

Developing Sustainable Human Resource Policies for Industry 5.0 in Manufacturing industry by using Fuzzy Logic–Based Evaluation of Training Needs

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Abstract

Industry 5.0 extends earlier digitalization efforts by emphasizing human well-being, customization, resilience, and long-term sustainability as core industrial goals rather than focusing solely on automation and connectivity. In this environment, Human Resource Management (HRM) must craft sustainable and future-oriented policies that keep employee capabilities aligned with fast-moving technological and societal shifts.

Industry 5.0 training needs must also be addressed within governance arrangements that protect human dignity and strengthen workers' voice. From this angle, training does not merely offer a technical remedy for skill gaps; it also signals how organizations intend to treat their employees as disruptive technologies are introduced.

This study proposes an integrated framework that employs a fuzzy multi-criteria decision-making (MCDM) approach to identify training priorities and to order sustainable HR policy options suitable for Industry 5.0 settings. Building on work in Industry 5.0, sustainable HRM, fuzzy decision methods, and training evaluation, the paper develops a conceptual fuzzy MCDM model for training-needs diagnosis and shows, in principle, how it can be used in organizational practice.

The framework is designed to accommodate ambiguity in expert opinions, integrate economic, environmental, and social dimensions, and yield actionable guidance for recruitment, capability development, work and job design, and employee well-being initiatives. The paper concludes by highlighting implications for HR practitioners, main constraints of the approach, and avenues for subsequent empirical validation.

Keywords: Sustainable Human Resource Management; Training Needs Assessment; Multi-Criteria Decision-Making; Human-centric manufacturing etc.

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Introduction

The transition from Industry 4.0 to Industry 5.0 is commonly portrayed as a shift from a production logic centred on automation and data toward one in which humans, resilience, and sustainability again become central to value creation. (Rame, 2024; *Perceptions of Industry 5.0*, 2024). In this newer paradigm, collaboration between people and advanced technologies such as cobots, intelligent decision aids, and the IoT is combined with an explicit concern for environmental and social outcomes. European Commission (2024).

Technological, environmental, and social changes are steadily broadening what is expected from human resource management. HR professionals are now under pressure to connect everyday people-management practices with wider environmental, social, and economic objectives, instead of concentrating only on short-term performance indicators. This implies building a workforce that can combine digital capabilities with strong interpersonal skills and sustainability-related competences that fit the emerging Industry 5.0 context. (Zadeh, 1965; Dursun et al., 2010). At the same time, organizations require training and development programmes that are tightly targeted, support continuous learning, safeguard fair and decent working conditions, and encourage careful use of material, financial, and human resources.

Conventional approaches to Training Needs

Assessment typically rely on fixed rating scales or rigid rule-based procedures. These instruments can handle basic skills audits but are less able to reflect the complexity and uncertainty of fast-changing roles and technologies. As a result, they only weakly capture the fuzziness that characterizes expert judgements about both current and future competences (Al Mohamed et al., 2023).

Over several decades, fuzzy logic and fuzzy MCDM methods have become well-established tools for incorporating imprecise, subjective, and linguistically expressed evaluations into decision processes in areas such as personnel selection, education, and organizational planning (Chrysafiadi & Virvou, 2012). When such fuzzy methods are integrated into TNA, HR professionals can bring together multiple, and sometimes competing, sustainability-related and performance-related criteria while still making transparent and defensible choices about where to concentrate training resources.

Industry 5.0 increases the pressure on organizations to reconsider how they diagnose and respond to training needs, because the skills required now go beyond traditional technical competence to include human-centric and sustainability-oriented capabilities (Karnavas, 2025). Rather than treating training as a narrow instrument for raising productivity, firms are expected to construct broader learning architectures that prepare employees for ongoing collaboration with advanced technologies while

also protecting well-being, autonomy, and employability over the life course. In this context, Training Needs Assessment (TNA) becomes a strategic tool rather than a limited diagnostic exercise: it must identify existing gaps and also anticipate new digital roles, more sustainable production models, and the psychosocial pressures associated with rapid technological change. A forward-looking TNA can translate these evolving demands into clear development pathways that support a just and inclusive transition for different groups of workers.

Industry 5.0 policy documents and empirical studies repeatedly point to a cluster of capabilities that now shape organizational training agendas. Alongside core digital skills—data literacy, basic programming, interaction with intelligent systems, and familiarity with integrated production environments—employees are expected to demonstrate higher-order soft skills such as creativity, sound ethical judgement, effective communication in hybrid and geographically dispersed teams, and the ability to work across disciplinary boundaries.

Sustainability-related competences have become equally central in workforce planning. Employees increasingly need a practical grasp of life-cycle impacts, resource-efficiency principles, circular-economy logics, and the foundations of environmental reporting, even when sustainability is not explicitly mentioned in their job descriptions. The social dimension of sustainability, in turn, emphasises inclusive leadership, intercultural cooperation, and the ability to sustain psychological safety in settings where automation and intelligent systems may reshape job content and heighten uncertainty.

For supervisors and middle managers, training therefore has to combine material on data-informed decision making, redesign of

workflows for effective human–technology collaboration, and coaching skills that help staff manage role transitions. For HR and senior leaders, there is a parallel need for development in workforce analytics, the design of sustainable talent pipelines, and the governance of digital systems in ways that address bias risks and regulate the responsible use of monitoring tools. These different layers reinforce one another, so a TNA framework designed for Industry 5.0 has to surface not only individual skill gaps but also wider organisational capability deficits that could slow or derail the shift towards a genuinely human-centred production model.

The paper therefore develops a structured framework for sustainable HR policy that is anchored in a fuzzy-based TNA procedure. Industry 5.0 priorities are translated into specific HR levers—such as re-skilling initiatives, green HR practices, redesigned roles, and flexible work arrangements—and a fuzzy MCDM process is used to rank potential training investments. The work contributes by linking Industry 5.0 and Sustainable HRM conceptually and by outlining a transparent fuzzy MCDM process that helps HR decision makers allocate training budgets efficiently while supporting environmental and social commitments. Key strands of the literature on Industry 5.0, SHRM, and fuzzy decision approaches are elaborated in the subsequent review sections.

Employee training has become an integral aspect of modern organizations. It is no longer treated as a secondary activity; instead, it is recognized as a core organizational function. Today, organizations ensure that training programs are planned, implemented, and evaluated with the same seriousness and structure as other essential operational functions. (Tiwari & Singh, 2019)

Literature review

Industry 5.0: definitions and workforce implications

Industry 5.0 is often described as the stage where digital technologies are combined with explicit concern for human value, resilience, and ecological responsibility. While Industry 4.0 largely focused on automation, data analytic's, and connectivity, Industry 5.0 highlights cooperation between employees and intelligent systems to achieve resilient, personalized, and low-impact production.

Overall, training requirements in Industry 5.0 are wide-ranging, cut across established job categories and draw on several disciplines. Employees who work with digital platforms and collaborative robots need not only safety training based on realistic situations but also opportunities to practise responses to ethical dilemmas and to think through how their routines affect other people. Many current policy debates, especially in Europe, together with a growing academic literature, portray Industry 5.0 as a shift towards production systems that are environmentally responsible, organized around human needs and robust in the face of disruption. Progress in this direction assumes a workforce that can combine creativity and flexibility with social intelligence, ethical awareness and solid technical skills .(Machado & Davim, 2024).

This agenda has immediate consequences for employees and for HR practice. Staff need continuous chances to up-skill and re-skill so that they can handle collaborative technologies safely and effectively. Job roles have to be redesigned so that human oversight remains substantive and employees retain time and space to exercise their own ethical judgement. At the same time, organisations face increasing pressure to treat

inclusive employment and employee well-being as core elements of social sustainability, rather than optional extras. In this situation, HR policy becomes a key instrument for shaping organisational responses to Industry 5.0 instead of operating mainly as an administrative support function.

Recent work on up-skilling and re-skilling in Industry 5.0 indicates that training needs cannot be met through isolated, short courses; instead, organisations must cultivate ongoing learning ecosystems. Comparative studies of Industry 5.0-related training initiatives show that practical, hands-on activities, project-based assignments and close partnerships between firms and educational providers are especially effective for building integrated skill profiles that link technical knowledge with socio-emotional capabilities. Experiential arrangements—such as simulated environments for human–machine interaction, real sustainability projects embedded in production processes and cross-functional innovation challenges—help employees see both the benefits and the risks of new technologies while also reinforcing their sense of agency in the transition. This shift expands the role of HR professionals, who are expected to design and manage blended learning portfolios that combine formal courses with mentoring, communities of practice and digital micro-learning pathways aligned with Industry 5.0 objectives. (Karam et al., 2020).

Empirical research also shows that the move towards Industry 5.0 exposes serious inequalities in access to training and in learning outcomes. These gaps are often more pronounced for older workers, employees with lower skill levels and those in insecure or short-term jobs. If TNA continues to focus narrowly on high-potential or technologically intensive roles, there is a risk of widening internal labour-market segmentation and reproducing skill polarization. Sustainable HRM

perspectives argue that training needs for vulnerable groups—such as basic digital literacy, adaptive learning strategies, and transferable green skills—must be explicitly recognized and weighted in decision processes, not treated as residual issues. Integrating such equity-oriented criteria into fuzzy MCDM-based TNA allows organizations to surface and debate trade-offs between short-term returns and long-term social sustainability, and to make transparent when distributive choices favour specific workforce segments.

Sustainable Human Resource Management

Sustainable HRM widens the scope of conventional HR by explicitly linking recruitment, training, performance management, rewards, and retention practices to environmental and social objectives. Sakib (2025). The broader aim is to maintain economic performance over the long term while limiting harm to workers and to natural ecosystems. Empirical work indicates that when these practices are embedded in a supportive organizational climate and reinforced by strong social relationships, they tend to enhance employee commitment, retention, and sustainability-oriented behaviour. Within this wider field, green HRM concentrates more specifically on HR tools and practices that encourage pro-environmental behaviour at the level of individual employees. (Cachón-Rodríguez et al., 2022)

In an Industry 5.0 context, SHRM is expected to extend further by actively fostering digital skills, enabling effective human–technology collaboration, and guaranteeing fair access to training opportunities and secure employment as technologies and work processes continue to evolve.

This calls for frameworks that link sustainability outcomes with human-centric digital capability

building and that treat training as a primary instrument for steering transitions in a responsible way.

Training Needs Assessment (TNA) and evaluation models

Common TNA practices—such as competency gap analysis, appraisals, and survey-based diagnostics—often interpret expert opinions as precise scores, ignoring the ambiguity in terms like “moderate” readiness or “high” need. Fuzzy logic allows such linguistic assessments to be modelled through membership functions, and fuzzy MCDM methods (for example, fuzzy AHP, TOPSIS, VIKOR) have been widely adopted for problems where multiple qualitative and quantitative criteria must be considered together. Zadeh (1965). In HR and education, these tools have supported candidate ranking, competence assessment, and prioritization of interventions under uncertainty. Kirkpatrick and Kirkpatrick (1994)

Fuzzy approaches applied to HR and training

Fuzzy approaches are attractive for Industry 5.0-oriented HR because they permit experts to work in ordinary language, incorporate criteria such as environmental impact or psychological safety alongside technical skills, and still produce numerical outputs suitable for ranking. Yang (2025). Chrysafiadi & Virvou (2012). This combination of interpretability and analytical rigour aligns with the need to design training portfolios that address productivity, sustainability, and worker well-being simultaneously. (Khawar et al., 2020).

Fuzzy logic introduces an approach that acknowledges and manages uncertainty and imprecision in both data and human knowledge. (Kumar Pushkar et al., 2020). The Fuzzy AHP method is adopted as an analytical framework to

examine brand-related attributes, emotional aspects, and individual-specific factors in a structured manner. (Singh et al., 2020)

Research Gaps

- Despite the growing emphasis of Industry 5.0 on human-centric and sustainable systems, HR decision-making practices remain weakly aligned with these priorities, particularly in the area of training investment selection.
- Current HR evaluation frameworks inadequately capture expert judgement expressed in linguistic and qualitative terms, limiting their usefulness in complex and evolving work environments.
- The literature lacks fuzzy logic-based decision frameworks that simultaneously address sustainability goals and the imprecise nature of human judgement in strategic HRM.

Objectives of the Study

- To develop a conceptually grounded framework that links Industry 5.0 principles, strategic human resource management, and training needs analysis.
- To design a fuzzy multi-criteria decision-making (MCDM) model capable of evaluating and prioritizing training needs under conditions of uncertainty.
- To operationalise linguistic and qualitative expert inputs using fuzzy logic for more realistic HR decision-making.

Research Methodology Fuzzy MCDM model for TNA

Overview and rationale

From a methodological perspective, the

complexity and ambiguity of Industry 5.0 skill profiles reinforce the value of fuzzy-based TNA models. Expert panels assessing readiness for roles such as “cobot operator”, “digital systems coordinator”, or “sustainability champion” tend to use qualitative labels—such as “emerging”, “adequate”, or “potentially critical”—that are difficult to capture with simple numerical scales. Fuzzy logic offers a natural way to encode these linguistic assessments and to bring together heterogeneous evidence sources, including performance metrics, self-ratings, peer feedback, and external benchmarks, into a coherent view of training needs. When this is embedded within a multi-criteria structure that explicitly incorporates environmental, social, and ethical dimensions, the resulting model supports richer dialogue among stakeholders about which capabilities truly matter for a human-centred Industry 5.0 trajectory.

Several recent applications of fuzzy logic in HRM illustrate how this can work in practice and reinforce the framework developed in the paper. Studies have used fuzzy inference systems to appraise candidate competencies under uncertainty, to design more nuanced performance appraisal schemes, and to identify priority areas for in-house training that enhance innovation capabilities. These contributions show that fuzzy models not only process vagueness but can also increase perceived fairness and transparency, because the linguistic rules and membership functions can be communicated and discussed with managers and employees. Extending such approaches to Industry 5.0-oriented TNA means, for example, that rules can capture how combinations of moderate digital skills, high willingness to learn, and strong pro-environmental attitudes might jointly justify investment in specific reskilling pathways, even when current technical proficiency is still low.

Industry 5.0 also reshapes the temporal horizon of

training needs, making foresight and scenario thinking integral to TNA. Organizations must anticipate not only immediate competence gaps but also future roles at the interface of technology, sustainability, and care for human well-being, such as AI ethicists, human–robot interaction designers, or circular-economy coordinators. Fuzzy MCDM models are well suited to incorporating such forward-looking judgments, because experts can express expectations about future relevance or obsolescence of skills in qualitative terms that are then systematically aggregated. This enables HR decision makers to simulate how different strategic orientations—for instance, prioritizing aggressive digital automation versus balanced green and social innovation—would change the ordering of training priorities, and to align TNA more closely with long-term industrial and societal goals.

In practice, managers and HR specialists rarely quantify skill gaps with exact numbers; they talk in terms such as “low”, “moderate”, or “very high” need. A fuzzy MCDM procedure is therefore adopted to encode these linguistic assessments and combine them in a structured way. Fuzzy aggregation makes it possible to integrate inputs from different expert groups and to assign weights to heterogeneous criteria—technical, social, and environmental—so that training options can be prioritized rather than treated as an undifferentiated list. The process design draws on existing applications of fuzzy MCDM in HR and education and adapts them to a sustainability-focused TNA setting.

Steps of the proposed method

Step 1: Clarifying objectives and identifying alternatives

The starting point is to link training objectives to key Industry 5.0 and SHRM themes, including digital capabilities, human–AI collaboration, sustainability literacy, soft skills, and psychological safety. On this basis, a set of candidate training programmes is defined, such as “Cobots and Safety”, “Sustainability in Operations”, “AI-Augmented Decision Making”, and “Soft Skills for Human–Robot Teams”.

Step 2: Defining and structuring criteria

A hierarchical criteria system is then constructed that combines familiar performance considerations with explicitly sustainability-oriented dimensions. Typical criteria include economic impact (productivity, cost–benefit), environmental impact (e.g., waste and energy use), social impact (equity, well-being), urgency of the training need, and feasibility in terms of resources, time, and availability of trainers. This structure follows general MCDA guidance while reflecting the value set associated with Industry 5.0. Analysis Function guide (2024).

Step 3: Collecting expert judgements using linguistic scales

HR professionals, line managers, sustainability staff, and technical experts provide ratings for each training alternative under each criterion. These judgements are expressed using a predefined linguistic scale (for example, Low, Medium, High, Very High). Each term on the scale is represented by a triangular or trapezoidal fuzzy number so that qualitative opinions can be processed within the fuzzy MCDM model.

Table 1: Fuzzy Scale of Preference

Linguistic Variable	CRISP AHP Scale	TFN	Reciprocal TFN
Extremely Preferred	9	(8, 9, 9)	(1/9, 1/9, 1/8)
Very Strongly To Extremely Preferred	8	(7, 8, 9)	(1/9, 1/8, 1/7)
Very Strongly Preferred	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Strongly To Very Strongly Preferred	6	(5, 6, 7)	(1/7, 1/6, 1/5)
Strongly Preferred	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Moderately To Strongly Preferred	4	(3, 4, 5)	(1/5, 1/4, 1/3)
Moderately Preferred	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Equally To Moderately Preferred	2	(1, 2, 3)	(1/3, 1/2, 1)
Equally Preferred	1	(1, 1, 1)	(1, 1, 1)

Step 4: Deriving weights for criteria

To reflect the relative importance of the criteria, a fuzzy pairwise comparison approach such as fuzzy AHP is applied. Experts compare criteria using

linguistic terms that are translated into fuzzy numbers, producing a fuzzy comparison matrix. After normalization and consistency checks, this yields a set of weights for the criteria.

Table 2: Main criteria weight by First Expert

Main criteria	p	rq	s
Collaborative Robots and Safety	0.4473	0.2470	0.2291
AI-augmented decision making	0.5527	0.2808	0.2474
Sustainability and Circular Practices	0.0000	0.1777	0.1795
Digital Literacy and data skills	0.0000	0.1058	0.1220
Human-centric skills	0.0000	0.1132	0.1270

Using equation (1), the process was carried out for each expert's evaluation, resulting in the

determination of the global weights for the primary criteria.

$$W_i = (a_i) / \sum_{i=1}^n a_i \dots \dots \dots (1)$$

Step 5: Aggregating and ranking alternatives

For each training option, fuzzy ratings across criteria are aggregated using a fuzzy weighted averaging operator that combines the fuzzy scores with the derived criterion weights. The composite fuzzy scores are then defuzzified—for example, through the centroid method—to obtain crisp

values. These values are used to generate a ranking of the training programmes.

Step 6: Sensitivity analysis

The robustness of the ranking is examined by varying criterion weights and, where relevant, the parameters of membership functions. This helps to

assess how sensitive the recommended priorities are to changes in stakeholder value judgements and supports transparent discussion of trade-offs.

Step 7: Translating results into HR policy

Finally, the ranked list of training priorities is

Table 3: De-fuzzified weight

	L1			L2			L3		
Sum of weights	0.404	0.385	0.372	0.307	0.316	0.318	0.219	0.294	0.305
Defuzzified weight		0.387			0.315			0.279	

Suitability of fuzzy MCDM

A fuzzy MCDM approach fits this problem setting because it mirrors the way HR experts and line managers actually think about competence gaps—using qualitative and sometimes uncertain language rather than precise scores. It also offers a structured way of embedding environmental and social criteria that are difficult to measure with high precision but are central to Industry 5.0. The model generates numerical scores that can be checked and interpreted, while still capturing the subtlety of expert judgement. In this way, it offers a defensible foundation for directing training investments towards human-centric and sustainability objectives.

Experimentation

Transparent and participatory TNA processes that use fuzzy logic to formalize, without oversimplifying, expert and worker judgements can support trust, since employees can see that concerns about safety, workload, and environmental impact are explicitly taken into account when training resources are allocated. Under these conditions, Industry 5.0-aligned TNA becomes a central component of sustainable HR policy, reinforcing not only adaptability and

interpreted in policy terms. HR can translate the results into budget allocations, phasing of training implementation, integration with recruitment and performance management systems, and monitoring indicators for sustainability outcomes.

performance but also resilience, inclusion, and socially legitimate innovation.

To demonstrate the framework, consider a medium-sized manufacturing firm preparing for an Industry 5.0 transformation and facing a fixed training budget. The organization must prioritize among five candidate programmes:

- A1. Collaborative Robots and Safety
- A2. AI-Augmented Decision Making
- A3. Sustainability and Circular Practices
- A4. Digital Literacy and Data Skills (basic to intermediate)
- A5. Human-Centric Skills: Communication, Ethics, and Well-Being

The firm evaluates these alternatives against five criteria:

- C1 Economic Impact,
- C2 Environmental Impact,
- C3 Social Impact/Well-being,
- C4 Urgency, and
- C5 Feasibility.

A panel of HR specialists, engineers, and the sustainability officer supplies linguistic ratings for each alternative–criterion pair, which are converted into triangular fuzzy numbers as inputs to the model.

Expert elicitation and fuzzy scoring

Individual expert judgements for a given alternative and criterion are combined into group fuzzy scores through appropriate aggregation of the fuzzy numbers. Weights for the criteria can be calculated using fuzzy AHP or a comparable multi-criteria weighting technique. In the illustrative case, environmental and social impacts (C2 and C3) are given relatively higher weights to reflect the company's sustainability priorities, while economic impact and urgency (C1 and C4) still carry significant weight to maintain operational viability.

Aggregation and ranking

Applying the fuzzy weighted aggregation and defuzzification steps produces an ordered list of training priorities.

In the example, the resulting ranking is:

A3: Sustainability and Circular Practices

A1: Collaborative Robots and Safety

A5: Human-Centric Skills

A4: Digital Literacy and Data Skills

A2: AI-Augmented Decision Making

The resulting ranking shows a deliberate focus on environmental and social outcomes, in line with an Industry 5.0 orientation, but at the same time acknowledges the immediate relevance of cobot

safety and human-centric capabilities. Sensitivity analysis indicates that the top three positions remain stable under moderate changes in the weights; only when the scheme is strongly shifted towards short-term economic results do alternatives such as A4 or A2 move up.

Analysis & Discussion

The proposed framework has several strengths. Using fuzzy membership functions to represent expert judgements avoids forcing decision-makers to provide artificially precise scores that do not reflect how they naturally think about skill gaps and priorities. Bringing environmental and social criteria directly into the TNA procedure helps to keep training choices consistent with Industry 5.0's human-centric and sustainability orientation instead of treating these dimensions as secondary. Furthermore, clear specification of the membership functions, weighting procedures and sensitivity analyses creates a transparent audit trail that can be used to justify and explain difficult allocation decisions.

Research Findings

A research findings can support practical adoption of the framework.

Phase 1 – Diagnosis (0–3 months). Establish a cross-functional steering group, identify strategic competencies, and agree sustainability-related criteria and initial weights with stakeholder participation, using fuzzy AHP templates where helpful.

Phase 2 – Pilot (3–9 months). Apply the fuzzy MCDM-based TNA in one or two units, implement the top two or three training programmes (for example, sustainability and cobot safety), and collect baseline data on learning and sustainability outcomes.

Phase 3 – Scale-up (9–24 months). Extend priority training across the organization, formalize green HRM practices, and embed sustainability indicators into performance management and reward systems.

Phase 4 – Continuous improvement (ongoing). Repeat the fuzzy assessment at regular intervals, update membership functions and weights using evaluation evidence, and maintain worker involvement in revision processes.

Conclusion

Industry 5.0 calls for HR systems that support digital transformation while simultaneously advancing environmental stewardship and social justice. A fuzzy-logic-based MCDM model provides a structured way to translate these broad aims into concrete training priorities under conditions of uncertainty and incomplete information.

By combining economic, environmental, and social criteria and making value judgements explicit, HR leaders can design training portfolios and related policies that contribute to resilient, inclusive, and human-centred production systems. Further empirical work in diverse organizational contexts will be necessary to refine the framework and evaluate its practical impact

Recommendations

Adopt a phased implementation approach

Organizations should introduce the proposed framework gradually rather than all at once. A structured, time-bound rollout helps reduce resistance, allows learning at each stage, and ensures that decisions remain aligned with strategic and sustainability goals.

Use participative methods for defining criteria and priorities

The findings suggest that involving stakeholders while identifying competencies, sustainability criteria, and their relative importance leads to more realistic and trusted outcomes.

Start with focused pilot projects before full deployment

Organizations are advised to test the fuzzy MCDM-based training needs assessment in limited units or departments. Implementing only the top-ranked training programmes initially allows managers to observe learning outcomes, feasibility, and sustainability impacts without excessive resource commitment.

Collect and document baseline performance data

Before scaling up, firms should systematically record learning outcomes, behavioural changes, and sustainability indicators. These benchmarks are essential for evaluating the effectiveness of training interventions and for refining future assessments.

Integrate sustainability into HR systems during scale-up

As the framework expands across the organization, sustainability-oriented training should be reinforced through formal green HRM practices. Linking sustainability indicators with performance appraisal and reward systems can help translate training into sustained employee behaviour.

Scope for future research

This article puts forward a conceptual framework and illustrates it with a single scenario rather than reporting multiple empirical cases or long-term

applications.

Comparative investigations of alternative fuzzy MCDM techniques—for example, fuzzy AHP, TOPSIS and VIKOR—could clarify differences in transparency, ease of use and stakeholder acceptance. Longer-term research might also analyse how sustainability-weighted training portfolios influence organisational performance, environmental outcomes and indicators of employee well-being. Future studies could implement the fuzzy MCDM-based TNA model in different sectors and national contexts to examine how well it transfers and where adjustments are needed.

Limitations

There are, however, important limitations to recognize. High-quality expert input depends on well-designed questionnaires or rating tools, careful selection of participants, and sensitivity to whose perspectives may be missing or marginalized. The selection of membership functions and defuzzification rules inevitably involves judgement, which makes systematic sensitivity analysis essential if the robustness of the rankings is to be understood. Finally, while fuzzy MCDM helps to structure prioritization, it cannot replace contextual interpretation: factors such as labour relations, regulatory constraints, and organizational culture may require adaptations that go beyond what the model itself suggests.

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