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A Fuzzy Decision Support System for the Effect Evaluation of GAI Application in HRM

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ABSTRACT

To alleviate the difficulties faced by enterprises in choosing which human resource management module to prioritize for the application of generative artificial intelligence, this study attempts to construct a hybrid framework. First, the relevant literature was sorted, and eight evaluation criteria were proposed, including quality, technology, and compatibility. Then, the expert language judgment is transformed into a picture fuzzy set. The CIMAS method was used to determine the weights and test consistency. Subsequently, VIKOR is introduced to balance group utility and individual regret, and the priority sequence is generated. This framework transforms the selection process from experience-driven to quantifiable and repeatable multi-attribute decision-making. Simultaneously, it provides suggestions for the introduction of generative artificial intelligence into the enterprise human resource management module.

1. Introduction

Approximately a decade ago, the United Nations (UN) General Assembly released the 2030 Agenda for Sustainable Development, which established a core framework for global sustainable development (SD). This agenda encompasses 17 key goals, covering nearly all dimensions of sustainable development, among which Sustainable Development Goal 8 (SDG 8) proposes to “promote sustained, inclusive, and sustainable economic growth, achieve full and productive employment, and ensure decent work for all” [1]. Digital technologies have become critical to achieving this goal. Integrating digital technologies into organizational operations, particularly through technological innovation, has emerged as a core pathway for advancing sustainable economic growth [2].

Among various digital technologies, the technology cluster centered on artificial intelligence (AI) serves as an important engine for leading organizational digital transformation. As a core variable reshaping organizational effectiveness, AI helps organizations reduce operational costs, enhance service quality, and improve collaboration efficiency [3]. Moreover, through its applications in

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production, management, and service scenarios, AI fosters new human-machine configuration models, continuously strengthening its strategic value in contemporary organizations [4]. Human resources are the core carriers of an organization's leverageable competitive advantages. Leveraging AI technologies to upgrade management effectiveness has become a key issue for enterprises to implement SDG 8 goals and adapt to digital economy transformation.

Technological breakthroughs and innovations in artificial intelligence (AI) and machine learning have enabled significant transformations in organizations across various domains. The integration of various technological tools and applications has significantly transformed employees' working styles from hard work to smart work [5]. For organizations, the efficient utilization of human resources is critical to sustaining success. Combining AI with human resource management has become an important pathway for optimizing the efficiency of human resource allocation [6]. Currently, the emerging knowledge economy and technological interventions are constantly reshaping traditional work patterns in the hospitality industry. Organizations urgently need to implement strategic human resource development initiatives to help employees enhance their professional skills and knowledge management capabilities, and AI plays an irreplaceable role in this process [7]. Given the broad application potential of AI, internationally renowned enterprises such as Google, IBM, Amazon, Tesla, and Apple have taken the lead in integrating AI into human resource management processes [8], innovatively addressing various issues, including employee recruitment, training, and performance evaluation [9].

Generative Artificial Intelligence (GAI), a highly innovative branch of AI technology [10], differs fundamentally from traditional AI, which focuses on prediction. As a machine learning model dedicated to generating new data, GAI can produce diverse content, including audio, code, images, text, simulated scenarios, and videos [11]. Currently, it has rapidly penetrated various fields, exerting a profound impact on personal lives, enterprise operations, and organizational development. In workplace scenarios, GAI has multiple values. It can not only provide diversified support for employees, such as automatically generating reports and optimizing work processes, but also stimulate their creativity. By promoting divergent thinking, optimizing idea evaluation mechanisms, and breaking professional knowledge biases, GAI enhances human creative output [12]. Today, GAI has become a disruptive force in the digital world. ChatGPT, a typical representative tool, further highlights the potential application of this technology in organizational management through its cross-application adaptability and diverse content generation capabilities [13].

Despite the numerous opportunities GAI brings to organizational management, its technical characteristics inevitably give rise to non-negligible issues during application. As the scope of its application expands from data-driven tasks to complex creative tasks, GAI may replace certain human jobs, thereby affecting the structure of human resources [14]. Owing to inherent technical deficiencies, problems including poor data quality and content "hallucinations"—defined as the generation of false or inaccurate information—have emerged in practical use, which may induce biases in management decisions [15]. Additionally, there are hidden risks of technology abuse, such as forging employee information and violating privacy, which impose higher requirements on the compliance of human resource management [16].

Existing studies have focused on the impact of GAI on human resource management; however, most of them concentrate on the technical characteristics or macro-transformative role of GAI. They fail to clarify the specific application scenarios of GAI in various modules of human resource management, such as recruitment, training, performance, and compensation, rendering enterprises unable to determine the aspects in which GAI can be applied [16]. Some studies mention factors influencing technology adoption, such as the usability and user acceptance of GAI, but they do not systematically sort out the full-dimensional factors that enterprises need to consider during application, leaving enterprises without a clear decision-making basis. In general, most existing studies are exploratory and descriptive analyses, or their scope is limited to a single module only. For example, some studies focus only on improving recruitment efficiency [17], while others focus only on supporting employee training. These studies fail to address the practical challenge of identifying the human resource management module suitable for prioritized integration with GAI through decision-making methods [18]. The lack of priority guidance may result in resource misallocations [19]. These motivations give rise to the following research questions.

i. What specific aspects of human resource management can GAI be applied to in enterprises?
ii. What factors should enterprises consider when applying GAI to human resource management?
iii. Which human resource management module is most suitable for prioritizing integration with GAI?

Based on the above discussion, this study develops a model to effectively evaluate and rank the application of GAI in human resource management. Herein, the main aspects of applying GAI in human resource management are identified through a review of the relevant literature. Subsequently, based on detailed surveys, several influencing factors that need to be considered when applying GAI to human resource management are selected.

In Human Resource Management (HRM), the integration of GAI has become a prominent trend, aiming to transform various HR modules. However, assessing the application effects and ranking them across different modules is a complex task that requires a comprehensive multi-criteria decision-making (MCDM)approach. MCDM methods have been widely used in various fields to address complex evaluation and ranking problems. Picture Fuzzy Sets (PFS), as an extension of fuzzy sets and intuitionistic fuzzy sets [20], have emerged as valuable tools for dealing with uncertainty and subjectivity in expert evaluations [21]. In the context of assessing GAI's application of GAI in HRM, PFS can effectively handle linguistic uncertainty and stabilize the criteria structures in the assessment. The Criteria Importance Assessment (CIMAS)method, when extended with PFS(PFS-CIMAS), offers a robust way to determine criterion weights [22]. It features a two-stage criterion evaluation process and reliability testing of weights, ensuring that the criteria used to assess the GAI application are weighted appropriately. This is fundamental for making reliable comparisons across different HR modules. VIKOR, a well-established MCDM technique, is used to rank alternatives in a compromise manner [23]. Compared with other ranking methods, such as AHP and TOPSIS, it closely mirrors human-driven decision-making, has a lower computational complexity than AHP, and has advantages over TOPSIS in ranking strategy and handling special cases [24]. In the context of GAI's application in HRM, VIKOR can effectively rank the different HR modules by considering the compromise between the best and worst performance scenarios of GAI in each module.

When exploring the application effect ranking of GAI in HRM's main modules of HRM, the PFS-CIMAS-VIKOR model is a comprehensive framework. PFS handles uncertainty and subjectivity in evaluating GAI's impact of the GAI. PFS-CIMAS ensures that the evaluation criteria are weighted reliably. Then, VIKOR utilizes these weights to rank the HR modules based on GAI's application effects, reflecting a balanced compromise that considers both optimal and suboptimal performances. Numerous studies have demonstrated the effectiveness of integrating fuzzy set theory with MCDM methods in diverse fields [25,26]. Similarly, the integration of PFS with CIMAS and VIKOR leverages the strengths of each component: PFS manages the uncertainty in evaluating GAI applications, PFS-CIMAS ensures robust criterion weight determination, and VIKOR provides a sound ranking mechanism. In summary, the PFS-CIMAS-VIKOR model was proposed to rank the application effects of GAI in HRM's main modules.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on the application of GAI. Section 3 elaborates on the study's methodological framework and research methods. Section 4 presents an application analysis of the proposed multi-criteria decision-making method. Section 5 discusses the research findings. Section 6 outlines the management and practical implications. Finally, Section 7 expounds on the limitations of this study and provides suggestions for further research.

2. Literature Review

Each human resource management module has various complex requirements. To address these heterogeneous demands, GAI tools exhibit significant variations across core dimensions, such as processing efficiency, scenario adaptability, and data security. Thus, it is essential to determine the criteria for assessing GAI tool performance.

2.1 Generate Quality

GAI can automatically generate new textual, visual, and video content, which supports employees in enhancing productivity. GAI also offers automated data analysis [27]. By analyzing large datasets to identify emerging patterns and provide personalized suggestions, employees can better and more quickly understand data and enable them to make informed decisions. For instance, GAI can generate job descriptions and advertisements, communicate with job seekers, develop new training content, and draft performance evaluations [28]. However, at the same time, the use of GAI may bring about the limitations of information hallucination. The possibility of information hallucination makes it necessary to monitor the information generated by GAI carefully. GAI systems can inherit or even enhance the biases found in the training data, which may lead to biased or unfair results and thus cause quality issues. If the content generated by GAI is mistakenly regarded as accurate, it will influence public opinion or decisions based on incorrect data. Malicious actors can use it to deceive audiences, tarnish their reputations, and influence political and social narratives. Therefore, the quality of the generated text deserves attention [29].

2.2 Technology

With the continuous development of AI technology, the process of generating new AI models has accelerated. However, creating pioneering AI models is challenging. Looking ahead, AI models need to be constantly evaluated, retrained, optimized, deployed, and observed to maintain their performance and adapt to the constantly changing environment and demands. [30]. With the emergence of new industry trends and skill requirements, the content generation model of tools should be adjusted promptly to provide more accurate and effective services. Model updates and optimizations also include the ability to learn from new data. AI can draw effective images from large amounts of data, improve itself when new data is available, increase the speed of task completion [31], and enhance the performance of the tool. The rapid development of GAI also means that systems and tools may soon become obsolete. This requires continuous financial investment, which seriously affects budget planning and demands a strategic approach to technology management and adoption.

2.3 Compatibility

The application of AI requires a large amount of computing resources, which may put pressure on systems that are not designed to handle such loads. This compatibility challenge extends to ensuring that GAI tools can be seamlessly integrated into existing systems. It is also considered a vital prerequisite for users to embrace information technology [32]; technological innovations that are perceived as more compatible with the current working methods and practices of potential adopters tend to have a higher likelihood of being adopted [33]. As the latest development in AI, GAI shows significant potential. Adopting this technological innovation can enhance transaction governance and the quality and efficiency of services [34]. Moreover, the human resource management process usually involves multiple systems and tools [35], so GAI tools need to have good compatibility [36]to integrate seamlessly with existing systems. At the same time, compatibility plays an important role in promoting human-machine collaboration. AI compatibility can facilitate collaborative organizational innovation. Developing algorithms tailored to various task scenarios and compatibility paths can enhance human-machine collaboration. Because of compatibility, data are transmitted smoothly in different systems, enhancing the overall synergy of the human resource management process [37].

2.4 Organizational Readiness

GAI offers significant potential for organizations, but its adoption implies high implementation complexity, which is different from other digital technologies that are usually easy to use and deploy [38]. As a key organizational factor influencing the adoption of technological innovation, organizational readiness is a vital prerequisite for companies to adopt GAI, providing an organizational incubator that supports the adoption of new technologies [39]. Pre-adoption organizational readiness emphasizes the evaluation of the necessity, commitment, and available resources within an organization to adopt a technological innovation. Specifically, GAI adoption involves assessing whether organizational assets, capabilities, and commitment are ready for GAI adoption. Embedding GAI into applications such as human resource management systems require significant investment [40]. Organizations must be fully prepared to cover infrastructure upgrades, the costs of changing existing processes, and specialized technical training expenses. Only in this way can GAI truly play a role within the enterprise. According to the theory of organizational change readiness, a higher level of organizational readiness increases the success of innovation adoption and reduces the risk of failure [41], further confirming the critical role of adequate OR in the successful application of GAI.

2.5 Communication

Studies have shown that many workers, especially knowledge workers, are not easily replaced by AI. However, as AI takes over certain aspects of their work, their roles and contributions will change. The integration of AI systems may require a new division of labor between workers and intelligent systems [42]. For effective human-GAI communication in HR contexts, two core dimensions demand attention: how humans engage with GAI tools and how GAI interacts with humans. On the human side, employees exhibit varied technical proficiency and usage habits; therefore, GAI tools must prioritize user-friendliness. They should feature simple and intuitive interfaces that enable non-technical personnel to operate them effortlessly, as the difficulty in adopting new technologies directly influences GAI's uptake and promotion of GAI [42,43]. ChatGPT serves as a typical example; its widespread acceptance stems from its low operational complexity and high practicality, which underscores the role of usability in facilitating human-GAI interaction [13]. On the GAI side, a critical limitation emerges due to its lack of emotional intelligence, which is a key requirement for HR communications, especially decisions with personal implications for employees, such as pay raises. Exclusive reliance on GAI for such communications may overlook employee feelings and relationships, even if it improves the rationality of HR decision recommendations. Consequently, GAI-driven HR communications risk being perceived as unfair and harmful without emotionally intelligent framing [16].

2.6 Ethics

AI brings tremendous benefits to economic growth, social development, and the improvement of human well-being and safety. However, the low-level interpretability, data bias, and ethical issues of AI-based technologies pose significant risks to users, developers, and society [17]. The possibility of GAI amplifying bias and creating realistic and completely fabricated content has raised questions about authenticity, truthfulness, and public trust. The moral aspect of AI is now and will continue to be at the core of the implementation and adoption of such systems. One major area of concern is the potential perpetuation or even worsening of biases in hiring, performance evaluation, and compensation decisions. Because GAI synthesizes existing data, existing biases in the data are reflected in the recommendations made by GAI. If no attention is given to where and how GAI capabilities may affect biases, these biases are likely to continue or grow. For example, GAI-generated job postings for technical jobs may inadvertently use language that dissuades women, older individuals, minorities, those with disabilities, and those from lower socioeconomic backgrounds from applying, resulting in perpetuating inequities and discrimination. In addition, the use of GAI to develop recommendations or provide feedback associated with performance or compensation decisions may draw on biased data, potentially leading to employee concerns about discrimination and fairness [16].

2.7 Privacy

GAI models are trained on large datasets. If safeguards are not in place, the training data may include data that should be kept private. When this occurs, the GAI may generate content that violates privacy norms and laws. In addition, GAI may inadvertently collect and process personal information. Privacy violations may violate regulations and laws. Human resource management involves a large amount of sensitive information about personnel, such as personal identity, work experience, salary, and benefits [33]. Therefore, GAI tools should comply with relevant data protection regulations [35]and adopt encryption technology to ensure data security during transmission and storage [34]. As more and more AI systems are used to coordinate tasks, for instance, collecting training data in the workplace, storing it in accessible or permeable storage, and taking action based on estimates inferred from the training data collected in the workplace, they can constitute surveillance that infringes upon employee privacy and fosters data colonialism [44]. Therefore, data management is vital. Only authorized personnel can access specific data to safeguard the privacy of the participants.

2.8 Benefit

When choosing GAI tools for human resource management scenarios, benefits are an important consideration. The implementation of AI technology incurs various costs, such as AI hardware equipment, software systems, technology development, and maintenance [45]. These expenditures should be matched with the enterprise's budget planning and expected returns. Studies have shown that although many enterprises have implemented AI technology and launched a series of related tools and services, they do not always achieve profitability through the application of AI. The profitability of applying AI technology mainly depends on the costs incurred during the application process [46]. Therefore, when evaluating the benefits of GAI tools, in addition to focusing on direct economic benefits such as savings in labor costs and the direct financial returns brought about by improved recruitment efficiency, it is more important to comprehensively consider the economic costs of the tools. The implicit benefits brought by tools include efficiency improvement, enhanced recruitment quality, and increased employee satisfaction.

3. Research Methodology

In this section, the basic ideas pertaining to picture fuzzy set (PFS) are presented, and then, the execution steps of the integrated approach are explained.

3.1 Preliminaries

Definition 1:

A Picture Fuzzy Set (PFS) is a set framework constructed within a specific discourse domain [47] that is used to describe the membership states of elements (positive, neutral, negative, and rejection) in a more detailed manner. Its formal definition is as follows

Set Framework: Let the specific discourse domain be B, and any element in the domain be b$(b \in B)$. Then, a PFS can be expressed as:

$$\left\{\left\langle \widetilde{W} = \{b, \mu_{\widetilde{W}}(b), \eta_{\widetilde{W}}(b), \nu_{\widetilde{W}}(b)\right\rangle \mid b \in B\right\} \quad (1)$$

The meanings of each component are as follows.

$\mu_{\widetilde{W}}(b)$: The positive membership degree of element b, representing the degree to which b clearly belongs to $\widetilde{W}$, and it satisfies $0 \leq \mu_{\widetilde{W}}(b) \leq 1$.

$\eta_{\widetilde{W}}(b)$: The neutral membership degree of element b, representing the degree to which the affiliation of b to $\widetilde{W}$ is in a fuzzy and uncertain state, and it satisfies $0 \leq \eta_{\widetilde{W}}(b) \leq 1$.

$\nu_{\widetilde{W}}(b)$: The negative membership degree of element b, representing the degree to which b clearly does not belong to $\widetilde{W}$, and it satisfies $0 \leq \nu_{\widetilde{W}}(b) \leq 1$.

The three functions must satisfy $0 \leq \mu_{\widetilde{W}}(b) + \eta_{\widetilde{W}}(b) + \nu_{\widetilde{W}}(b) \leq 1 (b \in B)$.

Define $\lambda_{\widetilde{W}}(b)$ as the rejection membership degree, which represents the degree of unclear affiliation of element b beyond the positive, neutral, and negative membership degrees.

$$\lambda_{\widetilde{W}}(b) = 1 - \mu_{\widetilde{W}}(b) - \eta_{\widetilde{W}}(b) - \nu_{\widetilde{W}}(b),\ \lambda_{\widetilde{W}}(b) \in [0,\ 1] \quad (2)$$

When $\lambda_{\widetilde{W}}(b) = 0$ and $\mu_{\widetilde{W}}(b) + \eta_{\widetilde{W}}(b) + \nu_{\widetilde{W}}(b) = 1$, at this time, the membership state of the PFS is completely clear.

Definition 2: Basic Operation Rules of PFS

Suppose there are three entities representing PFSs, denoted as

$$\widetilde{W} = (\mu_{\widetilde{W}}(b), \eta_{\widetilde{W}}(b), \nu_{\widetilde{W}}(b)), \widetilde{W}_1 = \left(\mu_{\widetilde{W}_1}(b), \eta_{\widetilde{W}_1}(b), \nu_{\widetilde{W}_1}(b)\right), \widetilde{W}_2 = \left(\mu_{\widetilde{W}_2}(b), \eta_{\widetilde{W}_2}(b), \nu_{\widetilde{W}_2}(b)\right)$$

The operation rules among these three entities [48] are specified as follows:

$$\widetilde{W}_1 \oplus \widetilde{W}_2 = \left\{\begin{pmatrix} \left(\left(\mu_{\widetilde{W}_1}(b)\right) + \left(\mu_{\widetilde{W}_2}(b)\right) - \left(\mu_{\widetilde{W}_1}(b)\mu_{\widetilde{W}_2}(b)\right)\right), \\ \left(\left(\eta_{\widetilde{W}_1}(b)\right)\left(\eta_{\widetilde{W}_2}(b)\right)\right), \\ \left(\left(\nu_{\widetilde{W}_1}(b)\right)\left(\nu_{\widetilde{W}_2}(b)\right)\right) \end{pmatrix} b \in B\right\},$$

$$\widetilde{W}_1 \otimes \widetilde{W}_2 = \left\{\begin{pmatrix} \left(\left(\mu_{\widetilde{W}_1}(b)\right)\left(\mu_{\widetilde{W}_2}(b)\right)\right), \\ \left(\left(\eta_{\widetilde{W}_1}(b)\right) + \left(\eta_{\widetilde{W}_2}(b)\right) - \left(\eta_{\widetilde{W}_1}(b)\eta_{\widetilde{W}_2}(b)\right)\right), \\ \left(\left(\nu_{\widetilde{W}_1}(b)\right) + \left(\nu_{\widetilde{W}_2}(b)\right) - \left(\nu_{\widetilde{W}_1}(b)\nu_{\widetilde{W}_2}(b)\right)\right) \end{pmatrix} b \in B\right\},$$

$$m\widetilde{W}\left\{\begin{pmatrix} \left(1 - \left(1 - (\mu_{\widetilde{W}}(b))\right)^m\right), \\ (\eta_{\widetilde{W}}(b))^m, \\ (\nu_{\widetilde{W}}(b))^m \end{pmatrix} b \in B\right\} m > 0,$$

$$\widetilde{W}^m\left\{\begin{pmatrix} (\mu_{\widetilde{W}}(b))^m, \\ \left(1 - \left(1 - (\eta_{\widetilde{W}}(b))\right)^m\right), \\ \left(1 - \left(1 - (\nu_{\widetilde{W}}(b))\right)^m\right) \end{pmatrix} b \in B\right\} m > 0.$$

According to the above principles, Definition 2 is anticipated to conform to the following criteria:
$\widetilde{W}_1 \oplus \widetilde{W}_2 = \widetilde{W}_2 \oplus \widetilde{W}_1$,
$\widetilde{W}_1 \otimes \widetilde{W}_2 = \widetilde{W}_2 \otimes \widetilde{W}_1$,
$m(\widetilde{W}_1 \oplus \widetilde{W}_2) = m\widetilde{W}_1 \oplus m\widetilde{W}_2$， $m > 0$,
$(\widetilde{W}_1 \otimes \widetilde{W}_2)^m = \widetilde{W}_1^m \otimes \widetilde{W}_2^m$， $m > 0$,
$m_1\widetilde{W} \oplus m_2\widetilde{W} = (m_1 + m_2)\widetilde{W}$， $m_1, m_2 > 0$,
$\widetilde{W}^{m_1} \otimes \widetilde{W}^{m_2} = \widetilde{W}^{(m_1+m_2)}$， $m_1, m_2 > 0$

Definition 3: Score Function and Accuracy Function of PFS

Consider a PFS entity $\widetilde{W}$, and let B be established in the universal set. The corresponding components are stated as follows: Then, the score and accuracy functions in the universal set are established.

Score Function $Sc(\widetilde{W})$, It is used to measure the comprehensive proportion of positive and clear information in the PFS entity.

$$Sc(\widetilde{W}) = \frac{1}{3}((\mu_{\widetilde{W}}(b)) + (1 - \eta_{\widetilde{W}}(b)) + (1 - \nu_{\widetilde{W}}(b))); Sc(\widetilde{W}) \in [0,1] \tag{3}$$

Accuracy Function $Ac(\widetilde{W})$: It is used to measure the sum of clear evaluations in the PFS entity. The formula is:

$$Ac(\widetilde{W}) = \mu_{\widetilde{W}}(b) + \nu_{\widetilde{W}}(b); Ac(\widetilde{W}) \in [-1,1] \tag{4}$$

Definition 4: Application Rules

Suppose there are two entities representing PFSs, denoted as $\widetilde{W}_2$, which are instantiated on the universal set. Their respective component descriptions are:
$\widetilde{W}_1 = (\mu_{\widetilde{W}_1}(b), \eta_{\widetilde{W}_1}(b), \nu_{\widetilde{W}_1}(b))$； $\widetilde{W}_2 = (\mu_{\widetilde{W}_2}(b), \eta_{\widetilde{W}_2}(b), \nu_{\widetilde{W}_2}(b))$.

Let $Sc(\widetilde{W}_i)$ and $Ac(\widetilde{W}_i)$ represent the score and accuracy functions of $\widetilde{W}_i = (i = 1,2)$, The rules for establishing the ordinal relationship are:
(1)If $Sc(\widetilde{W}_1) \succ Sc(\widetilde{W}_2)$,then $\widetilde{W}_1 \succ \widetilde{W}_2$,
(2)If $Sc(\widetilde{W}_1) = Sc(\widetilde{W}_2)$and $Ac(\widetilde{W}_1) \succ Ac(\widetilde{W}_2)$,then $\widetilde{W}_1 \succ \widetilde{W}_2$,
(3)If $Sc(\widetilde{W}_1) = Sc(\widetilde{W}_2)$and $Ac(\widetilde{W}_1) = Ac(\widetilde{W}_2)$,then $\widetilde{W}_1 = \widetilde{W}_2$.

3.2 Clarify Decision Boundaries

Alternative Set: $A = \{A_1, A_2, \ldots A_m\}$（m candidate alternatives）

Criterion Set: $C = \{C_1, C_2, \ldots C_n\}$（n evaluation criteria）

Expert Set: $E = \{E_1, E_2, \ldots E_H\}$（H experts participating in the evaluation）

Criterion Weights: The weight vector $\widetilde{w} = (\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_i)$ is determined by the CIMAS method, satisfying $\bar{w}_j \in [0,1]$ and $\sum_{j=1}^{n} \bar{w}_j = 1$.

3.3 Calculate Expert Weights

In a multi-expert decision-making scenario, the weight of each expert must first be determined (reflecting the importance level of the expert). The steps are as follows.

Step 1: Convert Linguistic Variables (LV) to PFS

To determine the expert weights, the linguistic variables (LV) described in Table 1 are first used Table 1 to determine the importance level of experts. Then, the linguistic variables are converted into PFS, and the decision matrix is obtained in the form of PFS.

Table 1 [49]
Expert weights linguistic variables

Linguistic variables	Picture fuzzy sets
Important (I)	(0.600, 0.035, 0.030)
Medium (M)	(0.260, 0.260, 0.260)
Unimportant (UI)	(0.210, 0.270, 0.325)

Step 2: To determine the importance level of experts, the clear value of the h-expert E_h is calculated using the score function as

$$Sc(E_{\hbar}) = \frac{1}{3}\left(\mu_{\hbar} + (1-\eta_{\hbar}) + (1-\nu_{\hbar})\right); (\hbar = 1,2,\dots,H); Sc(E_{\hbar}) \in [0,1]. \quad (5)$$

Step 3: Calculation of Weight Matrix

The weight of expert h is the proportion of their score function value to the sum of all experts' score function values.

$$w_{\hbar} = \frac{Sc(E_{\hbar})}{\sum_{\hbar=1}^{H} Sc(E_{\hbar})}, \sum_{\hbar=1}^{H} w_{\hbar} = 1 \quad (6)$$

In the weight matrix $W^E = \left(w_{\hbar,j}\right)_{H\times n}$, $w_{\hbar,j} = w_{\hbar}$ (that is, the initial weight contribution of each expert to all criteria is their own weight).

3.4 Determine Criterion Weights Using PFS - CIMAS Method

Step 4: Each criterion C_j is evaluated by each expert E_h (using the LVs listed in Table 2). Subsequently, the linguistic variables were converted into PFS. After this conversion, the criterion evaluation matrix was constructed based on the evaluations provided by each expert. Here, $Z = \left(Z_{\hbar,j}\right)_{H\times n}$, $Z_{\hbar,j} = \left(\mu_{\hbar,j}, \eta_{\hbar,j}, \nu_{\hbar,j}\right)(\hbar = 1,2,\dots,H; j = 1,2,\dots,n)$.

Table 2 [49]
Criterion linguistic variables

Linguistic variables	Picture fuzzy sets
Extremely good (EG)	(0.995, 0.000, 0.000)
Very very good (VVG)	(0.825, 0.015, 0.015)
Very good (VG)	(0.755, 0.043, 0.050)
Good (G)	(0.650, 0.131, 0.137)
Medium (M)	(0.260, 0.260, 0.260)
Medium bad (MB)	(0.225, 0.390, 0.263)
Bad (B)	(0.150, 0.400, 0.295)
Very bad (VB)	(0.060, 0.410, 0.400)
Very very bad (VVB)	(0.040, 0.400, 0.400)

Step 5: Calculate the Clear Criterion Evaluation Matrix $Z = \left(Sc\left(Z_{\hbar,j}\right)\right)_{H\times n}$

The clear value $Sc\left(Z_{\hbar,j}\right)$ of the criterion evaluation is calculated using the score function, and the formula is:

$$Sc(Z_{\hbar,j}) = \frac{1}{3}\left(\mu_{\hbar,j} + \left(1-\eta_{\hbar,j}\right) + \left(1-\nu_{\hbar,j}\right)\right); \\ (\hbar = 1,2,\dots,H), (j = 1,2,\dots,n); Sc(Z_{\hbar,j}) \in [0,1] \quad (7)$$

Step 6: Calculate the normalized criterion evaluation matrix $N = \left(n_{\hbar,j}\right)_{d\times n}$.

The formula is:

$$n_{\hbar,j} = \frac{Sc\left(Z_{\hbar,j}\right)}{\sum_{\hbar=1}^{H} Sc\left(Z_{\hbar,j}\right)}, (\hbar = 1,2,\dots,H), (j = 1,2,\dots,n) \quad (8)$$

Step 7: The expert-weighted criterion evaluation matrix $U = (u_{\hbar,j})_{H\times n}$ is obtained by multiplying expert weights with normalized values, and the formula is:

$$u_{\hbar,j} = w_{\hbar} \times n_{\hbar,j}, \hbar = 1,2,\ldots,H; j = 1,2,\ldots,n \tag{9}$$

Step 8: Calculate the Maximum Matrix and the Minimum Matrix

Maximum matrix $M^{+} = (m_j^{+})_{1\times n}$, where $(m_j^{+})_{1\times n} = max_{\hbar}(u_{\hbar,j})$ (10)

Minimum matrix $M^{-} = (m_j^{-})_{1\times n}$, where $(m_j^{-})_{1\times n} = min_{\hbar}(u_{\hbar,j})$ (11)

Step 9: Calculate Difference Matrix $D = (d_j)_{H\times n}$

It represents the difference between the maximum and minimum values, and the formula is

$$d_j = m_j^{+} - m_j^{-}; j = 1,2,\ldots,n \tag{12}$$

When $d_j \geq 0$, the larger d_j is, the greater the divergence in experts' assessment of this criterion. Therefore, a higher weight should be assigned to reflect the importance of divergent criteria.

Step 10: Criterion Weight Matrix$W^{C} = (w_j)_{1\times n}$.

Each element is the proportion of the difference value to the total difference in the same column, and the formula is

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j}; j = 1,2,\ldots,n;\ \sum_{j=1}^{n} w_j = 1;\ w_j \in [0,1] \tag{13}$$

Step 11: Calculate Reliability Index (RI)

Two rounds of evaluation and RI tests are required to verify the consistency of the criterion weighted. In the first round, the initial criterion weight $w_j^{(1)}$ is obtained based on the above steps. In the second round, experts reevaluate the criteria, repeat steps 4 to 10 to obtain the weights of the second-round criteria $w_j^{(2)}$, and calculate the average weight of the second round:

$$\bar{w}_{\hbar,j} = \frac{1}{H}\sum_{h=1}^{H} w_{\hbar,j}^{(2)} \tag{14}$$

The deviation between each expert's weight and the average weight was calculated. Then, the reliability index is expressed as follows:

$$RI = \frac{1}{100}\sum_{j=1}^{n}\left|w_j^{(1)} \times 100 - \bar{w}_j\right| \tag{15}$$

If RI < 0.1, it indicates that the weight consistency is good; If RI ≥ 0.1, the expert assessment is reorganized until the RI meets the requirements.

3.5 Calculate the Ranking of Alternative Schemes Using the PFS - VIKOR Method

Step 12: Criterion Evaluation Matrix of the Scheme Layer $F = (f_{\hbar,i,j})_{H\times m\times n}$

Experts use the Linguistic Variables (LVs) from Table 2 to evaluate each criterion for each HRM module and then convert the LVs into PFSs to obtain the decision matrix in the form of PFS. Then, the scheme evaluation score matrix $Sc = \left(Sc(Z_{\hbar,i,j})\right)_{H\times m\times n}$ is obtained through Eq. (6).

$$f_{\hbar,i,j} = Sc(Z_{\hbar,i,j}) \tag{16}$$

Step 13: Determine Ideal and Anti-ideal Solutions

Ideal solution $f_j^{+} = max_i\, f_{i,j}$ (the maximum score function value of all experts' evaluation for criterion *j*, indicating the best performance of the scheme); Anti-ideal solution $f_j^{-} = min_i\, f_{i,j}$ (the minimum score function value, indicating the worst performance of the scheme).

Integrate to form the ideal solution vector $F^{+} = (f_1^{+}, f_2^{+}, \ldots f_n^{+})$ and the anti-ideal solution vector $F^{-} = (f_1^{-}, f_2^{-}, \ldots f_n^{-})$ for the $H - t\hbar$ expert.

Step 14: Calculate VIKOR Core Indicators and Obtain the Sorting Result

Group utility value S_i: Reflects the comprehensive satisfaction degree of the scheme to all criteria.

$$S_i = \sum_{j=1}^{n} \left(w_j \cdot \frac{f_j^{+} - f_{i,j}}{f_j^{+} - f_j^{-}} \right), S_{\hbar,i} \in [0,1] \tag{17}$$

The smaller the value, the higher the comprehensive satisfaction degree of the scheme is.

Individual regret value R_i: Reflects the maximum regret degree of the scheme on the worst criterion.

$$R_i = max_{j=1}^{n} \left(w_j \cdot \frac{f_j^{+} - f_{i,j}}{f_j^{+} - f_j^{-}} \right), R_i \in [0,1] \tag{18}$$

The smaller the value, the better the performance of the scheme under the worst criterion.

Utility function value Q_i: Linearly combines group utility and individual regret, with a balance coefficient θ= 0.5.

$$Q_i = \theta \cdot \frac{S_i - S^{+}}{S^{-} - S^{-}} + (1 - \theta) \cdot \frac{R_i - R^{+}}{R^{-} - R^{+}};$$
$$S^{+} = min_{i=1}^{m} S_i, S^{-} = max_{i=1}^{m} S_i;$$
$$R^{+} = min_{i=1}^{m} R_i, R^{-} = max_{i=1}^{m} R_i;$$
$$Q_i \in [0,1] \tag{19}$$

The smaller the value, the better the comprehensive performance of the proposed scheme. Sort the schemes in ascending order of Q_i to obtain the personalized sorting result $R_{\hbar} = \left(r_{\hbar,1}, r_{\hbar,2}, \ldots, r_{\hbar,m}\right)$ of the experts.

Step 15: Compute Ranking Score Matrix

For the *H*-th expert's ranking, assign scores such that the 1st-ranked alternative gets m points, the 2nd-ranked gets m-1 points, …, and the *m*-th ranked gets 1 point. Let $r_{\hbar,i}$ be the score of alternative *i* from the *H*-th expert. Construct an *H*×*m* matrix, where each row corresponds to an expert ranking score for all alternatives. The cumulative score for the alternative is the weighted sum of its scores across all experts:

$$C_i = \sum_{\hbar=1}^{H} \left(w_{\hbar} \cdot r_{\hbar,i}\right) \tag{20}$$

This score reflects the overall weighted support for alternatives from the group of experts.

Step 16: Calculate Copeland Score and Generate Comprehensive Ranking

Find maximum cumulative score$C_{max} = maxC_i$ representing the highest cumulative support.

Calculate defeat score:

$$F_i = C_{max} - C_i \tag{21}$$

It measures the gap between the alternative and the most supported alternative.

The net victory score is computed as follows:

$$FRO_i = C_i - F_i \tag{22}$$

A higher FRO_i indicates stronger group support. The alternatives are sorted in descending order of FRO_i to obtain the final cumulative ranking that synthesizes the group consensus.

4. A Numerical Example

4.1 Experts, Criteria, and Modules

To comprehensively evaluate the application effect of GAI in HRM, we invited three experts to score the results. Based on the eight influencing factors given in Section 2, experts scored GAI' s performance in the four key modules of HRM- recruitment, training, performance, and compensation, as shown in Tables 3 to 5. These experts cover fields such as human resource management and artificial intelligence technology research. The aim is to demonstrate the overall impact of the GAI on various aspects of human resource management through these key factors. This is conducive to a deeper understanding of the role of GAI in optimizing HRM processes.

Table 3
Four key modules of HRM

Module	Module name
A_1	Recruitment
A_2	Training
A_3	Performance
A_4	Compensation

Table 4
Eight influencing factors

Criteria	Criteria name
C_1	Generate quality
C_2	Technology
C_3	Compatibility
C_4	Organizational readiness
C_5	Communication
C_6	Ethics
C_7	Privacy
C_8	Benefit

Table 5
The experts' panel

Expert	Professional field	Significance levels
E_1	HRM and GAI Practice	Important (I)
E_2	HRM Practice	Medium (M)
E_3	GAI Risk	Medium (M)

4.2 Evaluating the Application Effect of GAI Using the PFS-CIMAS-VIKOR Hybrid Method

Step 1: Use Table1 to determine expert importance levels to determine the expert weights. The LVs were then transformed into PFSs, as shown in Table 6.

Table 6
Expert weights with picture fuzzy sets

Expert	μ	η	v
E_1	0.600	0.035	0.030
E_2	0.260	0.260	0.260
E_3	0.260	0.260	0.260

Step 2: The computation of the decision matrix, which assessed the priorities of each expert, was achieved through the application of the score function. $Sc(E_{\hbar})$ outlined in Eq. (5).

Step 3: Utilizing the formula provided in Eq. (6), the prioritization matrix $W^E = (w_{\hbar,j})_{H\times n}$ for the experts was computed. The matrix is presented in Table 7.

Table 7
The prioritization matrix

	Sc(Eh)	wh
E_1	0.845	0.421
E_2	0.580	0.289
E_3	0.580	0.289

Step 4: Each expert evaluated each criterion using the LVs provided in Table 2. By transforming LVs into PFSs, the criterion assessment matrix $Z = \left(Z_{\hbar,j}\right)_{H\times n}$ was obtained. The matrix is presented in Table 8.

Table 8
Criterion assessment matrix with picture fuzzy sets

	C_1			C_2			C_3			C_4		
	μ	η	v	μ	η	v	μ	η	v	μ	η	v
E_1	0.995	0.000	0.000	0.825	0.015	0.015	0.650	0.131	0.137	0.650	0.131	0.137
E_2	0.825	0.015	0.015	0.755	0.043	0.050	0.650	0.131	0.137	0.650	0.131	0.137
E_3	0.755	0.043	0.050	0.755	0.043	0.050	0.755	0.043	0.050	0.755	0.043	0.050
	C_5			C_6			C_7			C_8		
	μ	η	v	μ	η	v	μ	η	v	μ	η	v
E_1	0.755	0.043	0.050	0.825	0.015	0.015	0.755	0.043	0.050	0.825	0.015	0.015
E_2	0.825	0.015	0.015	0.755	0.043	0.050	0.755	0.043	0.050	0.755	0.043	0.050
E_3	0.755	0.043	0.050	0.825	0.015	0.015	0.995	0.000	0.000	0.825	0.015	0.015

Step 5: Utilizing Eq. (7), the crisp criterion assessment matrix was calculated by employing the score function $Sc(Z_{\hbar,j})$. The matrix is presented in Table 9.

Step 6: Utilizing Eq. (8), the normalized matrix reflecting the assessment of criteria $N = \left(n_{\hbar,j}\right)_{d\times n}$ was calculated.

Step 7: Utilizing Eq. (9), the matrix reflecting the expert-weighted assessment of criteria $U = \left(u_{\hbar,j}\right)_{H\times n}$ was calculated.

Step 8: Utilizing Eq. (10) and Eq. (11), the matrices denoting the maximum values $M^{+} = \left(m_j^{-}\right)_{1\times n}$ and the minimum values $M^{-} = \left(m_j^{-}\right)_{1\times n}$ were sequentially determined.

Step 9: Utilizing Eq. (12), the computation of the matrix indicating the disparities between the minimum and maximum values $D = \left(d_j\right)_{H\times n}$ was performed.

Step 10: Utilizing Eq. (13), the calculation of the criteria weight matrix $W^C = \left(w_j\right)_{1\times n}$ was executed (Table 10).

Step 11: In the second round, the experts evaluated the criteria as a percentage. The evaluations in percentage are presented in Table 11. Subsequently, the criterion weights matrix $w_j^{(2)}$ was calculated. Then, the RI index was computed using Eq. (15) and presented in Table 11. RI was below 0.1.

Table 9
The score function matrix

		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
$Sc(Z_{h,j})$	E_1	0.998	0.932	0.794	0.794	0.887	0.932	0.887	0.932
	E_2	0.932	0.887	0.794	0.794	0.932	0.887	0.887	0.887
	E_3	0.887	0.887	0.887	0.887	0.887	0.932	0.998	0.932
$n_{h,j}$	E_1	0.354	0.344	0.321	0.321	0.328	0.339	0.320	0.339
	E_2	0.331	0.328	0.321	0.321	0.344	0.323	0.320	0.323
	E_3	0.315	0.328	0.358	0.358	0.328	0.339	0.360	0.339
$u_{h,j}$	E_1	0.149	0.145	0.135	0.135	0.138	0.143	0.135	0.143
	E_2	0.096	0.095	0.093	0.093	0.100	0.093	0.093	0.093
	E_3	0.091	0.095	0.104	0.104	0.095	0.098	0.104	0.098

Table 10
The criteria weight matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
m_j+	0.149	0.145	0.135	0.135	0.138	0.143	0.135	0.143
m_j-	0.091	0.095	0.093	0.093	0.095	0.093	0.093	0.093
d_j	0.058	0.050	0.042	0.042	0.043	0.049	0.042	0.049
w_j	0.153	0.132	0.112	0.112	0.114	0.130	0.111	0.130

Table 11
The second-round criterion weights matrix

Experts	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
E_1	14	13	11	12	11	13	13	13
E_2	15	13	12	10	14	12	12	12
E_3	15	11	14	9	12	13	15	11
w_j^2	14.667	12.333	12.333	10.333	12.333	12.667	13.333	12.000
$100w_j$-w_j^2	0.681	0.908	-1.159	0.890	-0.912	0.361	-2.186	1.028
RI	0.082175303							

Step 12: Each expert evaluated each criterion using the lv values provided in Table 2, and the evaluation results are presented in Table 12. Then, lv was converted to PFSs and calculated using the score function. Calculate the criterion evaluation matrix of the scheme layer using Eq. (16) and presented in Table 13.

Step 13: Calculate the ideal and anti-ideal solutions presented in Tables 13 to 15.

Step 14: Use Eq. (17) to (19) to calculate as S_i, R_i and Q_i presented in Table 16.

Step 15: Use Eq. (20) to compute ranking score matrix presented in Table 16.

Step 16: Use Eq. (22) to compute net victory score. The final rank is then obtained.

Table 12
Experts scored the GAI' s performance using eight criteria in the four key modules

Criteria	E_1				E_2				E_3			
	A_1	A_2	A_3	A_4	A_1	A_2	A_3	A_4	A_1	A_2	A_3	A_4
C_1	G	VG	MB	VVG	M	G	M	VG	MB	M	G	EG
C_2	VG	G	VVG	VG	G	G	G	G	MB	MB	VVG	VVG
C_3	VG	B	EG	VG	G	VG	VG	VG	G	EG	G	VG
C_4	M	B	VVG	M	G	M	G	G	M	G	G	M
C_5	VVG	G	MB	EG	M	M	M	VG	G	MB	M	M
C_6	B	MB	B	VVG	G	VG	G	VG	MB	M	G	G
C_7	M	VG	VG	MB	G	VG	G	VG	VG	G	VG	G
C_8	MB	VVG	M	VG	VG	G	G	G	G	G	G	VG

Table 13
The criterion evaluation matrix of the solution layer made by E_1

E_1	A_1	A_2	A_3	A_4	f+	f-
C_1	0.794	0.887	0.524	0.932	0.932	0.524
C_2	0.887	0.794	0.932	0.887	0.932	0.794
C_3	0.887	0.485	0.998	0.887	0.998	0.485
C_4	0.580	0.485	0.932	0.580	0.932	0.485
C_5	0.932	0.794	0.524	0.998	0.998	0.524
C_6	0.485	0.524	0.485	0.932	0.932	0.485
C_7	0.580	0.887	0.887	0.524	0.887	0.524
C_8	0.524	0.932	0.580	0.887	0.932	0.524

Table 14
Criterion evaluation matrix of the solution layer made by E_2

E_2	A_1	A_2	A_3	A_4	f+	f-
C_1	0.580	0.794	0.580	0.887	0.887	0.580
C_2	0.794	0.794	0.794	0.794	0.794	0.794
C_3	0.794	0.887	0.887	0.887	0.887	0.794
C_4	0.794	0.580	0.794	0.794	0.794	0.580
C_5	0.580	0.580	0.580	0.887	0.887	0.580
C_6	0.794	0.887	0.794	0.887	0.887	0.794
C_7	0.794	0.887	0.794	0.887	0.887	0.794
C_8	0.887	0.794	0.794	0.794	0.887	0.794

Table 15
Criterion evaluation matrix of the solution layer made by E_3

E_3	A_1	A_2	A_3	A_4	f+	f-
C_1	0.524	0.580	0.794	0.998	0.998	0.524
C_2	0.524	0.524	0.932	0.932	0.932	0.524
C_3	0.794	0.998	0.794	0.887	0.998	0.794
C_4	0.580	0.794	0.794	0.580	0.794	0.580
C_5	0.794	0.524	0.580	0.580	0.794	0.524
C_6	0.524	0.580	0.794	0.794	0.794	0.524
C_7	0.887	0.794	0.887	0.794	0.887	0.794
C_8	0.794	0.794	0.794	0.887	0.887	0.794

Table 16
The final rank

	A_1	A_2	A_3	A_4
Si	0.580	0.543	0.513	0.282
	0.624	0.405	0.643	0.131
	0.773	0.730	0.400	0.376
Ri	0.131	0.133	0.154	0.112
	0.154	0.131	0.154	0.131
	0.154	0.136	0.131	0.112
Qi	0.724	0.687	0.887	0.000
	0.982	0.268	1.000	0.000
	1.000	0.729	0.253	0.000
ranking score	2.000	3.000	1.000	4.000
	2.000	3.000	1.000	4.000
	1.000	2.000	3.000	4.000
sum	1.711	2.711	1.579	4.000
final rank	3	2	4	1

5. Results and Implications

In this study, to explore the application of GAI in HRM, eight standards were identified, and the PFS-CIMAS-VIKOR model was developed. According to the research results, the ranking of the standard weight importance is as follows:

"Generate quality" C1 > "Technology" C2 > "Ethics" C6 > "Benefit" C8 > "Communication" C5 > "Compatibility" C3 > "Organizational readiness" C4 > "Privacy" C7

In the numerical study, four main HRM modules were identified. When evaluating the application effect of GAI in these four modules, the importance level of experts and the weight of standards were comprehensively considered. The final ranking of the module applications is as follows:

"Compensation" A4 > "Training" A2 > "Recruitment" A1 > "Performance" A3

5.1 Sensitivity Analyses

Sensitivity analysis scenarios (SAS) were formulated within the scope of robustness testing for the research findings and the PFS-CIMAS-VIKOR hybrid model. These SAS examined variations in module rankings under different conditions. Three main SAS were created for the sensitivity analyses as follows:

SAS-1 – When the importance levels of the experts are assumed to be equal, how is the module ranking obtained when PFS-CIMAS-VIKOR is applied?

SAS-2 – θ is the balance coefficient between group utility and individual regret in VIKOR, with a value range of 0.1 to 0.9 (step size 0.1), consisting of nine sets of parameters. Observe whether the module sorting remains stable when θ changes.

The application results of the two scenarios identified above are as follows.

SAS-1 – When the expert weights are equal, the best module remains the same. The research results are presented in Figure 1.

SAS-2: As shown in Figure 2, when the value of θ changes, the proposed module remains robust.

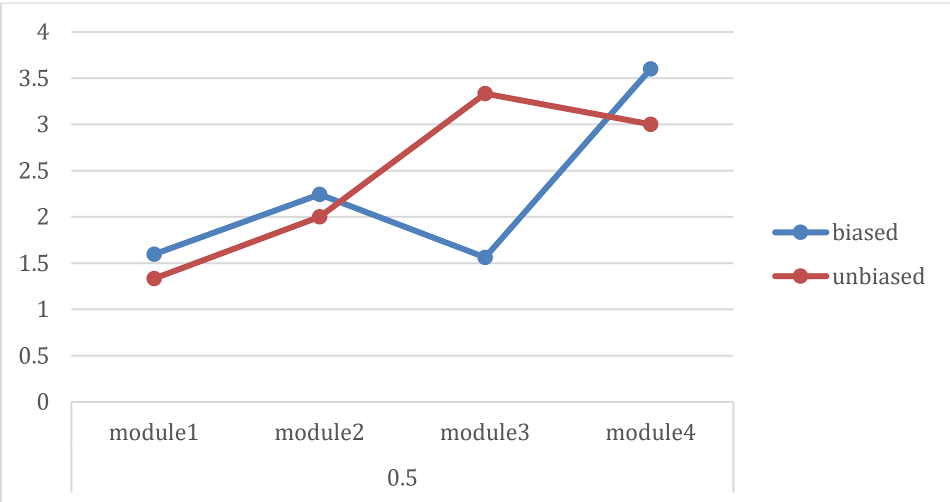

Fig. 1. Sensitivity analysis of criteria weights

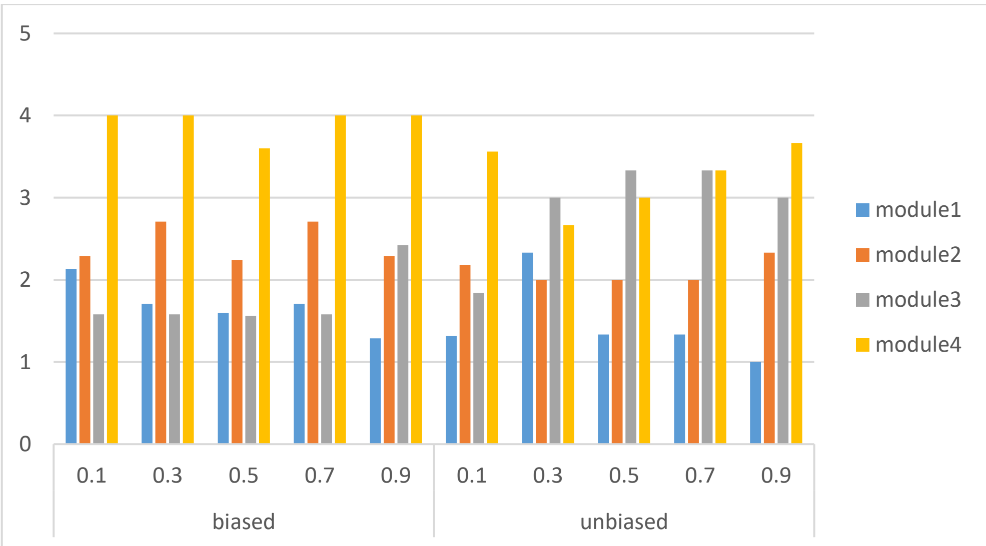

Fig. 2. Sensitivity analysis of criteria weights and strategy values

5.2 Research Implications

This study focuses on the decision-making issue of applying GAI to various modules of enterprise HRM and proposes a PFS-CIMAS-VIKOR hybrid model based on Picture Fuzzy Sets to provide system decision support for enterprises to apply GAI tools in the main HRM modules.

The research finds that traditional HRM tool evaluation methods struggle to handle experts' fuzzy linguistic evaluations of GAI tools, which easily leads to subjective biases that affect decision-making effectiveness. The PFS-CIMAS-VIKOR model addresses this issue. First, it transforms the qualitative language variables of experts into PFS, which include positive, neutral, and negative membership. Second, the fuzzy evaluation is quantified into computable values through the fractional function, which retains the expert experience while reducing the interference of fuzziness. Then, through a two-stage evaluation and reliability test of the CIMAS method, it was ensured that the weight distribution of the evaluation criteria of the GAI tool not only meets the actual human resource management needs but also has statistical stability. Finally, the personalized preferences of experts for different HRM modules are integrated through the VIKOR method, the adaptability of the tools to each module is calculated and ranked, and the optimal application scheme is determined.

Case verification showed that this module has high applicability and robustness in the selection of GAI tools for the human resource management module. In sensitivity analysis scenarios, such as different expert weight allocations and standard priority adjustments, the ranking results of the optimal tool remain consistent, which can effectively distinguish the adaptability differences of different tools in various human resource management modules.

5.3 Managerial Implications

HR managers can use the PFS-CIMAS-VIKOR model as a standardized process for selecting generative artificial intelligence tools. In actual operation, a cross-functional expert team should be formed, the core assessment criteria for each module should be clarified, and a phased application plan should be formulated based on the tool ranking results output by the model. The model can help enterprises align the application of generative artificial intelligence with their HRM strategic goals. For instance, if an enterprise's strategy focuses on "precise talent recruitment", it can prioritize enhancing the tool compatibility of the recruitment module based on the model. If the strategy focuses on "employee capability enhancement", then the key is to optimize the selection of tools for the training module to ensure that technological investment is closely related to business goals.

6. Conclusions

This study explored the decision-making needs for applying generative artificial intelligence within the scope of human resource management through expert scoring. The PFS CIMAS-VIKOR hybrid model proposed in this study provides a robust framework for generative artificial intelligence applications. The reliability of the criterion selection process was enhanced through a two-stage criterion evaluation and reliability testing of the criterion weights. The PFS-VIKOR method achieved successful results for the evaluation of GAI' s application in HRM. Expert opinions were used as evaluation criteria, and their weights were obtained using PFSs. The gradual development process of the PFS-CIMAS-VIKOR hybrid method is introduced, and an algorithm for a specific model is proposed. The robustness of the algorithm was tested through a numerical study, and the results verified the reliability of the decision analysis algorithm.

Although this study provides valuable insights into the development of decision support systems that apply GAI in human resource management, certain limitations must be acknowledged. First, the universality of the research results may be limited by the specific background and characteristics of the selected case studies. The results and proposed hybrid approach may be influenced by factors such as the type of industry and company size. Second, relying on expert opinions to evaluate standards and derive weights introduces subjective factors into the decision-making process. The effectiveness of a decision support system depends on the accuracy and relevance of the expert judgments. Finally, although the proposed PFS-CIMAS-VIKOR hybrid model has demonstrated robustness in ongoing case studies, it may require further validation in different industries and organizational environments. Acknowledging these limitations is crucial for accurately interpreting research results and provides opportunities for future research to address these limitations and improve the proposed decision-support systems.

As part of future research, the limitations of the proposed tool will be addressed first. Conduct experiments on the model in multiple enterprises to study its practical utility. Subsequently, industry-specific guidelines can be supplemented based on the human management characteristics of vertical industries to enhance the model's application value in specific fields. To reduce the subjective reliance of experts, big data technology can be utilized to collect the actual application data of generative artificial intelligence in enterprise human resource management in the market, convert it into supplementary evaluation information in the form of PFS, and combine it with the expert evaluation results to form a dual evaluation model that combines expert experience with objective data, further enhancing the objectivity and reliability of the evaluation results.

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Conflicts of Interest
The authors declare no conflicts of interest.

References
[1] Liu, Y., Abdul Rahman, A., Amin, S. I. M., & Ja'afar, R. (2023). How does digital finance affect sustainable economic growth? Evidence from China. *Environmental Science and Pollution Research, 30*(46), 103164-103178. https://doi.org/10.1007/s11356-023-29496-4
[2] Iansiti, M., & Lakhani, K. R. (2020). *Competing in the age of AI: Strategy and leadership when algorithms and networks run the world*. Harvard Business Press. https://doi.org/10.1080/09700161.2021.1918951
[3] Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *The Journal of Strategic Information Systems, 29*(2), 101614. https://doi.org/10.1016/j.jsis.2020.101614
[4] Prasad, K. D. V., & De, T. (2024). Generative AI as a catalyst for HRM practices: mediating effects of trust. *Humanities and Social Sciences Communications, 11*(1), 1-16. https://doi.org/10.1057/s41599-024-03842-4
[5] Chilunjika, A., Intauno, K., & Chilunjika, S. R. (2022). Artificial intelligence and public sector human resource management in South Africa: Opportunities, challenges and prospects. *SA Journal of Human Resource Management, 20*, 1972. https://doi.org/10.4102/sajhrm.v20i0.1972
[6] Malik, N., Tripathi, S. N., Kar, A. K., & Gupta, S. (2021). Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower, 43*(2), 334-354. https://doi.org/10.1108/IJM-03-2021-0173
[7] Aspan, H. (2020). Individual characteristics and job characteristics on work effectiveness in the state-owned company: the moderating effect of emotional intelligence. *International Journal of Innovation, Creativity and Change, 13*(6), 761-774.
[8] Singh, A., & Shaurya, A. (2021). Impact of Artificial Intelligence on HR practices in the UAE. *Humanities and Social Sciences Communications, 8*(1), 1-9. https://doi.org/10.1057/s41599-021-00995-4
[9] Michel-Villarreal, R., Vilalta-Perdomo, E., Salinas-Navarro, D. E., Thierry-Aguilera, R., & Gerardou, F. S. (2023). Challenges and opportunities of generative AI for higher education as explained by ChatGPT. *Education Sciences, 13*(9), 856. https://doi.org/10.3390/educsci13090856
[10] Taulli, T. (2023). *Generative AI: How ChatGPT and other AI tools will revolutionize business*. Apress. https://doi.org/10.1007/978-1-4842-9367-6

[11] Patel, N. S., & Lim, J. T. H. (2025). Critical design futures thinking and GenerativeAI: a Foresight 3.0 approach in higher education to design preferred futures for the industry. *foresight, 27*(2), 380-402. https://doi.org/10.1108/fs-11-2023-0228
[12] Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307-320. https://doi.org/10.1177/109467050024001
[13] Bonomi Savignon, A., Zecchinelli, R., Costumato, L., & Scalabrini, F. (2024). Automation in public sector jobs and services: a framework to analyze public digital transformation's impact in a data-constrained environment. *Transforming Government: People, Process and Policy, 18*(1), 49-70. https://doi.org/10.1108/TG-04-2023-0044
[14] Huang, L., Yu, W., Ma, W., Zhong, W., Feng, Z., Wang, H., ... & Liu, T. (2025). A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. *ACM Transactions on Information Systems, 43*(2), 1-55. https://doi.org/10.1145/3703155
[15] Andrieux, P., Johnson, R. D., Sarabadani, J., & Van Slyke, C. (2024). Ethical considerations of generative AI-enabled human resource management. *Organizational Dynamics, 53*(1), 101032. https://doi.org/10.1016/j.orgdyn.2024.101032
[16] Abdelhay, S., AlTalay, M. S. R., Selim, N., Altamimi, A. A., Hassan, D., Elbannany, M., & Marie, A. (2025). The impact of generative AI(ChatGPT)on recruitment efficiency and candidate quality: the mediating role of process automation level and the moderating role of organizational size. *Frontiers in Human Dynamics, 6*, 1487671. https://doi.org/10.3389/fhumd.2024.1487671
[17] Kim, S., Khoreva, V., & Vaiman, V. (2025). Strategic human resource management in the era of algorithmic technologies: key insights and future research agenda. *Human Resource Management, 64*(2), 447-464. https://doi.org/10.1002/hrm.22268
[18] Brown, O., Davison, R. M., Decker, S., Ellis, D. A., Faulconbridge, J., Gore, J., ... & Hibbert, P. (2024). Theory-driven perspectives on generative artificial intelligence in business and management. *British Journal of Management, 35*(1), 3-23. https://doi.org/10.1111/1467-8551.12788
[19] Cuong, B. C., & Kreinovich, V. (2013). Picture fuzzy sets-a new concept for computational intelligence problems. *Journal of Computational Science and Cybernetics, 30*(4), 409-409. https://doi.org/10.15625/1813-9663/30/4/5032
[20] Le, H. P., & Son, N. T. (2021). Some operations on picture fuzzy sets and their applications. *Journal of Intelligent & Fuzzy Systems, 41*(3), 3307-3317. https://doi.org/10.3233/JIFS-201056
[21] Bošković, S., et al. (2023). A New Criteria Importance Assessment (CIMAS)Method In Multi-Criteria Group Decision-Making. *Facta Universitatis, Series: Mechanical Engineering*. https://doi.org/10.22190/FUME230730050B
[22] Opricovic, S. (1998). Multicriteria optimization of civil engineering systems. *Faculty of Civil Engineering, Belgrade, 2*(1), 5-21.
[23] Opricović, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research, 156*(2), 445-455. https://doi.org/10.1016/S0377-2217(03)00020-7
[24] Carlsson, C. (1982). Tackling an MCDM-problem with the help of some results from fuzzy set theory. *European Journal of Operational Research, 10*(3), 270-281. https://doi.org/10.1016/0377-2217(82)90226-0
[25] Dursun, M., & Karsak, E. E. (2010). A fuzzy MCDM approach for personnel selection. *Expert Systems with Applications, 37*(6), 4324-4330. https://doi.org/10.1016/j.eswa.2009.11.067
[26] Park, H. E. (2024). The double-edged sword of generative artificial intelligence in digitalization: An affordances and constraints perspective. *Psychology & Marketing, 41*(11), 2924-2941. https://doi.org/10.1002/mar.22094
[27] Malik, A., Budhwar, P., Mohan, H., & NR, S. (2023). Employee experience–the missing link for engaging employees: Insights from an MNE's AI-based HR ecosystem. *Human Resource Management, 62*(1), 97-115. https://doi.org/10.1002/hrm.22133
[28] Ali, H., & Aysan, A. F. (2025). Ethical dimensions of generative AI: a cross-domain analysis using machine learning structural topic modeling. *International Journal of Ethics and Systems, 41*(1), 3-34. https://doi.org/10.1108/IJOES-04-2024-0112
[29] Surianarayanan, C., Lawrence, J. J., Chelliah, P. R., Prakash, E., & Hewage, C. (2023). A survey on optimization techniques for edge artificial intelligence (AI). *Sensors, 23*(3), 1279. https://doi.org/10.3390/s23031279
[30] Bansal, A., Padappayil, R. P., Garg, C., Singal, A., Gupta, M., & Klein, A. (2020). Utility of artificial intelligence amidst the COVID 19 pandemic: a review. *Journal of Medical Systems, 44*(9), 156. https://doi.org/10.1007/s10916-020-01617-3
[31] Xu, S., Kee, K. F., Li, W., Yamamoto, M., & Riggs, R. E. (2024). Examining the diffusion of innovations from a dynamic, differential-effects perspective: A longitudinal study on AI adoption among employees. *Communication Research, 51*(7), 843-866. https://doi.org/10.1177/00936502231191832

[32] Liang, Y., Qi, G., Wei, K., & Chen, J. (2017). Exploring the determinant and influence mechanism of e-Government cloud adoption in government agencies in China. *Government Information Quarterly, 34*(3), 481-495. https://doi.org/10.1016/j.giq.2017.06.002

[33] Zhou, Z., Liu, D., Chen, Z., & Pancho, M. (2025). Government adoption of generative artificial intelligence and ambidextrous innovation. *International Review of Economics & Finance, 98*(C). https://doi.org/10.1016/j.iref.2025.103953

[34] Zazon, D., Fink, L., Gordon, S., & Nissim, N. (2023). Can NeuroIS improve executive employee recruitment? Classifying levels of executive functions using resting state EEG and data science methods. *Decision Support Systems, 168*, 113930. https://doi.org/10.1016/j.dss.2023.113930

[35] wael AL-khatib, A. (2023). Drivers of generative artificial intelligence to fostering exploitative and exploratory innovation: A TOE framework. *Technology in Society, 75*, 102403. https://doi.org/10.1016/j.techsoc.2023.102403

[36] Holm, A. B. (2012). E-recruitment: Towards an ubiquitous recruitment process and candidate relationship management. *German Journal of Human Resource Management, 26*(3), 241-259. https://doi.org/10.1177/239700221202600303

[37] Lokuge, S., Sedera, D., Grover, V., & Dongming, X. (2019). Organizational readiness for digital innovation: Development and empirical calibration of a construct. *Information & Management, 56*(3), 445-461. https://doi.org/10.1016/j.im.2018.09.001

[38] Lutfi, A., Alrawad, M., Alsyouf, A., Almaiah, M. A., Al-Khasawneh, A., Al-Khasawneh, A. L., ... & Ibrahim, N. (2023). Drivers and impact of big data analytic adoption in the retail industry: A quantitative investigation applying structural equation modeling. *Journal of Retailing and Consumer Services, 70*, 103129. https://doi.org/10.1016/j.jretconser.2022.103129

[39] Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

[40] Weiner, B. J. (2020). A theory of organizational readiness for change. In *Handbook on implementation science* (pp. 215-232). Edward Elgar Publishing. https://doi.org/10.1186/1748-5908-4-67

[41] Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior, 45*(2), 159-182. https://doi.org/10.1002/job.2735

[42] Marchena Sekli, G., & Portuguez-Castro, M. (2025). Fostering entrepreneurial success from the classroom: Unleashing the potential of generative AI through technology-to-performance chain. A multi-case study approach. *Education and Information Technologies*, 1-29. https://doi.org/10.1007/s10639-025-13316-y

[43] Jarrahi, M. H., Lutz, C., Boyd, K., Oesterlund, C., & Willis, M. (2023). Artificial intelligence in the work context. *Journal of the Association for Information Science and Technology, 74*(3), 303-310. https://doi.org/10.1002/asi.24730

[44] Wang, Q., Ji, X., & Zhao, N. (2024). Embracing the power of AI in retail platform operations: Considering the showrooming effect and consumer returns. *Transportation Research Part E: Logistics and Transportation Review, 182*, 103409. https://doi.org/10.1016/j.tre.2023.103409

[45] Yang, L., He, J., & Shi, W. (2025). Application of artificial intelligence: Equilibrium analysis of e-commerce platform supply chain sales formats. *Electronic Commerce Research*, 1-31. https://doi.org/10.1007/s10660-025-10016-0

[46] Cuong, B. C., & Kreinovich, V. (2013). Picture fuzzy sets-a new concept for computational intelligence problems. In *2013 Third World Congress on Information and Communication Technologies (WICT 2013)* (pp. 1-6). IEEE. https://doi.org/10.1109/WICT.2013.7113099

[47] Wei, G. (2017). Some cosine similarity measures for picture fuzzy sets and their applications to strategic decision making. *Informatica, 28*(3), 547-564. https://doi.org/10.15388/Informatica.2017.144

[48] Ambrin, R., Ibrar, M., De La Sen, M., Rabbi, I., & Khan, A. (2021). Extended TOPSIS method for supplier selection under picture hesitant fuzzy environment using linguistic variables. *Journal of Mathematics, 2021*(1), 6652586. https://doi.org/10.1155/2021/665258