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Assessing organizational efficiency in AI-based GHRM using fuzzy SWARA and MOORA mathematical modeling

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Introduction: This study explores the shift in Green Human Resource Management (GHRM) through Artificial Intelligence (AI) adoption by looking at sustainability-driven practices and assessing how they affect organizational eco-efficiency in six different companies in order to run them efficiently and effectively. This research paper evaluates the efficiency of six companies in implementing AI-GHRM practices using ten key criteria.

Methods: To ensure a robust and structured decision-making process under conditions of uncertainty, two prominent fuzzy Multi-Criteria Decision-Making (MCDM) mathematical modeling—Fuzzy Step-wise Weight Assessment Ratio Analysis (F-SWARA) and Fuzzy Multi-Objective Optimization on the basis of Ratio Analysis (F-MOORA) are applied in a fuzzy environment. Applying linguistic factors to account for the subjectivity and ambiguity of human evaluations, the SWARA approach is used to calculate the relative relevance of the ten AI-GHRM criteria based on buying managers' judgments expressed in terms of triangular fuzzy numbers. These criteria weights are then used in the fuzzy MOORA mathematical modeling method to rank the companies in terms of their overall efficiency in AI-GHRM adoption.

Results and discussions: The results provide a comprehensive ranking of the companies, highlighting best practices and offering insights into strategic areas for improvement. This paper offers a unique hybrid paradigm for performance evaluation under fuzzy settings, advancing both academic and practical knowledge of sustainable HRM integration with AI technology. The findings of the paper are that the fifth company was placed first.

KEYWORDS

green human resource management (GHRM), artificial intelligence (AI), fuzzy stepwise weight assessment ratio analysis (F-SWARA), fuzzy multi-objective optimization ratio analysis (F-MOORA), AI-GHRM adoption

1 Introduction

GHRM is based on the convergence of environmental sustainability and human resource management. It evolved in response to the growing global awareness of environmental degradation and the realization that organizational behavior plays a critical role in advancing sustainable practices. In the latter half of the 20th century, the concept of GHRM started to take shape. Around the world, environmental movements grew rapidly in the 1970s and 1980s.

Events like the Brundtland Report in 1987 and the Stockholm United Nations Conference on the Human Environment in 1972 introduced the concept of "sustainable development" to the global community.

By the 1990s, businesses had started integrating sustainability into their operations as a result of stakeholder expectations, regulatory requirements, and growing knowledge of the financial benefits of sustainable practices. CSR, or corporate social responsibility, became quite popular at this time. Academics and professionals understood that achieving environmental goals required workforce-driven organizational and cultural changes in addition to technological developments. Consequently, it became evident that Human Resource Management (HRM) may have an impact on employees' attitudes and actions towards sustainability.

Companies began implementing GHRM by integrating environmentally friendly practices into routine Human Resource (HR) functions. These basically are: Green Recruitment, which emphasizes the company's environmental goals throughout the hiring process to attract candidates that value sustainability. For instance, Patagonia emphasizes their environmental commitment to attract eco-conscious personnel. Another practice is green training and development that involves teaching employees to be environmentally friendly, namely procurement, waste reduction, and energy saving. Such as, Toyota trains its employees on ecologically friendly and energy-efficient production techniques. Green performance management is the next one which includes incorporating environmental performance. For instance, the plan of Marks & Spencer is to take initiative to link employee success to environmental aims. The last one is green compensation and rewards which is related to offering incentives, prizes, or recognition for achieving sustainability goals. For instance, Google offers rewards to its employees for eco-friendly innovations and sustainable activities.

Green workplace projects involve implementing workplace strategies such as energy-efficient buildings, remote work options, and waste management programs. To cut carbon footprints, Unilever, for instance, has promoted flexible work arrangements and implemented green workplace designs. These initiatives often involve eco-friendly and incorporating environmental performance indicators into assessments. In the era while AI is transforming businesses, integrating AI into GHRM is turning into a strategic endeavor to advance sustainability and operational efficiency. The use of advanced technology in GHRM aims to optimize organizational processes, employee engagement, and environmental responsibility. Successful implementation requires careful consideration of multiple components to ensure sustainability and long-term benefits.

Another factor influencing the adoption of AI in GHRM is the availability of technological infrastructure. Implementing AI requires a robust foundation that includes advanced computer systems, cloud-based solutions, and high-speed internet connectivity. Without adequate infrastructure, the deployment of AI becomes challenging, even though advanced technologies enhance the effectiveness of AI in automating GHRM processes such as eco-friendly recruitment, training, and workforce management. The cost of implementation is another critical consideration. The initial investment in AI-covering licensing, maintenance, and customization-can be substantial, posing a challenge for small or resource-constrained organizations. The scalability and cost-effectiveness of AI technologies significantly influence their adoption. Furthermore, ongoing expenses related to system upkeep, data management, and adherence to ethical standards add to the total cost of ownership. Although AI has the potential to offer long-term benefits in terms of efficiency and sustainability, the high initial costs often delay or limit its integration into HR practices aimed at environmental responsibility (1). This cost factor is especially relevant when examining how AI adoption varies across organizations of different sizes and resource levels. While modern digital HR solutions promise long-term advantages, small and medium-sized enterprises (SMEs) may struggle to afford them due to high installation costs. In contrast, larger companies with more financial resources are typically better positioned to absorb initial expenditures and benefit from economies of scale.

Within the fuzzy SWARA-MOORA framework used in the study, cost of implementation is treated as a non-beneficial criterion, meaning lower costs are preferred when evaluating organizational efficiency. By assigning fuzzy linguistic values to cost perceptions and converting them into crisp scores, the model ensures a more accurate and nuanced evaluation of cost-efficiency. This approach allows organizations with lower relative AI implementation expenses to be ranked more favorably, reflecting their efficient use of resources in adopting AI technologies. This aligns with practical realities, where organizations seek to optimize resource allocation while advancing green HR objectives. Moreover, this criterion contributes to a holistic understanding of AI-GHRM performance by complementing other beneficial criteria such as technological infrastructure, employee acceptance, and ROI. Including cost as a formalized criterion in the Fuzzy MCDM model ensures that economic feasibility is integrated with sustainability and technological capability, thereby supporting a balanced and realistic evaluation of AI-driven GHRM strategies.

AI requires vast amounts of accurate, relevant, and high-quality data to make informed decisions. In the context of GHRM, this includes well-organized data on energy consumption, employee behavior, and environmental impact. Poor data quality can lead to inaccurate outcomes and ineffective AI models. Another critical factor influencing AI adoption is leadership and organizational culture. The support of innovative cultures and proactive leadership plays a crucial role in driving AI initiatives. Leaders must endorse AI implementation and ensure it aligns with the goals of green HRM (2). Resistance to change or a lack of clear vision can delay implementation, whereas leaders who advocate for both sustainability and digital transformation act as key facilitators in aligning AI efforts with environmental objectives. Further consideration is employee acceptance and understanding. Employees need to comprehend how AI contributes to sustainability goals and how it affects their roles. Without adequate training and clear communication, there may be resistance to adopting AI or fear of job displacement, which can hinder successful integration.

Another challenge in adopting AI in GHRM is ensuring privacy and ethical compliance. Since AI in GHRM deals with sensitive environmental and personnel data, it raises significant concerns regarding data security and ethical usage. Companies must ensure that AI applications do not result in bias, misuse, or violations of privacy regulations. Additionally, the nature and characteristics of industry play a role in how AI is utilized within GHRM. Different industries adopt AI in unique ways industrial firms, for example, may use AI to manage their workforce in a more energy-efficient manner, while service-based industries might implement AI to monitor remote employees' adherence to sustainability goals. The suitability of GHRM strategies significantly influences the use of AI. Furthermore, the legal and regulatory framework is another crucial component. To guarantee that AI-driven GHRM is in line with both organizational sustainability objectives and fundamental human rights, ethical governance, transparency, and data protection rules are crucial (3, 4).

Governments and regulatory bodies may impose rules related to GHRM and AI, including compliance with environmental standards and data protection laws. Adherence to these regulations can either support or hinder the adoption of AI, depending on how restrictive or enabling they are. Another key factor is technological knowledge and proficiency. Successful implementation of AI in GHRM requires skilled personnel capable of designing, developing, and managing AI systems. A lack of technical expertise can slow down adoption and increase reliance on external vendors. Finally, the perceived advantages and return on investment (ROI) play a significant role in influencing AI adoption in GHRM. Organizations evaluate AI initiatives based on their potential to deliver measurable outcomes and support green HRM goals. When the perceived benefits such as reduced carbon emissions, cost savings, and enhanced employee engagement—outweigh the potential drawbacks, companies are more likely to invest in and implement AI solutions.

Fuzzy theory is the best way to resolve the ambiguity of concepts pertaining to people's opinion, typically incorrect assessments. Through language considerations, it is the easiest method by which we can easily understand these subjective assessments. Linguistic terms are useful for addressing problems that are either too complicated or inadequately defined. Triangular as well as trapezoidal fuzzy numerals are the most often utilized fuzzy numbers in both theory and application. TFNs make calculation easier. Thus, in this study, the language components are represented as TFNs. The study's objective is to estimate the best as well as the worst company based on linguistic concepts using F-SWARA and F-MOORA through TFNs. This will be advantageous to the business's management.

The primary purpose of this research is to examine how AI-based GHRM techniques influence organizational sustainability. The study aims to explore the integration of AI technologies into various GHRM processes, including recruitment, training, performance appraisal, and employee engagement, to enhance both operational efficiency and environmental responsibility. It investigates the factors that influence, hinder, or result from the adoption of AI in GHRM, offering insights into how organizations can leverage AI to meet their sustainability objectives while maintaining effective HR practices. Additionally, the research seeks to contribute to the understanding of the interconnections between AI, sustainability, and human resource management, both in academic discourse and practical application.

The paper is structured in five sections. The first section is an introduction which includes an introduction of GHRM followed by role and importance of AI in GHRM. Additionally, a fuzzy approach was explained and then the purpose of the study was explained. Section 2 includes literature review, it provides the theoretical underpinnings of GHRM, AI in GHRM and various attributes based on current trends in AI in GHRM. It defines the research gap in various literatures to determine the objective of the study. Third section is Research methodology, which explains the fuzzy techniques SWARA and MOORA. Section four comprises analysis of data and interpretation of data and the last section specifies conclusion and result, limitations of the study and future scope of the study.

2 Literature review

One revolutionary strategy for improving sustainable HR practices is the use of AI into GHRM. AI-driven GHRM facilitates data-driven decision-making, HR process automation, and workforce sustainability strategy optimization as businesses place a greater emphasis on environmental issues. This overview of the literature highlights important trends, difficulties, and methodological methods in the current study on AI adoption in GHRM. In particular, it looks at how fuzzy mathematical modeling might be used to evaluate AI adoption, spot obstacles, and improve sustainable HR procedures. The goal of the study is to provide readers a comprehensive understanding of how AI-driven GHRM might enhance organizational performance.

Fuzzy mathematical modeling provides a strong analytical framework for handling ambiguous, qualitative, and imprecise aspects impacting AI adoption in order to overcome these issues. Fuzzy was discovered by Zadeh in the year 1965; organizations may make more accurate and flexible decisions by using fuzzy logic to quantify ambiguous factors like employee sentiments, managerial support, and policy consequences (5). Specifically, it explores the role of fuzzy mathematical modeling in assessing AI implementation, identifying barriers, and optimizing sustainable HR practices. The review aims to bridge theoretical insights with practical applications, providing a comprehensive understanding of how AI-driven GHRM can enhance environmental and organizational performance.

In recent years, the SWARA and MOORA methods are useful in decision-making research due to their computational simplicity and ability to handle complex multi-criteria evaluation problems. The SWARA method has been increasingly applied in fuzzy environments to determine the relative importance of subjective attributes, especially in areas like sustainable supply chain evaluation, digital transformation, and HRM practices (6). For instance, Fuzzy SWARA was used (7) to prioritize sustainability indicators in manufacturing, demonstrating its flexibility in handling linguistic uncertainty through Triangular Fuzzy Numbers (TFNs). Similarly, Saeidi et al. (8) employed fuzzy SWARA in green HR decision-making, showcasing its relevance in balancing expert opinions during sustainability-focused HR assessments.

The MOORA method, known for its robustness and multi-criteria ranking capabilities, has been extensively used in evaluating alternatives in fields such as healthcare, renewable energy, and organizational performance. In a recent study, Ahmed et al. (9) integrated fuzzy MOORA with other MCDM techniques to assess service quality in higher education institutions, reinforcing its adaptability in handling non-beneficial and beneficial attributes simultaneously. Furthermore, Kavafoğlu (10) utilized a hybrid fuzzy SWARA–MOORA model to evaluate digital HRM adoption in Indian SMEs, providing a comprehensive framework for performance ranking under uncertainty.

The usability of AI in HRM dates to the early 2000s, when businesses started using AI to automate workforce engagement, performance appraisal, and selection (11). In staffing, AI-powered HRM solutions like chat bots and applicant tracking systems (ATS) have gained popularity (12). As the importance of sustainability increased, HRM changed into GHRM, which includes eco-friendly workplace regulations, green training, and sustainable leadership development (13). Green hiring, environmental training, performance reviews that focus on sustainability, and eco-friendly workplace regulations are all part of GHRM (14).

Emerging technologies including biometrics, virtual reality, big data, machine learning, mobile technology, the Internet of Things, geo-tagging, and artificial intelligence (AI) are being useful more often because of the Fourth Industrial Revolution (4IR) (15, 16). A set of HR practices known as GHRM is designed to promote environmental sustainability in companies. To promote environmentally conscious conduct among workers, GHRM includes green hiring, training, performance management, and incentive programs (13). GHRM is essential to business sustainability since it guarantees that employee behavior and organizational goals are in line (14, 17).

By tracking sustainability measures, optimizing energy consumption, and enabling remote work practices that lessen environmental footprints, artificial intelligence (AI) supports green activities in enterprises (18). AI-powered solutions also help find and hire eco-friendly workers, matching workforce competencies with company sustainability objectives (19). Leadership and Organizational Culture: Adoption is greatly impacted by leadership's readiness to accept AI and cultivate an innovative culture (20). Companies with an adaptable culture are more likely to overcome opposition to the use of AI (21, 22). Additionally, AI in GHRM is more likely to be implemented by leaders who place a high priority on sustainability and technical innovation (2, 18, 23).

2.1 Cost of implementation

AI adoption is typically hampered by the financial resources needed, such as purchases of software, gear, and qualified staff. Budget constraints disproportionately impact small and medium-sized businesses (SMEs) (24). Despite AI's long-term advantages, industries may be discouraged from incorporating them into GHRM due to high upfront expenditures (25). Technological Infrastructure: The adoption of AI is significantly influenced by the maturity and accessibility of the technological infrastructure. AI tools are more suited to be included in GHRM procedures in industries with sophisticated digital systems. AI-powered solutions for green hiring, training, and performance management may be easily implemented by companies with strong IT infrastructure (26, 27).

2.2 Data availability and quality

For precise analysis and decision-making, AI systems significantly depend on high-quality data. The successful use of AI in GHRM may be hampered by inadequate data quality or a dearth of pertinent datasets in many (28, 29). To optimize AI's potential, enterprises must give data collecting, standardization, and security top priority (30–32). Employee Awareness and Acceptance: One typical obstacle is employee opposition to AI technology, which is frequently brought either by ignorance or worries about losing their jobs. Businesses need to spend money on training staff members on the advantages of AI in GHRM, including increased productivity and sustainability (3). Employee participation in the adoption process may promote cooperation and lessen opposition.

2.3 Privacy and ethics issues

The use of AI brings up moral dilemmas pertaining to data security and employee privacy. To gain the trust of stakeholders and employees, industries need to solve these issues. The asserts that responsible AI deployment in GHRM requires strong ethical standards and open AI usage norms (4, 5, 24). Industry type and features: the adoption of AI is greatly influenced by the industry. Industry characteristics. For example, whereas service sectors may priorities AI for employee engagement and green training, manufacturing industries may concentrate on AI-powered energy optimization in their GHRM practices (26, 33). Adoption is shaped by industry-specific requirements and obstacles.

2.4 Regulatory and legal frameworks

Adoption of AI in GHRM is influenced by adherence to environmental rules and governmental laws (34, 35). AI is more likely to be used by businesses in areas with stringent environmental and data protection regulations for compliance and sustainability (18). Adoption is also influenced by regulatory incentives, such as subsidies for green technology. Technological Expertise and Skills: Successful deployment of AI systems depends on the availability of qualified staff that can oversee and enhance them. Businesses are better prepared to incorporate AI into GHRM if they have access to sustainability experts and AI professionals (30). Insufficient knowledge can hinder the efficacy of AI-driven projects and postpone their acceptance.

2.5 Perceived benefits and ROI

The deployment of AI is significantly influenced by the perceived ROI and concrete advantages of its adoption. If industries expect quantifiable increases in sustainability indicators, cost savings, and employee engagement, they are more inclined to implement AI in GHRM (36). Adoption across sectors may be accelerated by showcasing measurable results.

Organizational goals, particularly in HRM, have changed because of the quick development of AI technology and the growing emphasis on environmental sustainability throughout the world. A deliberate method to integrating environmental issues into fundamental HR tasks including staffing, training, performance appraisal, and workforce engagement is called GHRM (28). Simultaneously, AI technologies are being used more and more to optimize and automate these HR procedures, supporting sustainability initiatives with better decision-making, greener workflows, and real-time environmental monitoring (37, 38).

3 Research methodology

This research employs a new and enhanced fuzzy MCDM model dubbed fuzzy SWARA-MOORA to measure the performance of enterprises. Fuzzy set theory was used in several previous studies to produce more realistic results under uncertain circumstances. A strong mathematical framework that can examine the indefinite conceptual situation is provided by integrating fuzzy with conventional MCDM approaches like SWARA and MOORA. This framework may be closely examined to address the study's identification issue.

3.1 Fuzzy set and its membership functions

The set $A = \langle x, \mu_A(x) \rangle$, defined over the non-empty universal set U, is a fuzzy set, where $\mu_A(x): U \to [0,1]$ is called membership of x in A.

The value $\mu_A(x)=0$ indicates that x is not a member of A and $\mu_A(x)=1$ indicates full membership, and values between 0 and 1 represent partial membership.

Fuzzy sets enable incremental evaluation of an element's membership, unlike classical (crisp) sets where an element either belongs or does not. This makes them appropriate for modelling ambiguity, vagueness, and imprecision, all of which are prevalent in real-world issues.

Depending on how the vagueness is modelled and the application's needs, the membership function can be triangular, trapezoidal, Gaussian, or another shape.

3.2 Fuzzy number

When expressing imprecise or ambiguous numerical values, a fuzzy number is utilised as a mathematical representation of uncertainty. Instead of providing a specific number, the membership function describes it by providing a range of degrees of belonging (between 0 and 1) that indicate its possibility. Triangular and trapezoidal fuzzy numbers are common varieties that are frequently used to describe subjective judgements in decision-making.

3.3 Triangular fuzzy number (TFN)

The fuzzy set $B=\langle b_1,b_2,b_3\rangle$ on R is called TFN. Its membership function is shown in Figure 1.

The simplicity and ease of comprehension of triangular fuzzy numbers (TFNs) make them popular, especially among non-experts. They are simple and obvious, representing uncertainty with only three values. TFNs require fewer parameters and are less complicated and computationally efficient than other fuzzy numbers. In MCDM techniques like Fuzzy AHP, TOPSIS, and DEMATEL, they are frequently used because they successfully capture the ambiguity in human judgment. When precise data is unavailable but expert advice is accessible, TFNs are also useful approximations. They are also adaptable when it comes to expressing language phrases like "low," "medium," and "high" in qualitative evaluations.

This study examines the application of MCDM techniques, known as SWARA and MOORA, in fuzzy contexts to assess business performance based on acknowledged attributes. SWARA is helpful for determining the weight age of the attributes, whereas MOORA is good for identifying the best and worst company as well as the rankings of the companies in a probabilistic environment generated by linguistic phrases utilizing TFNs established by buying managers.

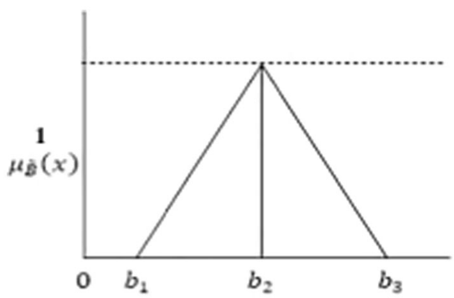

FIGURE 1
Membership function in fuzzy set.

3.4 Methodology of F-SWARA model

The classic SWARA approach for crisp numerals was proposed in 2010 (39). For selecting the best option, the criteria are ranked based on their weights. It is also used to evaluate the criterion's weights. In this paper, purchasing managers convey their preferences for specific criteria using exact numerical data in terms of triangular fuzzy numbers with respect to linguistic variables in a fuzzy environment. In this way data is generated. A linguistic expression in a fuzzy environment is a term or phrase from natural language that is used to model fuzzy logic ideas that are ambiguous or imprecise. Fuzzy logic is perfect for managing the ambiguity present in human language since it permits different degrees of truth, in contrast to binary logic, which only deals with true or false values.

However, addressing uncertain surroundings is not a good fit for this method. As a remedy to this issue, an updated fuzzy SWARA technique is presented. Using language expressions in the form of fuzzy triangular numbers. The purchasing managers use F-SWARA model to verify the fuzzy preference numerals of the criteria.

Step 1: Preparing list of attributes—firstly, a list of criteria is estimated in terms of expert's judgments.

Step 2: Set linguistic expressions (l_e)—starting from 2^{nd} attribute, $(j-1)^{th}$ attribute is distinguished by j^{th} attribute through linguistic expression by TFNs determined by experts.

Step 3: Estimating fuzzy coefficient numeral (f_{cn})—It is estimated as:

$$f_{cn}=\{1, if\ j=1 \tag{1}$$

$$l_e+1, if\ j>1$$

Step 4: Evaluating fuzzy re-calculated weights (f_{rcw})—these are evaluated as:

$$f_{rcw}=\{1, if\ j\ is\ 1 \tag{2}$$

$$\frac{f_{rcw-1}}{f_{cn}}\ if\ j>1$$

Step 5: Finding fuzzy weights (f_w)—they are determined as:

$$f_w=\frac{f_{rcw}}{\sum f_{rcw}} \tag{3}$$

Where $f_w=(f_w^a, f_w^b, f_w^c)$

Step 6: Transfiguring weights from fuzzy to crisp (c_w)—these are transfigured as:

$$c_w=\frac{1}{3}\left(f_w^a+f_w^b+f_w^c\right) \tag{4}$$

3.5 Methodology of F-MOORA approach

The MOORA approach was first put forth in 2009 (40). MOORA approaches fall into three categories: the Ratio System, Reference Point Approach, and Full Multiplicative Form. This model consists of the following phrases.

Step 1: The first stage is to establish a group of experts, confirm the companies, and define the attributes.

Step 2: Finding criteria weights and the performance ratings of the companies by linguistic variables through TFNs by experts' opinions.

Step 3: Decision matrix formation: expert experiences are shaped by linguistic ideas using TFNs.

Step 4: The fourth step involves using a ranking function to convert a fuzzy into a crisp matrix. In a ranking function (41), a fuzzy value is mapped to a real value, i.e., $\Re : F(\mathbb{R}) \rightarrow \mathbb{R}$, where F(R) denotes a fuzzy set. For two TFNs, $m = (\alpha, \beta, \gamma)$ and n, [1] analyzed a ranking function by:

(i) $\tilde{m} \precsim \tilde{n}$ iff $\Re(\tilde{m}) \leq \Re(\tilde{n})$
(ii) $\tilde{m} \approx \tilde{n}$ iff $\Re(\tilde{m}) = \Re(\tilde{n})$
(iii) $\tilde{m} \succsim \tilde{n}$ iff $\Re(\tilde{m}) \geq \Re(\tilde{n})$

$$\Re = \frac{\alpha + 2\beta + \gamma}{4} \tag{5}$$

Step 5: Formation of normalized decision matrix $\left(a_{ij}^*\right)$—this can be solved by:

$$a_{ij}^* = \frac{a_{ij}}{\sqrt{\sum a_{ij}^2}} \tag{6}$$

Step 6: Formation of weighted-normalized decision matrix $\left(v_{ij}\right)$ —it can be solved by:

$$v_{ij} = w_j * a_{ij}^* \tag{7}$$

Step 7: Final preference values (p_i^*)—It can be solved by

$$p_i^* = \sum_{j=1}^{l} v_{ij} - \sum_{l+1}^{n} v_{ij} \tag{8}$$

Where $j = 1, 2, \ldots, l$ denotes the beneficial factors while $j = l + 1, l + 2, \ldots, n$ denotes the cost factors.

Step 8: Calculating the alternatives' estimated rankings (r_a)—Final preference values are used to rank the alternatives. An option is ranked 1 if its final preference values are the highest of all the options.

$$r_a = \max\left(p_i^*\right) \tag{9}$$

4 Numerical analysis

In this section, we found 10 qualities in total from the literature research, six corporations (C1–C6), and three experts. AI adoption in GHRM includes Technological Infrastructure (TI), Cost of Implementation (COI), Data Availability and Quality (DAQ), Leadership and Organizational Culture (LOC), Employee Awareness and Acceptance (EAA), Privacy and Ethics Issues (PEI), Industry Type and Features (ITF), Regulatory and Legal Frameworks (RLF), Technological Expertise and Skills (TES), Perceived Benefits and ROI (PBROI). All criteria except Privacy and Ethics Issues (PEI), Regulatory and Legal Frameworks (RLF) Cost of Implementation (COI) are beneficial criteria. In this paper, the fuzzy matrix is converted into crisp matrix. Purchasing managers' opinions, expressed by TFNs, which are shown in Tables 1, 2, determine linguistic ideas of characteristics and fuzzy evaluations of the criteria and firms.

Estimating f_{cv} as well as f_{rw} by making the use of Equations 1, 2 respectively which in Table 3.

Equations 3, 4, respectively, are used to calculate the fuzzy and crisp weights of each characteristic, as shown in Table 4.

Linguistic expressions of all the attributes decided by all the purchasing managers are in the Tables 5–7.

As seen in Tables 8–10, the fuzzy decision matrix is now being constructed after being evaluated by all of the experts via TFNs.

Constructing a combined fuzzy decision matrix using TFNs to evaluate researchers' linguistic notions in order to determine the fuzzy performance evaluations of businesses, as shown in Table 11.

Now, using the ranking function and Equation 5, which shows Table 12, a combined fuzzy decision matrix is constructed into a crisp matrix.

Creating a normalized decision matrix using Equation 6 in Table 13.

Using Equation 7 to create a weighted-normalized decision matrix that shows Table 14.

Equations 8, 9 are now used to estimate the firms' final preference values and rankings, which are displayed in Table 15.

Rankings of the companies are; C5 > C1 > C3 > C4 > C6 > C2.

TABLE 1 Linguistic variables of criteria.

Linguistic variables	TFNs
Extremely low (EL)	(0.0, 0.0, 0.1)
Very Low (VL)	(0.0, 0.1, 0.3)
Low (L)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
High (H)	(0.5, 0.7, 0.9)
Very High (VH)	(0.7, 0.9, 1.0)
Extremely High (EH)	(0.9, 1.0, 1.0)

TABLE 2 Linguistic concepts of fuzzy ratings of companies.

Linguistic concepts	Fuzzy numerals
Very Low (VL)	1,1,3
Low (L)	1,3,5
Average (AVG)	3,5,7
High (H)	5,7,9
Very High (VH)	7,9,9

TABLE 3 Computing f_{CV} and f_{rW}.

Attributes	l_e	f_{cn}	f_{rcw}
Leadership and Organization Culture		(1, 1, 1)	(1, 1, 1)
Technological infrastructure	(0.9, 1, 1)	(1.9, 2, 2)	(0.53, 0.50, 0.50)
Technological expertise and skills	(0.7, 0.9, 1)	(1.7, 1.9, 2)	(0.31, 0.26, 0.25)
Perceived benefits and ROI	(0.7, 0.9, 1)	(1.7, 1.9, 2)	(0.21, 0.13, 0.12)
Data availability and quality	(0.5, 0.7, 0.9)	(1.5, 1.7, 1.9)	(0.14, 0.08, 0.06)
Employee awareness and acceptance	(0.5, 0.7, 0.9)	(1.5, 1.7, 1.9)	(0.09, 0.04, 0.03)
Industry type and features	(0.3, 0.5, 0.7)	(1.3, 1.5, 1.7)	(0.07, 0.03, 0.02)
Cost of implementation	(0.3, 0.5, 0.7)	(1.3, 1.5, 1.7)	(0.06, 0.02, 0.02)
Privacy and ethics issues	(0.1, 0.3, 0.5)	(1.1, 1.3, 1.5)	(0.05, 0.02, 0.01)
Regulatory and Legal frameworks	(0.1, 0.3, 0.5)	(1.1, 1.3, 1.5)	(0.05, 0.02, 0.007)

TABLE 4 Finding f_W and c_W.

Attributes	w_f	w_c
Leadership and organization culture	(0.40,0.48,0.50)	0.46
Technological infrastructure	(0.21,0.23,0.25)	0.23
Technological expertise and skills	(0.12,0.12,0.12)	0.12
Perceived benefits and ROI	(0.08,0.06,0.06)	0.06
Data availability and quality	(0.06,0.04,0.03)	0.04
Employee awareness and acceptance	(0.04,0.02,0.015)	0.03
Industry type and features	(0.03,0.01,0.009)	0.012
Cost of implementation	(0.02,0.009,0.009)	0.016
Privacy and ethics issues	(0.02,0.009,0.005)	0.011
Regulatory and legal frameworks	(0.02,0.009,0.003)	0.010

TABLE 5 Linguistic concepts of company's ratings by first purchasing manager.

Companies/Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
C1	H	VH	L	H	VL	VH	H	A	L	H
C2	VH	H	A	L	H	VL	A	H	VH	L
C3	A	VH	H	VH	L	VH	H	A	L	VH
C4	L	A	VH	A	VH	H	L	A	VH	L
C5	H	VH	A	VL	A	H	VH	H	A	L
C6	H	L	VL	A	H	VH	A	H	L	A

TABLE 6 Linguistic concepts of company's ratings by second purchasing manager.

Companies/Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
C1	VH	H	VH	A	H	L	A	VH	H	VL
C2	H	VL	A	L	VH	A	H	VH	A	L
C3	A	VH	L	VH	H	VL	A	L	VH	H
C4	VL	A	H	H	VH	VH	L	A	VH	VH
C5	H	VH	VH	L	A	VH	VL	H	A	L
C6	L	A	H	VH	H	A	VH	H	VL	A

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TABLE 7 Linguistic concepts of company's ratings by third purchasing manager.

Companies/Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
C1	H	VH	L	A	H	A	VL	VH	H	L
C2	VL	A	A	H	A	VH	H	L	A	VH
C3	A	L	H	VH	VL	A	VH	H	VH	L
C4	VH	H	L	A	H	VH	A	VH	VL	VH
C5	VH	VH	A	H	VL	A	L	VH	A	H
C6	H	L	A	VH	H	VL	VH	H	VH	A

TABLE 8 Fuzzy decision matrix evaluated by first purchasing manager.

Companies/Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
C1	5,7,9	7,9,9	1,3,5	5,7,9	1,1,3	7,9,9	5,7,9	1,3,5	1,3,5	5,7,9
C2	7,9,9	5,7,9	3,5,7	1,3,5	5,7,9	1,1,3	3,5,7	5,7,9	7,9,9	1,3,5
C3	3,5,7	7,9,9	5,7,9	7,9,9	1,3,5	7,9,9	5,7,9	3,5,7	1,3,5	7,9,9
C4	1,3,5	3,5,7	7,9,9	3,5,7	7,9,9	5,7,9	1,3,5	3,5,7	7,9,9	1,3,5
C5	5,7,9	7,9,9	3,5,7	1,1,3	3,5,7	5,7,9	7,9,9	5,7,9	3,5,7	1,3,5
C6	5,7,9	1,3,5	1,1,3	3,5,7	5,7,9	7,9,9	3,5,7	5,7,9	1,3,5	3,5,7

TABLE 9 Fuzzy decision matrix evaluated by second purchasing manager.

Companies/Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
SS1	7,9,9	5,7,9	7,9,9	3,5,7	5,7,9	1,3,5	3,5,7	7,9,9	5,7,9	1,1,3
SS2	5,7,9	1,1,3	3,5,7	1,3,5	7,9,9	3,5,7	5,7,9	7,9,9	3,5,7	1,3,5
SS3	3,5,7	7,9,9	1,3,5	7,9,9	5,7,9	1,1,3	3,5,7	1,3,5	7,9,9	5,7,9
SS4	1,1,3	3,5,7	5,7,9	5,7,9	7,9,9	7,9,9	1,3,5	3,5,7	7,9,9	7,9,9
SS5	5,7,9	7,9,9	7,9,9	1,3,5	3,5,7	7,9,9	1,1,3	5,7,9	3,5,7	1,3,5
SS6	1,3,5	3,5,7	5,7,9	7,9,9	5,7,9	3,5,7	7,9,9	5,7,9	1,1,3	3,5,7

TABLE 10 Fuzzy decision matrix evaluated by third purchasing manager.

Companies/Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
C1	5,7,9	7,9,9	1,3,5	3,5,7	5,7,9	3,5,7	1,1,3	7,9,9	5,7,9	1,3,5
C2	1,1,3	3,5,7	3,5,7	5,7,9	3,5,7	7,9,9	5,7,9	1,3,5	3,5,7	7,9,9
C3	3,5,7	1,3,5	5,7,9	7,9,9	1,1,3	3,5,7	7,9,9	5,7,9	7,9,9	1,3,5
C4	7,9,9	5,7,9	1,3,5	3,5,7	5,7,9	7,9,9	3,5,7	7,9,9	1,1,3	7,9,9
C5	7,9,9	7,9,9	3,5,7	5,7,9	1,1,3	3,5,7	1,3,5	7,9,9	3,5,7	5,7,9
C6	5,7,9	1,3,5	3,5,7	7,9,9	5,7,9	1,1,3	7,9,9	5,7,9	7,9,9	3,5,7

TABLE 11 Combined fuzzy matrix evaluated by all the purchasing managers.

Companies/ Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
C1	5.6,7.6,9	6.3,8.3,7	3,5,6.3	3.6,5.6,7.6	3.6,5,7	3.6,3,7	3,4.3,6.3	5,7,7.6	3.6,5.6,7.6	2.3,3.6,5.6
C2	4.3,5.6,7	3,4.3,6.3	3,5,7	2.3,4.3,6.3	5,7,7.6	3.6,5,6.3	4.3,6.3,8.3	4.3,6.3,7.6	4.3,6.3,7.6	3,5,6.3
C3	3,5,7	5,7,7.6	3.6,5.6,7.6	7,9,9	2.3,3.6,5.6	3.6,5,6.3	5,7,8.3	3,5,8.3	5,7,7.6	4.3,6.3,7.6
C4	3,4.3,5.7	3.6,5.6,7.6	4.3,6.3,7.6	3.6,5.6,7.6	6.3,8.3,9	6.3,8.3,9	1.6,3.6,5.6	4.3,6.3,7.6	5,6.3,7	5,7,7.6
C5	5.6,7.6,9	7,9,9	4.3,6.3,7.6	2.3,3.6,5.6	2.3,3.6,5.6	3,7,8.3	3,4.3,5.6	5.6,7.6,9	3,5,7	2.3,4.3,6.3
C6	3.6,5.6,7.6	3,3.6,5.6	3,4.3,6.3	5.6,7.6,8.3	5,7,9	3.6,5,6.3	5.6,7.6,8.3	5,7,9	3,4.3,5.6	3,5,7

TABLE 12 Combined crisp decision matrix.

Companies/Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
C1	6.625	7.475	4.825	5.6	5.15	4.15	4.475	5.65	5.6	3.775
C2	5.62	4.475	5	4.3	6.65	4.975	6.3	6.125	6.125	4.825
C3	5	6.65	5.6	8.5	3.775	4.975	6.825	5.325	6.65	6.125
C4	4.65	5.6	6.125	5.6	7.975	7.975	3.6	6.125	6.15	6.65
C5	7.45	8.5	6.125	3.775	3.775	6.325	4.3	6.625	5	4.3
C6	5.6	3.95	4.475	7.275	7	4.975	7.275	7	4.3	5

TABLE 13 Normalized decision matrix.

Companies/Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
C1	0.458	0.311	0.356	0.377	0.353	0.297	0.324	0.374	0.402	0.296
C2	0.389	0.289	0.378	0.289	0.457	0.356	0.457	0.405	0.439	0.378
C3	0.355	0.429	0.432	0.572	0.259	0.356	0.495	0.352	0.477	0.480
C4	0.321	0.361	0.463	0.377	0.548	0.571	0.261	0.405	0.441	0.521
C5	0.515	0.549	0.463	0.254	0.259	0.453	0.312	0.438	0.359	0.337
C6	0.387	0.255	0.338	0.49	0.481	0.356	0.527	0.463	0.308	0.392

TABLE 14 Weighted-normalized decision matrix.

Companies/Criteria	LOC	TI	TES	PBROI	DAQ	EAA	ITF	COI	PEI	RLF
C1	0.211	0.072	0.043	0.023	0.014	0.009	0.004	0.006	0.004	0.003
C2	0.179	0.066	0.045	0.017	0.018	0.011	0.005	0.006	0.005	0.004
C3	0.163	0.099	0.052	0.034	0.010	0.011	0.006	0.006	0.005	0.005
C4	0.148	0.083	0.056	0.023	0.022	0.017	0.003	0.006	0.005	0.005
C5	0.237	0.126	0.056	0.015	0.010	0.014	0.004	0.007	0.004	0.003
C6	0.178	0.059	0.041	0.029	0.019	0.011	0.006	0.007	0.003	0.004

TABLE 15 Finding ranking of companies.

Companies	Final preference values	Ranking of companies
C1	0.363	2
C2	0.326	6
C3	0.359	3
C4	0.336	4
C5	0.448	1
C6	0.329	5

5 Conclusion and results, limitations of the study and future scope of the study

To assess the success of AI-GHRM practices across six firms, this study shows how to integrate fuzzy MCDM methodologies, specifically F-SWARA and F-MOORA. The methodology offers a systematic and sophisticated approach to performance evaluation by accounting for human judgement uncertainty and recording expert opinions through triangular fuzzy numbers. According to the investigation, the fifth organisation out of the six had the greatest AI-GHRM efficiency ranking, demonstrating a superior application of AI-supported sustainability-oriented HR practices. These results have applications for businesses looking to integrate AI into HRM and increase eco-efficiency. Furthermore, the hybrid fuzzy technique used in this study offers a reproducible framework for further investigation and organisational evaluations in uncertain, dynamic settings.

According to the study's findings, the firm with the greatest final preference value ranked first, while the company with the lowest final preference value ranked last. The corporation with the biggest worth, C5, was placed first, followed by C1 and C3. Finally were C6 and C2. By using the SWARA and MOORA methodologies in a fuzzy environment, this study also establishes the order of the firms' rating based on their final preference values. Future business assessment problems in many fields pertaining to both manufacturing as well as service firms may be addressed using the fuzzy SWARA and fuzzy MOORA techniques.

This study has limitations even if it provides insightful information on the effectiveness of AI-driven GHRM practices employing fuzzy MCDM approaches. First off, there are only six organizations included in the research, which could not adequately represent the variety of AI-GHRM implementations in various sectors or geographical areas. Second, the reliance on expert judgment—specifically from purchasing managers—may introduce subjectivity, despite the use of fuzzy logic to mitigate this effect. Additionally, the selection of ten criteria, though comprehensive, may not encompass all relevant factors influencing AI-GHRM performance.

For future research, the scope can be expanded by including a larger and more diverse sample of companies across multiple sectors and geographies. Incorporating inputs from a broader range of stakeholders, such as HR professionals, sustainability officers, and IT managers, could further enrich the assessment. Additionally, the assessment framework's robustness and applicability might be improved by investigating additional sophisticated hybrid decision-making models and including dynamic or real-time performance data. This would help us comprehend AI's role in promoting sustainable HRM practices in a more profound and flexible way.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

NK: Supervision, Writing – review & editing, Writing – original draft, Methodology. RA: Writing – original draft. NS: Writing – review & editing, Formal analysis, Methodology, Data curation, Visualization. KA: Writing – review & editing, Funding acquisition, Project administration, Supervision, Investigation. AA: Writing – review & editing, Project administration, Formal analysis.

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