality has increased significantly, especially in the last decade. This is also transforming the work environment within organizations. AI tools integrated into work processes sometimes act as a coordinator connecting team members, as a problem solver and sometimes as a creative force generating new ideas (Nguyen & Elbanna, 2025). Examples where AI facilitates information transfer within teams and improves the quality of work further encourage human-AI collaboration (Wu et al., 2025). Zhang et al. (2025), in their study on how AI-employee collaboration affects employee behavior, stated that AI has a facilitating effect on employees' work and, consequently, increases their confidence in their own innovative abilities. The use of artificial intelligence is considered a socio-technical transformation that fosters a partnership between humans and technology. It is argued that instead of replacing employees, it should be positioned as a supportive and motivating factor that provides employees with autonomy within the organization and facilitates career planning (Kong et al., 2023). The main goal is to achieve more efficient use of organizational resources and gain a competitive advantage through human-AI collaboration (Przegalinska et al., 2025). Liu et al., in their study examining the contributions of human-centered AI use to social and operational performance, also

underlined that this transformation can offer comprehensive benefits that will affect organizational value creation and social responsibility issues.

In industries suitable for AI-supported business processes, AI helps reduce simple error rates. It reduces losses due to simple human errors in repetitive tasks and improves the efficiency of these tasks, raising the minimum organizational quality level (Morales et al. 2025). Furthermore, it improves the ability to make quick and accurate decisions by assisting in identifying and evaluating alternatives at management levels (Neiroukh, 2025). Artificial intelligence, as a useful tool in terms of quality standardization, also affects organizational costs. It increases organizational efficiency due to positive outcomes such as reducing defective production and decreasing the need for costly quality control methods (Singh, 2025). Vadisetty et al. (2024), in their study on the benefits of cloud resource utilization for businesses, stated that this technology allows businesses to offer the same product or service with lower infrastructure and coordination costs. Dash (2025), on the other hand, highlighted the positive impact of artificial intelligence on overall system efficiency by reducing energy consumption in corporate activities and its importance in terms of environmental responsibility.

In repetitive, non-specialized A-level positions, where mostly recent graduates or inexperienced candidates are employed, implementing AI transformation to automate these roles may have negative impacts on employee and organizational commitment (Nguyen et al., 2025). Indeed, VuongThi et al. (2025) found that employee commitment to the organization and their jobs only increased when they felt they had high levels of AI competence. Mayer et al. (2025) supported this finding in their study, noting that entry-level professionals were reshaping their jobs to better embrace them and align them with their career plans. Another factor influencing employee satisfaction with their workplace is the organization's wage policy. The use of artificial intelligence and increasing automation can be said to cause polarization and wage inequality among employee groups because they affect ways of conducting business (Brynjolfsson et al., 2023). Jaccoud (2025) also revealed wage inequality in professions where the use of robots and artificial intelligence is widespread, noting that this is more pronounced in high-paying professions. Wang et al. (2025), on the other hand, showed how the use of artificial intelligence weakens the employment of new generation workers by stating that the need for skilled workers requiring expertise has increased and therefore employment is experiencing an upstream shift.

While repetitive tasks can be delegated to artificial intelligence for reasons such as time savings, increased productivity, and lower error rates, this can also lead to employee laziness (Saluja et al., 2024). Gerlich (2025), in his study on employees from different age groups regarding the use of artificial intelligence, stated that younger employees who are more inclined to use AI have lower critical thinking skills. Wang (2024) also states that employees with lower cognitive abilities have a higher risk of job loss in professions suitable for the use of artificial intelligence. While artificial intelligence (AI) can cause such negative consequences for employees, it can also pose a risk of organizational knowledge loss for institutions. The information that AI focuses on is often coded information. Therefore, if the human-AI partnership is not well-designed, there is a risk of losing some information (Rezaei, 2025). This tacit knowledge becomes a challenge for knowledge management specialists. Kirchner et al. (2025) also states that with the increasing use of generative AI, there is a risk of losing tacit corporate knowledge produced and carried by employees.

The literature review allows us to draw some conclusions about the effects of artificial intelligence (AI) use on organizations and their employees. It is accepted that the collaboration between humans and AI is becoming increasingly intense due to the benefits it provides. However, this transformation has both positive and negative consequences. AI is seen as an advantage that increases organizational efficiency by reducing operational errors and using resources efficiently. Thus, quality standardization becomes possible to a certain extent in the long term. On the other hand, it can be said that it reduces job opportunities for many new graduates because it replaces the jobs of A-level employees. There is concern that this collaboration will negatively impact white-collar employment in the future and create problems in training middle-level managers. Alternative solutions will be developed to address these concerns using multi-criteria decision-making methods.

3. Methodology

This part includes the introductions of SFSs, distance-based experts' weighting, IDOCRIW, and RAM, respectively. Thanks to the distance-based weighting approach for experts, the coefficient of experts' evaluations is calculated under the assumption that the closer an expert's evaluations are to those of other experts, the higher their weight. Criterion priority values are objectively obtained with IDOCRIW, while alternatives are ranked with RAM based on the difference in compensation levels of the benefit and cost criteria. In the analysis process, linguistic expressions and calculations are performed using SFSs. The steps of the analysis process are illustrated in Figure 1.

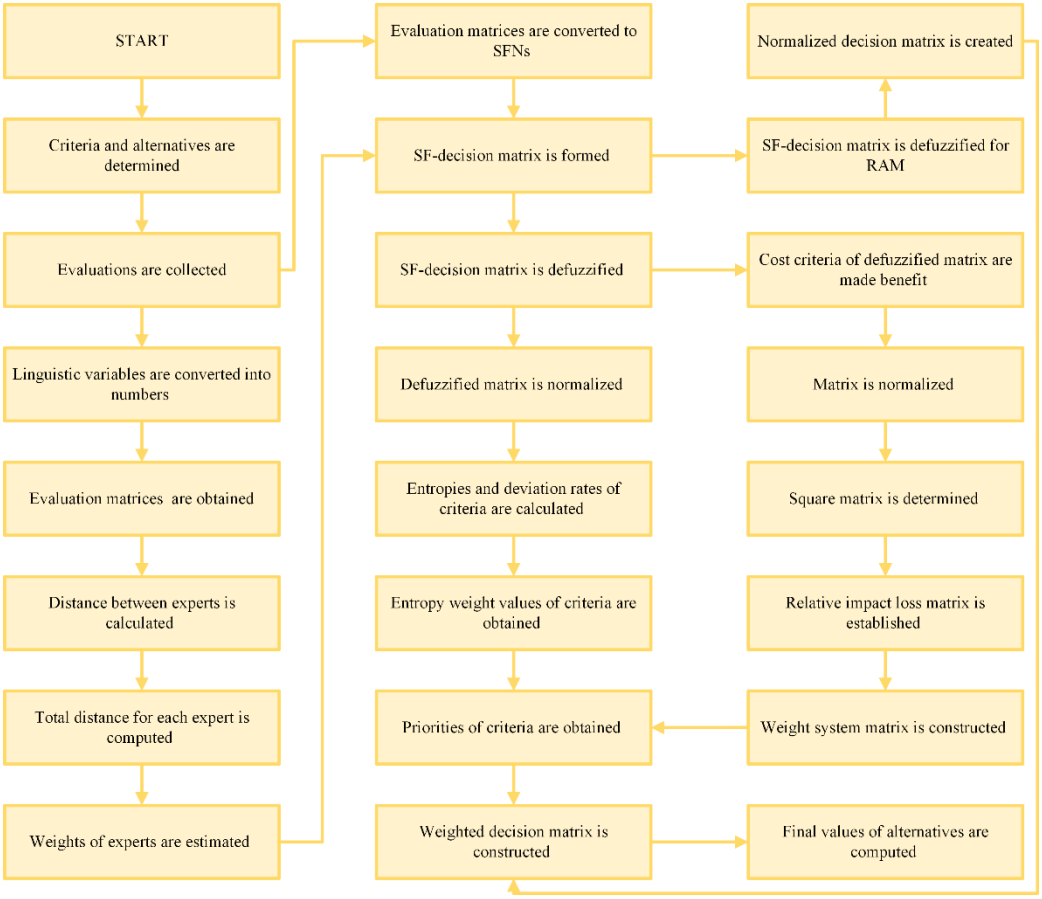
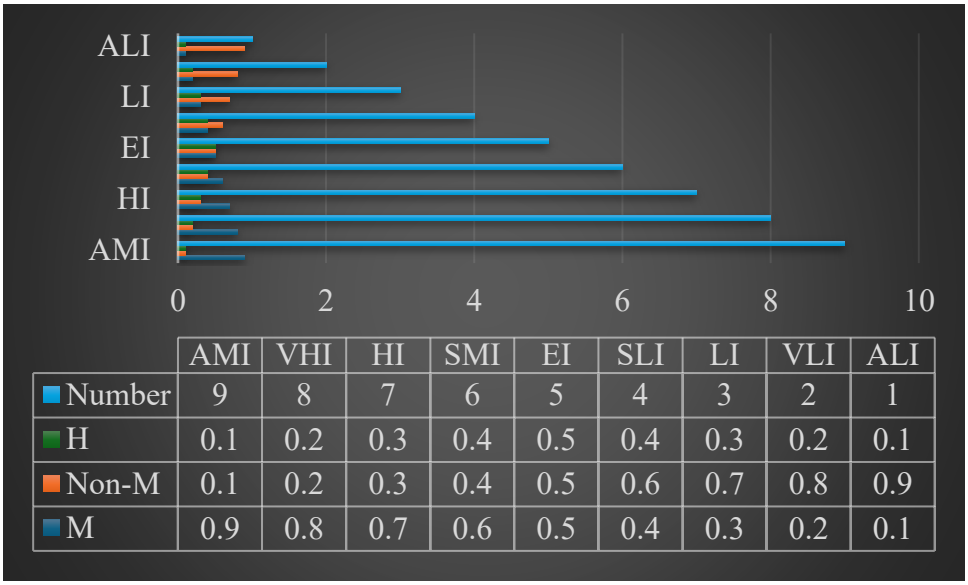


Figure 1: Steps of Analysis Process

3.1. Distance-based Experts' Weighting

This approach, which assumes that an expert's evaluation has a higher weight the closer it is to that of other experts, considers the evaluation matrices of the experts. In other words, the coefficient of the experts' evaluations is calculated according to the Euclidean distance between the elements of the evaluation matrices obtained from the experts. The calculation steps can be summarized as follows (Yaylalı et al., 2025).

First, criteria and alternatives are determined. Each expert evaluates the alternatives according to the criteria using linguistic variables in Figure 2.



	AMI	VHI	HI	SMI	EI	SLI	LI	VLI	ALI
Number	9	8	7	6	5	4	3	2	1
H	0.1	0.2	0.3	0.4	0.5	0.4	0.3	0.2	0.1
Non-M	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
M	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1

Figure 2: Linguistic Variables

Afterwards, these linguistic variables are converted into numbers according to Figure 2. Thus, evaluation matrices formed in Eq. (1) are obtained.

$$X^{(k)} = \left[x_{ij}^{(k)}\right]_{m\times n} \tag{1}$$

Where m and n are the numbers of alternatives and criteria, respectively. The k is the index of expert. Next, distance between a^{sh} expert and b^{th} expert is calculated using Eq. (2).

$$\Delta_{a,b} = \sqrt{\sum_{i=1}^{m}\sum_{j}^{n}\left(x_{ij}^{(a)} - x_{ij}^{(b)}\right)^2} \tag{2}$$

Later, total distance for each expert is computed by Eq. (3).

$$D_k = \sum_{l\neq k} \Delta_{k,l} \tag{3}$$

Finally, the weights of experts are estimated with the help of Eq. (4).

$$ew_k = \frac{\frac{1}{D_k}}{\sum_{k=1}^{e}\left(\frac{1}{D_k}\right)} \tag{4}$$

Where e is the number of experts.

3.2. SFSs

A fuzzy logic theory is proposed for processing linguistic variables. Within this theory, the degrees of an element to a set are defined as being between 0 and 1. These degrees can be degrees of membership (μ), non-membership (ϑ), hesitation (π), or refusal (χ), depending on the type of fuzzy set. SFSs are constructed using the definition of these degrees. A SFS $(\tilde{S})$ of the universe of discourse (D) is identified with Eq. (5) (Aygün et al., 2025).

$$\tilde{S} = \{\langle x, (\mu_{\tilde{S}}(x), \vartheta_{\tilde{S}}(x), \pi_{\tilde{S}}(x)) : x \in D\} \tag{5}$$

These degrees have this condition in Eq. (6).

$$0 \leq \mu_{\tilde{S}}^2(x) + \vartheta_{\tilde{S}}^2(x) + \pi_{\tilde{S}}^2(x) \leq 1 \tag{6}$$

The refusal degree of $\tilde{S}$ is described by Eq. (7).

$$\chi_{\tilde{S}}(x) = \sqrt{1 - \mu_{\tilde{S}}^2(x) - \vartheta_{\tilde{S}}^2(x) - \pi_{\tilde{S}}^2(x)} \tag{7}$$

Consider that $\tilde{S}_1$ and $\tilde{S}_2$ are two SFNs and $\lambda > 0$, then basic operations are determined using Eq.s (8) - (11).

$$\tilde{S}_1 + \tilde{S}_2 = \left(\sqrt{\mu_{\tilde{S}_1}^2 + \mu_{\tilde{S}_2}^2 - \mu_{\tilde{S}_1}^2\mu_{\tilde{S}_2}^2}, \vartheta_{\tilde{S}_1}\vartheta_{\tilde{S}_2}, \sqrt{\left(1 - \mu_{\tilde{S}_2}^2\right)\pi_{\tilde{S}_1}^2 + \left(1 - \mu_{\tilde{S}_1}^2\right)\pi_{\tilde{S}_2}^2 - \pi_{\tilde{S}_1}^2\pi_{\tilde{S}_2}^2}\right) \tag{8}$$

$$\tilde{S}_1 \times \tilde{S}_2 = \left(\mu_{\tilde{S}_1}\mu_{\tilde{S}_2}, \sqrt{\vartheta_{\tilde{S}_1}^2 + \vartheta_{\tilde{S}_2}^2 - \vartheta_{\tilde{S}_1}^2\vartheta_{\tilde{S}_2}^2}, \sqrt{\left(1 - \vartheta_{\tilde{S}_2}^2\right)\pi_{\tilde{S}_1}^2 + \left(1 - \vartheta_{\tilde{S}_1}^2\right)\pi_{\tilde{S}_2}^2 - \pi_{\tilde{S}_1}^2\pi_{\tilde{S}_2}^2}\right) \tag{9}$$

$$\lambda\tilde{S}_1 = \left(\sqrt{1 - \left(1 - \mu_{\tilde{S}_1}^2\right)^{\lambda}}, \vartheta_{\tilde{S}_1}^{\lambda}, \sqrt{\left(1 - \mu_{\tilde{S}_1}^2\right)^{\lambda} - \left(1 - \mu_{\tilde{S}_1}^2 - \pi_{\tilde{S}_1}^2\right)^{\lambda}}\right) \tag{10}$$

$$\tilde{S}_1^{\lambda} = \left(\mu_{\tilde{S}_1}^{\lambda}, \sqrt{1 - \left(1 - \vartheta_{\tilde{S}_1}^2\right)^{\lambda}}, \sqrt{\left(1 - \vartheta_{\tilde{S}_1}^2\right)^{\lambda} - \left(1 - \vartheta_{\tilde{S}_1}^2 - \pi_{\tilde{S}_1}^2\right)^{\lambda}}\right) \tag{11}$$

The score and accuracy function of $\tilde{S}$ are calculated with the help of Eq.s (12) and (13).

$$\mathbb{S}(\tilde{S}) = (\mu_{\tilde{S}} - \pi_{\tilde{S}})^2 - (\vartheta_{\tilde{S}} - \pi_{\tilde{S}})^2 \tag{12}$$

$$\hbar(\tilde{S}) = \mu_{\tilde{S}}^2 + \vartheta_{\tilde{S}}^2 + \pi_{\tilde{S}}^2 \tag{13}$$

Spherical distance among any two SFNs on the surface of a sphere is established with the help of Eq. (14).

$$\mathrm{D}(\tilde{S}_1, \tilde{S}_2) = \arccos\left(1 - \frac{1}{2}\left(\left(\mu_{\tilde{S}_1} - \mu_{\tilde{S}_2}\right)^2 + \left(\vartheta_{\tilde{S}_1} - \vartheta_{\tilde{S}_2}\right)^2 + \left(\pi_{\tilde{S}_1} - \pi_{\tilde{S}_2}\right)^2\right)\right) \tag{14}$$

Spherical weighted arithmetic and geometric means are computed via Eq.s (15) and (16), respectively.

$$SWAM(\tilde{S}_i) = \left(\sqrt{1 - \prod_{i=1}^{n}\left(1 - \mu_{\tilde{S}_i}^2\right)^{w_i}}, \prod_{i=1}^{n}\vartheta_{\tilde{S}_i}^{w_i}, \sqrt{\prod_{i=1}^{n}\left(1 - \mu_{\tilde{S}_i}^2\right)^{w_i} - \prod_{i=1}^{n}\left(1 - \mu_{\tilde{S}_i}^2 - \pi_{\tilde{S}_i}^2\right)^{w_i}}\right) \tag{15}$$

$$SWGM(\tilde{S}_i) = \left(\prod_{i=1}^{n}\mu_{\tilde{S}_i}^{w_i}, \sqrt{1 - \prod_{i=1}^{n}\left(1 - \vartheta_{\tilde{S}_i}^2\right)^{w_i}}, \sqrt{\prod_{i=1}^{n}\left(1 - \vartheta_{\tilde{S}_i}^2\right)^{w_i} - \prod_{i=1}^{n}\left(1 - \vartheta_{\tilde{S}_i}^2 - \pi_{\tilde{S}_i}^2\right)^{w_i}}\right) \tag{16}$$

3.3. SF-IDOCRIW-based RAM

The IDOCRIW method is built from a combination of the entropy and CILOS methods. Because it incorporates the advantages of both methods, IDOCRIW offers an objective criterion prioritization. RAM is a method that ranks alternatives without converting two different types of criteria into each other. In other words, RAM includes the difference in compensation levels between two different types of criteria in the analysis. This ensures more accurate results. The calculation of the approach created by integrating these two methods with SFS can be summarized as follows.

The evaluation matrices in Eq. (1) are converted to SFNs according to Figure 2. Afterwards, a SF-decision matrix is formed from these matrices by Eq. (15). The SF-decision matrix is illustrated in Eq. (17) (Butt et al., 2025).

$$\widetilde{H} = \left[\tilde{h}_{ij}\right]_{m\times n} \tag{15}$$

Where $\tilde{h}_{ij} = \left(\mu_{\tilde{h}_{ij}}, \vartheta_{\tilde{h}_{ij}}, \pi_{\tilde{h}_{ij}}\right)$ is computed with Eq. (16)

$$\tilde{h}_{ij} = \left(\sqrt{1 - \prod_{k=1}^{e} \left(1 - \mu_{\tilde{x}_{ij}^{(k)}}^2\right)^{ew_i}}, \prod_{k=1}^{e} \vartheta_{\tilde{x}_{ij}^{(k)}}^{ew_i}, \sqrt{\prod_{k=1}^{e} \left(1 - \mu_{\tilde{x}_{ij}^{(k)}}^2\right)^{ew_i} - \prod_{k=1}^{e} \left(1 - \mu_{\tilde{x}_{ij}^{(k)}}^2 - \pi_{\tilde{x}_{ij}^{(k)}}^2\right)^{ew_i}} \right) \quad (16)$$

Afterwards, SF-decision matrix is defuzzified using Eq. (17).

$$r_{ij} = \mathbb{S}(\tilde{h}_{ij}) = \left(\mu_{\tilde{h}_{ij}} - \pi_{\tilde{h}_{ij}}\right)^2 - \left(\vartheta_{\tilde{h}_{ij}} - \pi_{\tilde{h}_{ij}}\right)^2 \quad (17)$$

The defuzzified matrix is normalized via Eq. (18).

$$\mathfrak{y}_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \quad (18)$$

Next, the entropies and deviation rates of criteria are calculated by Eq.s (19) and (20), respectively.

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{m} \left(\mathfrak{y}_{ij} \ln \mathfrak{y}_{ij}\right) \quad (19)$$

$$dr_j = 1 - E_j \quad (20)$$

Thus, the entropy weight values of criteria are obtained as Eq. (21).

$$w_j = \frac{dr_j}{\sum_{j=1}^{n} dr_j} \quad (21)$$

In the next step, cost criteria of defuzzified matrix are made benefit using Eq. (22). Then, this matrix is normalized with Eq. (18).

$$r_{ij} = \frac{\min_i r_{ij}}{r_{ij}} \quad (22)$$

Square matrix is determined according to Eq. (23).

$$a_j = \max_i \mathfrak{y}_{ij} = a_{k,j} \quad (23)$$

The relative impact loss matrix is established by Eq. (24).

$$\mathfrak{Z}_{ij} = \frac{a_{jj} - a_{ij}}{a_{jj}} \quad (24)$$

Weight system matrix is constructed using Eq. (25) (Zandi et al., 2025).

$$F = \begin{bmatrix} -\sum_{i=1}^{n} \mathfrak{Z}_{i1} & \cdots & \mathfrak{Z}_{1n} \\ \mathfrak{Z}_{21} & -\sum_{i=1}^{n} \mathfrak{Z}_{i2} & \mathfrak{Z}_{2n} \\ \vdots & \ddots & \vdots \\ \mathfrak{Z}_{n1} & \cdots & -\sum_{i=1}^{n} \mathfrak{Z}_{in} \end{bmatrix} \quad (25)$$

The CILOS weights of criteria are defined by solving in Eq. (26).

$$Fq^T = 0 \quad (26)$$

In the last step of IDOCRIW, the priorities of criteria are obtained with Eq. (27).

$$pr_j = \frac{q_j w_j}{\sum_{j=1}^{n} (q_j w_j)} \quad (27)$$

Within the scope of RAM analysis, SF-decision matrix is defuzzified using Eq. (28).

$$y_{ij} = \mathbb{S}\left(\tilde{h}_{ij}\right) + 1 \tag{28}$$

Afterwards, the normalized decision matrix is created by Eq. (29).

$$f_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{29}$$

Weighted decision matrix is constructed via Eq. (30).

$$z_{ij} = pr_j f_{ij} \tag{30}$$

The totals weighted decision values by types of criteria are calculated with the help of Eq.s (31) and (32).

$$T_{+i} = \sum_{j=1}^{n} z_{+ij} \tag{31}$$

$$T_{-i} = \sum_{j=1}^{n} z_{-ij} \tag{32}$$

Finally, the final values of alternatives are computed using Eq. (33).

$$RV_i = \sqrt[2+T_{-i}]{2 + T_{+i}} \tag{33}$$

4. Analysis

This part includes the results of methodology.

4.1. Computing the Experts' Weights

Firstly, criteria are determined. The list with abbreviations and types of criteria is shown in Table 1.

Table 1: Criteria with Abbreviations and Types

Criterion	Abbreviation	Type
Human-AI collaboration intensity (co-working intelligence)	HAICI	Benefit
Decreased corporate commitment and belonging	DECCB	Cost
Reduction in error rates / quality standardization	ERRQD	Benefit
Cost effectiveness (wages, training, supervision)	CSTEF	Benefit
Risk of devaluation of basic cognitive skills	COGDR	Cost
Income inequality and narrowing of career ladders	INQCL	Cost
Risk of corporate knowledge loss	KNWLS	Cost
Ethical and accountability uncertainty (AI accountability)	ETHAU	Cost
Maintaining the quality of strategic decisions in the long term	STRQL	Benefit
Potential for human-centered transformation	HCTRP	Benefit

Human–AI collaboration intensity reflects the extent to which human judgment and artificial intelligence operate jointly rather than independently, shaping whether intelligence is augmented or merely substituted. Decreased corporate commitment and belonging may emerge when employees perceive themselves as replaceable within AI-driven systems, which can weaken motivation and long-term organizational stability. Reductions in error rates and quality standardization represent key operational advantages of vibeworking, yet excessive standardization may limit contextual flexibility and adaptive problem solving. Cost effectiveness encompasses wages, training, and supervision requirements, where short-term savings from automation may generate long-term inefficiencies if human development is neglected. The risk of devaluation of basic cognitive skills arises when routine analytical tasks are fully automated, potentially undermining foundational competencies needed for advanced reasoning. Income inequality and the narrowing of career ladders reflect uneven access to AI-

complementary roles, restricting upward mobility for early-career employees. The risk of corporate knowledge loss increases when experienced workers exit without effective knowledge transfer mechanisms, as tacit knowledge is difficult to replicate algorithmically. Ethical and accountability uncertainty becomes prominent when decision authority is delegated to AI systems, creating ambiguity in responsibility and governance. Maintaining the quality of strategic decisions in the long term requires preserving human judgment in complex and uncertain environments where AI outputs require interpretation. Finally, the potential for human-centered transformation depends on whether vibeworking enhances human capabilities and inclusion rather than marginalizing human contributions. According to Table 1, five of the criteria are of the cost type. The others are of the benefit type. Then, alternatives are identified. The alternative list with abbreviations is given in Table 2.

Table 2: Alternatives with Abbreviations

Alternative	Abbreviation
AI-Powered Entry Positions (Human-in-the-Loop Entry Jobs)	AIEPJ
Artificial Internship and Simulation-Based Career Launch	AISIM
Vibe working-Based Project Pool Model	VIBPM
Protected Areas for Training Middle-Level Managers	PRTMM
AI-Human Hybrid Career Ladder	AIHCL
University-Company-AI Platform Integration	UCAPI
Full Automation and Reskilling Model	FARSM

AI-powered entry positions, designed as human-in-the-loop entry jobs, enable early-career employees to perform meaningful tasks under AI assistance while maintaining human oversight and learning opportunities. Artificial internship and simulation-based career launch models provide structured, low-risk environments in which individuals can develop practical skills through AI-supported scenarios before entering full organizational roles. The vibeworking-based project pool model allows organizations to assign newcomers to short-term, AI-enhanced projects, thereby facilitating experiential learning and flexible workforce integration. Protected areas for training middle-level managers limit premature automation of coordination and leadership functions, ensuring the development of critical managerial judgment and organizational knowledge. The AI–human hybrid career ladder supports gradual professional progression by combining automated support with increasing human responsibility at each career stage. University–company–AI platform integration strengthens alignment between educational outcomes and labor market demands by embedding AI tools into joint training and development ecosystems. Finally, the full automation and reskilling model addresses displacement risks by coupling extensive automation with systematic reskilling initiatives that redirect workers toward newly created, AI-complementary roles. To evaluate these alternatives, ten experts with at least 14 years of experience in the field are consulted. Each expert evaluates these alternatives using linguistic variables in Figure 2. The linguistic evaluations are shared in Table 3.

Table 3: Linguistic Evaluations

	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	VHI	LI	HI	VHI	EI	SLI	LI	SLI	VHI	HI
AISIM	EI	VLI	HI	SMI	VLI	VLI	SLI	LI	SMI	SMI
VIBPM	SLI	LI	EI	EI	VLI	VLI	LI	VLI	SMI	SMI
PRTMM	SMI	LI	SMI	SMI	LI	ALI	LI	LI	EI	SMI
AIHCL	HI	LI	AMI	VHI	SLI	LI	LI	SMI	AMI	HI
UCAPI	VHI	VLI	AMI	AMI	ALI	ALI	VLI	ALI	VHI	VHI
FARSM	VHI	EI	VHI	HI	EI	SLI	SLI	SLI	HI	HI
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	VHI	LI	VHI	HI	LI	LI	LI	LI	VHI	HI
AISIM	HI	LI	SMI	EI	VLI	LI	VLI	VLI	SMI	EI
VIBPM	HI	VLI	SLI	SMI	LI	VLI	VLI	LI	HI	EI
PRTMM	EI	LI	SMI	SMI	VLI	LI	LI	LI	EI	EI
AIHCL	AMI	EI	VHI	VHI	EI	EI	SMI	EI	VHI	AMI
UCAPI	VHI	VLI	VHI	VHI	ALI	VLI	ALI	VLI	VHI	VHI
FARSM	HI	EI	HI	HI	EI	SLI	EI	SLI	VHI	HI
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	HI	SLI	VHI	VHI	LI	SLI	LI	EI	HI	VHI
AISIM	SMI	VLI	SMI	EI	VLI	SLI	SLI	LI	HI	SMI
VIBPM	HI	LI	SMI	EI	LI	LI	VLI	VLI	SLI	SLI
PRTMM	SMI	ALI	EI	EI	ALI	ALI	ALI	LI	SMI	SMI
AIHCL	AMI	SMI	AMI	AMI	LI	EI	EI	LI	AMI	AMI
UCAPI	AMI	VLI	AMI	AMI	ALI	VLI	ALI	VLI	AMI	AMI
FARSM	VHI	EI	HI	HI	SLI	EI	SLI	EI	VHI	VHI
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	HI	SLI	HI	VHI	SLI	EI	SLI	EI	HI	VHI
AISIM	HI	SLI	EI	SMI	LI	VLI	LI	SLI	SMI	SMI
VIBPM	EI	VLI	SMI	EI	VLI	VLI	LI	VLI	EI	SLI
PRTMM	SMI	LI	EI	EI	ALI	ALI	VLI	ALI	SMI	EI
AIHCL	HI	LI	VHI	VHI	EI	LI	LI	SLI	HI	HI
UCAPI	AMI	VLI	AMI	AMI	ALI	VLI	ALI	VLI	VHI	AMI
FARSM	HI	EI	HI	VHI	EI	SLI	SLI	SLI	HI	HI
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	HI	SLI	VHI	VHI	LI	SLI	EI	SLI	HI	HI
AISIM	SMI	LI	SMI	SMI	LI	VLI	VLI	SLI	EI	HI
VIBPM	SLI	LI	SLI	HI	VLI	VLI	LI	LI	SMI	SMI
PRTMM	SMI	VLI	SMI	EI	VLI	ALI	VLI	ALI	SMI	SMI
AIHCL	VHI	LI	VHI	VHI	LI	SMI	SLI	SMI	HI	AMI
UCAPI	AMI	ALI	VHI	VHI	VLI	ALI	VLI	VLI	VHI	AMI
FARSM	VHI	SLI	VHI	VHI	EI	EI	EI	EI	VHI	HI
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**

AIEPJ	VHI	LI	HI	VHI	EI	LI	EI	SLI	VHI	VHI
AISIM	HI	VLI	HI	EI	VLI	LI	LI	VLI	EI	EI
VIBPM	EI	VLI	SMI	EI	LI	VLI	VLI	LI	EI	SMI
PRTMM	SMI	VLI	EI	EI	ALI	VLI	VLI	ALI	SMI	SMI
AIHCL	AMI	SLI	AMI	HI	LI	LI	SMI	EI	VHI	VHI
UCAPI	AMI	VLI	VHI	AMI	ALI	VLI	ALI	VLI	AMI	VHI
FARSM	HI	EI	HI	HI	SLI	SLI	SLI	SLI	VHI	VHI
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	VHI	LI	HI	VHI	EI	LI	SLI	EI	HI	HI
AISIM	HI	SLI	EI	HI	LI	SLI	SLI	VLI	SMI	SMI
VIBPM	EI	VLI	SMI	SLI	LI	LI	VLI	VLI	EI	SMI
PRTMM	SMI	VLI	EI	EI	ALI	LI	LI	LI	EI	SMI
AIHCL	HI	LI	AMI	HI	EI	SMI	LI	SLI	HI	HI
UCAPI	AMI	VLI	VHI	VHI	VLI	ALI	ALI	ALI	AMI	AMI
FARSM	VHI	SLI	HI	VHI	SLI	EI	EI	SLI	HI	VHI
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	VHI	SLI	HI	VHI	LI	SLI	EI	EI	HI	VHI
AISIM	SMI	LI	SMI	HI	LI	VLI	VLI	SLI	SMI	EI
VIBPM	HI	VLI	SMI	SMI	VLI	VLI	LI	VLI	EI	EI
PRTMM	SMI	VLI	SMI	SMI	LI	LI	LI	VLI	EI	EI
AIHCL	VHI	SLI	HI	HI	EI	SMI	LI	SLI	HI	AMI
UCAPI	VHI	VLI	AMI	AMI	ALI	ALI	ALI	ALI	AMI	AMI
FARSM	VHI	SLI	HI	VHI	SLI	SLI	SLI	EI	HI	VHI
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	HI	EI	HI	VHI	LI	LI	SLI	EI	HI	HI
AISIM	SMI	SLI	SMI	HI	LI	VLI	LI	VLI	EI	HI
VIBPM	SLI	LI	SLI	SLI	LI	LI	LI	VLI	EI	EI
PRTMM	EI	ALI	EI	EI	ALI	LI	VLI	VLI	SMI	SMI
AIHCL	AMI	SMI	VHI	AMI	SLI	EI	SMI	LI	VHI	AMI
UCAPI	VHI	ALI	VHI	AMI	VLI	VLI	VLI	ALI	AMI	AMI
FARSM	HI	EI	HI	VHI	SLI	EI	SLI	EI	VHI	VHI
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	VHI	SLI	HI	VHI	LI	EI	LI	LI	VHI	HI
AISIM	HI	VLI	HI	SMI	SLI	LI	LI	LI	EI	SMI
VIBPM	HI	LI	SLI	HI	VLI	LI	VLI	LI	EI	SLI
PRTMM	SMI	VLI	SMI	EI	VLI	ALI	ALI	ALI	EI	EI
AIHCL	VHI	EI	VHI	AMI	EI	EI	SMI	SLI	HI	AMI
UCAPI	VHI	VLI	VHI	VHI	ALI	ALI	ALI	VLI	AMI	VHI
FARSM	HI	SLI	VHI	HI	SLI	SLI	SLI	EI	HI	VHI

After that, these linguistic evaluations are transformed into numbers in Figure 2. Thus, evaluation matrices are obtained. The evaluation matrices are summarized in Table 4.

Table 4: Evaluation Matrices

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
AIEPJ	8	3	7	8	5	4	3	4	8	7
AISIM	5	2	7	6	2	2	4	3	6	6
VIBPM	4	3	5	5	2	2	3	2	6	6
PRTMM	6	3	6	6	3	1	3	3	5	6
AIHCL	7	3	9	8	4	3	3	6	9	7
UCAPI	8	2	9	9	1	1	2	1	8	8
FARSM	8	5	8	7	5	4	4	4	7	7
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	8	3	8	7	3	3	3	3	8	7
AISIM	7	3	6	5	2	3	2	2	6	5
VIBPM	7	2	4	6	3	2	2	3	7	5
PRTMM	5	3	6	6	2	3	3	3	5	5
AIHCL	9	5	8	8	5	5	6	5	8	9
UCAPI	8	2	8	8	1	2	1	2	8	8
FARSM	7	5	7	7	5	4	5	4	8	7
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	7	4	8	8	3	4	3	5	7	8
AISIM	6	2	6	5	2	4	4	3	7	6
VIBPM	7	3	6	5	3	3	2	2	4	4
PRTMM	6	1	5	5	1	1	1	3	6	6
AIHCL	9	6	9	9	3	5	5	3	9	9
UCAPI	9	2	9	9	1	2	1	2	9	9
FARSM	8	5	7	7	4	5	4	5	8	8
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	7	4	7	8	4	5	4	5	7	8
AISIM	7	4	5	6	3	2	3	4	6	6
VIBPM	5	2	6	5	2	2	3	2	5	4
PRTMM	6	3	5	5	1	1	2	1	6	5
AIHCL	7	3	8	8	5	3	3	4	7	7
UCAPI	9	2	9	9	1	2	1	2	8	9
FARSM	7	5	7	8	5	4	4	4	7	7
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	7	4	8	8	3	4	5	4	7	7
AISIM	6	3	6	6	3	2	2	4	5	7
VIBPM	4	3	4	7	2	2	3	3	6	6
PRTMM	6	2	6	5	2	1	2	1	6	6
AIHCL	8	3	8	8	3	6	4	6	7	9
UCAPI	9	1	8	8	2	1	2	2	8	9
FARSM	8	4	8	8	5	5	5	5	8	7
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**

AIEPJ	8	3	7	8	5	3	5	4	8	8
AISIM	7	2	7	5	2	3	3	2	5	5
VIBPM	5	2	6	5	3	2	2	3	5	6
PRTMM	6	2	5	5	1	2	2	1	6	6
AIHCL	9	4	9	7	3	3	6	5	8	8
UCAPI	9	2	8	9	1	2	1	2	9	8
FARSM	7	5	7	7	4	4	4	4	8	8
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	8	3	7	8	5	3	4	5	7	7
AISIM	7	4	5	7	3	4	4	2	6	6
VIBPM	5	2	6	4	3	3	2	2	5	6
PRTMM	6	2	5	5	1	3	3	3	5	6
AIHCL	7	3	9	7	5	6	3	4	7	7
UCAPI	9	2	8	8	2	1	1	1	9	9
FARSM	8	4	7	8	4	5	5	4	7	8
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	8	4	7	8	3	4	5	5	7	8
AISIM	6	3	6	7	3	2	2	4	6	5
VIBPM	7	2	6	6	2	2	3	2	5	5
PRTMM	6	2	6	6	3	3	3	2	5	5
AIHCL	8	4	7	7	5	6	3	4	7	9
UCAPI	8	2	9	9	1	1	1	1	9	9
FARSM	8	4	7	8	4	4	4	5	7	8
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	7	5	7	8	3	3	4	5	7	7
AISIM	6	4	6	7	3	2	3	2	5	7
VIBPM	4	3	4	4	3	3	3	2	5	5
PRTMM	5	1	5	5	1	3	2	2	6	6
AIHCL	9	6	8	9	4	5	6	3	8	9
UCAPI	8	1	8	9	2	2	2	1	9	9
FARSM	7	5	7	8	4	5	4	5	8	8
	HAICI	**DECCB**	**ERRQD**	**CSTEF**	**COGDR**	**INQCL**	**KNWLS**	**ETHAU**	**STRQL**	**HCTRP**
AIEPJ	8	4	7	8	3	5	3	3	8	7
AISIM	7	2	7	6	4	3	3	3	5	6
VIBPM	7	3	4	7	2	3	2	3	5	4
PRTMM	6	2	6	5	2	1	1	1	5	5
AIHCL	8	5	8	9	5	5	6	4	7	9
UCAPI	8	2	8	8	1	1	1	2	9	8
FARSM	7	4	8	7	4	4	4	5	7	8

Next, distances across experts are calculated using Eq. (2). The distance matrix is illustrated int Table 5.

Table 5: Distance Matrix

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
E1		9.165	10.100	7.874	8.485	8.185	8.660	9.055	10.247	9.747
E2	9.165		8.944	9.592	8.944	7.810	9.434	8.367	8.888	7.416
E3	10.100	8.944		9.055	10.000	8.185	9.434	9.055	7.810	8.062
E4	7.874	9.592	9.055		8.246	8.185	7.810	7.483	8.718	8.775
E5	8.485	8.944	10.000	8.246		8.775	9.220	8.000	8.544	8.185
E6	8.185	7.810	8.185	8.185	8.775		8.485	9.110	8.485	8.485
E7	8.660	9.434	9.434	7.810	9.220	8.485		7.810	8.718	10.100
E8	9.055	8.367	9.055	7.483	8.000	9.110	7.810		8.888	8.062
E9	10.247	8.888	7.810	8.718	8.544	8.485	8.718	8.888		8.602
E10	9.747	7.416	8.062	8.775	8.185	8.485	10.100	8.062	8.602	

Later, distances of experts are summed by Eq. (3). Finally, the weights of experts are estimated with the help of Eq. (4). The results are summarized in Table 6.

Table 6: Total Distances and Weights of Experts

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
D	81.519	78.561	8.646	75.739	78.400	75.708	79.671	75.832	78.901	77.435
ew	.096	.100	.097	.103	.100	.103	.098	.103	.099	.101

When Table 6 is examined, the most important evaluation is expert 8 with .103.

4.2. Assessing the Alternatives

The evaluation matrices in Table 3 are transformed to SFNs according to Figure 2. Afterwards, a SF-decision values are calculated by Eq.s (15) and (16). The SF-decision matrix is illustrated in Table 7.

Table 7: SF-decision Matrix

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
AIEPJ	(.766,.235,.239)	(.378,.626,.383)	(.735,.266,.269)	(.792,.208,.21)	(.385,.623,.397)	(.391,.615,.399)	(.403,.603,.414)	(.44,.565,.449)	(.746,.255,.259)	(.747,.254,.258)
AISIM	(.649,.353,.359)	(.304,.705,.31)	(.619,.384,.39)	(.611,.392,.4)	(.279,.727,.283)	(.282,.726,.288)	(.311,.697,.315)	(.305,.704,.31)	(.577,.426,.431)	(.598,.404,.411)
VIBPM	(.579,.43,.392)	(.255,.749,.256)	(.525,.48,.413)	(.559,.447,.423)	(.255,.749,.257)	(.245,.759,.247)	(.256,.748,.257)	(.246,.758,.247)	(.541,.463,.453)	(.521,.483,.435)
PRTMM	(.583,.418,.42)	(.222,.787,.225)	(.554,.447,.451)	(.534,.468,.47)	(.188,.826,.191)	(.214,.804,.218)	(.233,.777,.236)	(.219,.797,.223)	(.554,.447,.45)	(.563,.438,.441)
AIHCL	(.831,.171,.183)	(.443,.568,.401)	(.843,.159,.167)	(.818,.184,.195)	(.433,.573,.444)	(.492,.518,.43)	(.481,.533,.388)	(.458,.551,.414)	(.788,.215,.226)	(.853,.149,.163)
UCAPI	(.859,.141,.147)	(.185,.819,.185)	(.849,.152,.157)	(.869,.132,.137)	(.138,.869,.139)	(.159,.848,.159)	(.138,.869,.138)	(.168,.838,.169)	(.869,.132,.137)	(.869,.132,.137)
FARSM	(.755,.246,.249)	(.464,.538,.468)	(.735,.266,.269)	(.756,.245,.248)	(.444,.558,.449)	(.443,.558,.448)	(.433,.568,.438)	(.454,.548,.459)	(.756,.245,.249)	(.766,.235,.239)

Afterwards, defuzzified matrix is created using Eq. (17). This matrix is exhibited in Table 8.

Table 8: Defuzzifed Matrix

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
AIEPJ	.278	-.059	.217	.339	-.051	-.047	-.036	-.013	.237	.239
AISIM	.084	-.156	.052	.044	-.197	-.192	-.145	-.155	.021	.035
VIBPM	.034	-.243	.008	.018	-.242	-.262	-.241	-.261	.008	.005
PRTMM	.026	-.316	.011	.004	-.404	-.344	-.293	-.330	.011	.015
AIHCL	.419	-.026	.457	.388	-.017	-.004	-.012	-.017	.316	.476
UCAPI	.508	-.402	.479	.536	-.534	-.475	-.534	-.448	.536	.535
FARSM	.256	-.005	.217	.258	-.012	-.012	-.017	-.008	.257	.278

The defuzzified matrix is normalized via Eq. (18). The normalized matrix is expressed in Table 9.

Table 9: Normalized Matrix

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
AIEPJ	.173	.049	.150	.214	.035	.035	.028	.011	.171	.151
AISIM	.052	.129	.036	.028	.135	.144	.114	.126	.015	.022
VIBPM	.021	.201	.006	.011	.166	.197	.189	.212	.006	.003
PRTMM	.016	.262	.007	.003	.277	.257	.229	.268	.008	.009
AIHCL	.261	.022	.317	.244	.011	.003	.010	.014	.228	.301
UCAPI	.317	.333	.333	.338	.367	.355	.418	.364	.387	.338
FARSM	.160	.004	.151	.163	.008	.009	.013	.006	.185	.175

Next, the entropies and deviation rates of criteria are calculated by Eq.s (19) and (20), respectively. Thus, the entropy weight values of criteria are obtained as Eq. (21). The results are presented in Table 10.

Table 10: Entropy, Deviation Rate, and Entropy Weights of Criteria

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
E	.829	.800	.764	.772	.771	.767	.753	.745	.745	.753
dr	.171	.200	.236	.228	.229	.233	.247	.255	.255	.247
w	.074	.087	.103	.099	.100	.101	.107	.111	.111	.107

In the next step, cost criteria of defuzzified matrix are made benefit using Eq. (22). Then, this matrix is normalized with Eq. (18). The transformed normalized matrix is shown in Table 11.

Table 11: Transformed Normalized Matrix

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
AIEPJ	.173	.061	.150	.214	.111	.057	.152	.269	.171	.151
AISIM	.052	.023	.036	.028	.029	.014	.037	.023	.015	.022
VIBPM	.021	.015	.006	.011	.023	.010	.022	.014	.006	.003
PRTMM	.016	.011	.007	.003	.014	.008	.019	.011	.008	.009
AIHCL	.261	.138	.317	.244	.339	.686	.442	.216	.228	.301
UCAPI	.317	.009	.333	.338	.011	.006	.010	.008	.387	.338
FARSM	.160	.743	.151	.163	.474	.219	.318	.459	.185	.175

Square matrix values are determined regarding to Eq. (23). The square matrix is illustrated in Table 12.

Table 12: Square Matrix

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
HAICI	.317	.009	.333	.338	.011	.006	.010	.008	.387	.338
DECCB	.160	.743	.151	.163	.474	.219	.318	.459	.185	.175
ERRQD	.317	.009	.333	.338	.011	.006	.010	.008	.387	.338
CSTEF	.317	.009	.333	.338	.011	.006	.010	.008	.387	.338
COGDR	.160	.743	.151	.163	.474	.219	.318	.459	.185	.175
INQCL	.261	.138	.317	.244	.339	.686	.442	.216	.228	.301
KNWLS	.261	.138	.317	.244	.339	.686	.442	.216	.228	.301
ETHAU	.160	.743	.151	.163	.474	.219	.318	.459	.185	.175
STRQL	.317	.009	.333	.338	.011	.006	.010	.008	.387	.338
HCTRP	.317	.009	.333	.338	.011	.006	.010	.008	.387	.338

Afterwards, the relative impact loss matrix is established by Eq. (24). Relative impact loss matrix is shared in Table 13.

Table 13: Relative Impact Loss Matrix

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
HAICI	.000	.988	.000	.000	.978	.992	.977	.982	.000	.000
DECCB	.496	.000	.548	.519	.000	.680	.280	.000	.520	.481
ERRQD	.000	.988	.000	.000	.978	.992	.977	.982	.000	.000
CSTEF	.000	.988	.000	.000	.978	.992	.977	.982	.000	.000
COGDR	.496	.000	.548	.519	.000	.680	.280	.000	.520	.481
INQCL	.175	.815	.047	.276	.286	.000	.000	.529	.411	.110
KNWLS	.175	.815	.047	.276	.286	.000	.000	.529	.411	.110
ETHAU	.496	.000	.548	.519	.000	.680	.280	.000	.520	.481
STRQL	.000	.988	.000	.000	.978	.992	.977	.982	.000	.000
HCTRP	.000	.988	.000	.000	.978	.992	.977	.982	.000	.000

Weight system matrix is constructed using Eq. (25). The weighted system matrix is given in Table 14.

Table 14: Weighted System Matrix

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
HAICI	-1.838	.988	.000	.000	.978	.992	.977	.982	.000	.000
DECCB	.496	-6.569	.548	.519	.000	.680	.280	.000	.520	.481
ERRQD	.000	.988	-1.736	.000	.978	.992	.977	.982	.000	.000
CSTEF	.000	.988	.000	-2.109	.978	.992	.977	.982	.000	.000
COGDR	.496	.000	.548	.519	-5.459	.680	.280	.000	.520	.481
INQCL	.175	.815	.047	.276	.286	-7.000	.000	.529	.411	.110
KNWLS	.175	.815	.047	.276	.286	.000	-5.725	.529	.411	.110
ETHAU	.496	.000	.548	.519	.000	.680	.280	-5.971	.520	.481
STRQL	.000	.988	.000	.000	.978	.992	.977	.982	-2.382	.000
HCTRP	.000	.988	.000	.000	.978	.992	.977	.982	.000	-1.664

The CILOS weights of criteria are defined by solving in Eq. (26). The q obtained from solving this equation is summarized in Table 15.

Table 15: CILOS Weights of Criteria

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
q	.150	.062	.159	.131	.074	.035	.042	.068	.116	.165

In the last step of IDOCRIW, the priorities values of criteria are obtained with Eq. (27). The results are drawn in Figure 3.

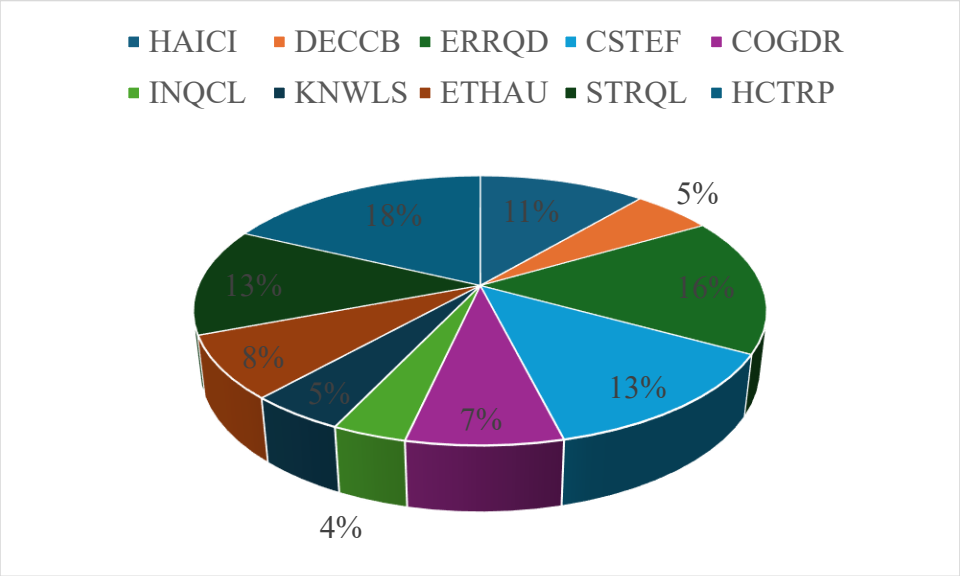


Figure 3: Priorities of Criteria

According to the priority values of the criteria presented in Figure 3, the potential for human-centered transformation emerges as the most influential criterion with a weight of 0.179, followed by reduction in error rates and quality standardization with a weight of 0.164. This finding indicates that, within vibe working environments, strategies are primarily evaluated based on their capacity to preserve and enhance human roles rather than solely maximizing technological efficiency. The prominence of human-centered transformation suggests that decision makers attach greater importance to whether AI-driven work models support skill development, inclusion, and long-term employability. In contrast, although operational efficiency remains highly valued, it is considered secondary to sustaining a balanced human–AI relationship. The relationship between these two criteria reflects a strategic trade-off rather than a contradiction. Human-centered transformation provides the structural foundation that ensures efficiency gains do not erode human capabilities, while quality standardization represents the tangible performance outcomes enabled by AI integration. When these criteria are aligned, organizations can achieve reliable outputs without marginalizing human judgment. From a policy perspective, this alignment calls for the development of governance frameworks that explicitly prioritize human augmentation over replacement. Organizational strategies should promote human-in-the-loop systems, continuous reskilling programs, and protected learning pathways for early and mid-career employees. In addition, performance metrics should balance efficiency indicators with human development outcomes. Such policy and strategic orientations can help organizations achieve sustainable vibe working models that combine operational excellence with long-term workforce resilience.

Within the scope of RAM analysis, SF-decision values are defuzzified using Eq. (28). The defuzzified decision values are shown in Table 16.

Table 16: Defuzzifed Decision Values

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
AIEPJ	1.278	.941	1.217	1.339	.949	.953	.964	.987	1.237	1.239
AISIM	1.084	.844	1.052	1.044	.803	.808	.855	.845	1.021	1.035
VIBPM	1.034	.757	1.008	1.018	.758	.738	.759	.739	1.008	1.005
PRTMM	1.026	.684	1.011	1.004	.596	.656	.707	.670	1.011	1.015
AIHCL	1.419	.974	1.457	1.388	.983	.996	.988	.983	1.316	1.476
UCAPI	1.508	.598	1.479	1.536	.466	.525	.466	.552	1.536	1.535
FARSM	1.256	.995	1.217	1.258	.988	.988	.983	.992	1.257	1.278

Afterwards, the defuzzified decision values are normalized by Eq. (29). The normalized decision values are given in Table 17.

Table 17: Normalized Decision Values

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
AIEPJ	.148	.162	.144	.156	.171	.168	.169	.171	.148	.144
AISIM	.126	.146	.125	.122	.145	.143	.149	.146	.122	.121
VIBPM	.120	.131	.119	.119	.137	.130	.133	.128	.120	.117
PRTMM	.119	.118	.120	.117	.108	.116	.124	.116	.121	.118
AIHCL	.165	.168	.173	.162	.177	.176	.173	.170	.157	.172
UCAPI	.175	.103	.175	.179	.084	.093	.081	.096	.183	.179
FARSM	.146	.172	.144	.146	.178	.174	.172	.172	.150	.149

The normalized decision values are multiplied by the priority values of criteria via Eq. (30). Weighted decision matrix is presented in Table 18.

Table 18: Weighted Decision Matrix

	HAICI	DECCB	ERRQD	CSTEF	COGDR	INQCL	KNWLS	ETHAU	STRQL	HCTRP
AIEPJ	.017	.009	.024	.020	.013	.006	.008	.013	.019	.026
AISIM	.014	.008	.020	.016	.011	.005	.007	.011	.016	.022
VIBPM	.013	.007	.020	.015	.010	.005	.006	.010	.016	.021
PRTMM	.013	.006	.020	.015	.008	.004	.006	.009	.016	.021
AIHCL	.018	.009	.028	.021	.013	.006	.008	.013	.020	.031
UCAPI	.020	.006	.029	.023	.006	.003	.004	.007	.024	.032
FARSM	.016	.009	.024	.019	.013	.006	.008	.013	.019	.027

The weighted decision values are summed regarding to types of criteria with the help of Eq.s (31) and (32). Finally, the final values of alternatives are computed using Eq. (33). The results are summarized in Table 19.

Table 19: Totals and Final Values of Alternatives

	T^+	T^-	RV
AIEPJ	.106	.048	1.438
AISIM	.088	.042	1.434
VIBPM	.085	.038	1.434
PRTMM	.085	.033	1.435
AIHCL	.119	.049	1.443
UCAPI	.127	.026	1.452
FARSM	.105	.050	1.438

As can be seen from the RV values reported in Table 18, university–company–AI platform integration emerges as the most appropriate alternative with a score of 1.452, followed closely by the AI–human hybrid career ladder with a score of 1.443. This result indicates that strategies emphasizing systemic collaboration and long-term capability building are perceived as more effective than isolated or short-term solutions. The high ranking of university–company–AI platform integration suggests that aligning educational institutions, organizational practices, and AI technologies creates a coherent ecosystem that supports sustainable skill development, smoother school-to-work transitions, and continuous adaptation to technological change. Such integration enables early exposure to AI-supported work environments while preserving structured learning processes. The close priority relationship between the two alternatives reflects their complementary nature. While university–company–AI platform integration focuses on preparing individuals before and during organizational entry, the AI–human hybrid career ladder ensures continuity of development after entry by providing clear progression paths that combine automation with increasing human responsibility. Together, these strategies form a pipeline that addresses both entry-level disruption and long-term career sustainability. From a policy perspective, this finding highlights the need for collaborative governance models that encourage partnerships between universities, firms, and AI service providers. Strategic initiatives should include co-designed curricula, shared digital platforms, and jointly funded training programs. At the organizational level, firms should institutionalize hybrid career frameworks that formally recognize human contribution alongside AI capabilities. Such coordinated strategies can mitigate vibe working-related risks while fostering inclusive and resilient workforce structures.

4.3. Sensitivity Analysis

A sensitivity analysis is conducted to evaluate the reliability of the findings obtained through the proposed methodology and to examine the robustness of the overall decision-making framework. This analysis aims to determine whether the ranking results remain stable under alternative methodological assumptions and evaluation structures. In this context, the outcomes derived from the proposed model are systematically compared with those generated by an alternative and well-established ranking approach, namely the MUNRA method. By employing a second ranking model, potential methodological bias is reduced, and the consistency of the priority structure is tested. The comparative evaluation allows for the identification of possible ranking shifts and highlights the degree of agreement between different analytical perspectives. The results of this comparative sensitivity analysis are summarized in Table 20, providing empirical evidence on the stability and credibility of the proposed model's outcomes.

Table 20: MUNRA Result

	MUNRA
AIEPJ	.570
AISIM	.501
VIBPM	.509
PRTMM	.539
AIHCL	.642
UCAPI	.848
FARSM	.562

When examining the correlation coefficients between the results obtained from the two ranking methods presented in Tables 19 and 20, a very high level of consistency is observed. The Pearson correlation coefficient reaches a value of 0.993, indicating a strong linear relationship between the ranking scores produced by the two methods. In addition, the Spearman correlation coefficient is equal to 1, which demonstrates a perfect agreement in the ordinal ranking of the alternatives. These findings clearly indicate that the relative positions of the alternatives remain unchanged across different methodological approaches, confirming the reliability and stability of the ranking results. To further strengthen the robustness analysis, additional sensitivity scenarios are constructed by increasing each criterion's priority value by 10 percent. These scenario-based adjustments aim to simulate potential fluctuations in

decision-maker preferences and to test whether small changes in criterion importance affect the final rankings. Under each updated criterion-prioritized scenario, the RAM analysis is repeated to observe possible variations in alternative performance. The outcomes of these recalculated scenarios are systematically summarized in Table 21. The consistency of the results across these scenarios provides further empirical support for the robustness of the proposed methodology and enhances confidence in the validity of the decision-making outcomes.

Table 21: Scenarios Results

	HAICI+10 %	**DECCB+10 %**	**ERRQD+10 %**	**CSTEF+10 %**	**COGDR+10%**	**INQCL+10 %**	**KNWLS+10 %**	**ETHAU+10 %**	**STRQL+10 %**	**HCTRP+10 %**
AIEPJ	1.439	1.438	1.439	1.439	1.438	1.438	1.438	1.438	1.439	1.439
AISIM	1.434	1.434	1.435	1.434	1.434	1.434	1.434	1.434	1.434	1.435
VIBPM	1.434	1.434	1.435	1.434	1.434	1.434	1.434	1.434	1.435	1.435
PRTMM	1.436	1.435	1.436	1.436	1.435	1.435	1.435	1.435	1.436	1.436
AIHCL	1.443	1.442	1.443	1.443	1.442	1.442	1.442	1.442	1.443	1.443
UCAPI	1.452	1.451	1.452	1.452	1.451	1.451	1.451	1.451	1.452	1.452
FARSM	1.438	1.438	1.438	1.438	1.437	1.438	1.438	1.437	1.438	1.438

As can be observed from the results reported in Table 21, minor variations in the priority values assigned to the criteria do not lead to any changes in the ranking order of the alternatives. This finding indicates that even when criterion priorities are increased, the relative performance of the alternatives remains stable and their positions in the ranking are preserved. In other words, the decision outcomes are not sensitive to small fluctuations in criterion importance, which suggests a high level of methodological stability. Such stability is particularly important in multi-criteria decision-making problems where subjective judgments and uncertain evaluations are unavoidable. The ability of the model to produce consistent rankings under modified priority structures demonstrates that the results are not driven by extreme or fragile assumptions. Accordingly, this sensitivity analysis provides strong evidence that the proposed methodology exhibits a high degree of robustness and can be considered reliable for supporting strategic decision-making in complex vibe working contexts.

5. Discussion

One of the key criteria in examining the transformative impact of artificial intelligence on entry-level jobs is human-centered transformation potential. In AI-supported business models, the goal is to focus on the quality of human-machine interaction rather than technological efficiency (Liang et al., 2025). This concept is particularly critical for entry-level jobs. AI is used as a supportive tool in human-centered transformation potential (Yanytska, 2025). Artificial intelligence automates low value-added jobs, directing human labor to more skilled areas. Indeed, Brückner et al. (2025) focused on technological development and Industry 5.0 technologies. The study stated that increasing technological developments should emphasize social criteria. Furthermore, artificial intelligence will assist in reaching the current maturity level. In a similar study, Hu et al. (2025) argued that human-machine collaboration contributes to the transformation of the industrial ecosystem. A decrease in error rates and quality standardization can be considered another effective criterion in evaluating the transformative impact of artificial intelligence on entry-level tasks. In one study, Cheng et al. (2025) evaluated the role of artificial

intelligence in work processes. The study stated that artificial intelligence evaluates interregional operations and provides technical support in developing service capabilities. In another similar study, Kampik et al. (2025) said that productive artificial intelligence technologies can be used effectively in business process management. The study observed that artificial intelligence tools increased process performance.

Universities, companies, and artificial intelligence working in harmony to determine new strategies for entry-level jobs are considered one of the important alternatives affecting the employment of new graduates. This integration should be evaluated as a skill transformation effect rather than a substitution effect of artificial intelligence. Creating AI-supported learning areas will contribute to addressing the skills mismatch in the labor market (Ersanlı et al., 2025). Indeed, Sun et al. (2025) stated that the integration of AI applications in human resources and business development processes facilitates group digitalization. The study also emphasized the need to establish an appropriate infrastructure for artificial intelligence to guide business operations. In a similar study, Oprea et al. (2025) argued that artificial intelligence-supported business models increase efficiency and facilitate decision-making processes. The study also particularly highlighted that artificial intelligence should be a support mechanism. In another study, Ghosh (2025) recommended the use of artificial intelligence applications in the development of business processes. However, it is pointed out that the use of artificial intelligence applications will save costs and transform a company. It is noted that this transformation and reduction in costs will negatively affect new graduates in terms of finding employment.

Entry-level jobs generally provide opportunities for recent graduates to gain experience, learn corporate norms, and gradually increase their responsibilities (Richards and Spanjaard, 2025). However, artificial intelligence tools used in developing work processes shorten or eliminate some of the career steps. This situation means that the value of human labor is defined more by production capacity with artificial intelligence than by seniority (Bobitan et al., 2024). In this regard, another strategy that affects new graduates' job search is an AI-supported career ladder, reflecting the transformative effect of artificial intelligence in entry-level jobs. Indeed, Deng and Sun (2025) conducted a study on university students to shape their individual career development. The study emphasized that students' creation of an AI-supported career would contribute to their job search processes. In another study, Pisica et al. (2025) highlighted the need for students to set job-oriented career goals while pursuing higher education. The study also stated that the use of artificial intelligence in job applications would shape institutions' job expectations regarding human resources. Furthermore, the study stressed that students should also develop their career plans in this manner.

6. Conclusion

This study aims to identify the most prioritized alternative transformation strategies for minimizing the challenges associated with vibe working in artificial intelligence–driven work environments. To achieve this objective, a novel fuzzy multi-criteria decision-making framework is developed by integrating distance-based expert weighting, the IDOCRIW method for determining criterion priorities, the RAM technique for ranking strategic alternatives, and spherical fuzzy sets to better manage uncertainty. Based on expert evaluations, the analysis results reveal that the potential for human-centered transformation is the most critical evaluation criterion, followed by reduction in error rates and quality standardization. In terms of strategic alternatives, university–company–AI platform integration emerges as the most appropriate strategy, closely followed by the AI–human hybrid career ladder. These findings highlight the importance of collaborative, inclusive, and capability-oriented transformation pathways rather than purely efficiency-driven solutions. The study contributes to the existing literature by addressing a significant research gap in vibe working research through a structured prioritization approach and by offering a robust methodological model that incorporates expert heterogeneity and uncertainty into strategic decision-making.

Despite its contributions, this study has several theoretical and methodological limitations that should be acknowledged. From a theoretical perspective, the analysis focuses on a predefined set of criteria and strategies derived from the current literature, which may not fully capture emerging dynamics or sector-specific characteristics of vibe working. Methodologically, the proposed model relies on expert judgments, which, although systematically weighted, remain subject to subjective bias. In addition, the

application of spherical fuzzy sets and integrated decision-making techniques increases model complexity, potentially limiting its practical accessibility for organizations with limited analytical capabilities. Future research can address these limitations by expanding the criteria and strategy sets, conducting sectoral or cross-country comparative analyses, and integrating longitudinal data to capture dynamic changes over time. Moreover, alternative fuzzy environments and hybrid decision-making models may be explored to test the generalizability and scalability of the proposed framework. Such extensions would further strengthen the theoretical foundations and practical applicability of vibe working-oriented decision support models.

Declarations

Data Availability Statement: The datasets used in this study are available from the corresponding author upon reasonable request. The shared materials include the raw dataset, processed dataset and variable definitions used for the analysis.

Ethical Approval and Informed Consent Statement: This article does not contain any studies with human participants performed by any of the authors.

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