

A COMPARATIVE NUMERICAL STUDY OF ARTIFICIAL INTELLIGENCE AND HUMAN INTELLIGENCE IN SOLVING SUSTAINABILITY PROBLEMS

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ABSTRACT

PURPOSE: This study contrasts Artificial Intelligence (AI) and Human Intelligence (HI) in addressing sustainability issues that require a trade-off between technical efficiency, ethical judgement and contextual interpretation.

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DESIGN/METHODOLOGY/APPROACH: This study uses triangular fuzzy numbers, fused Analytic Hierarchy Process (AHP)-entropy weights and fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to compare AI and HI across five sustainability-governance scenarios. Sensitivity analysis is applied to identify the technical-weight thresholds where AI or HI becomes more suitable.

FINDINGS: AI outperforms HI in structured, information-rich tasks such as renewable energy dispatch and circular waste logistics. HI outperforms AI in unstructured, context-rich, ethically dense tasks such as climate-smart agriculture and Environmental, Social and Governance (ESG)-oriented public procurement. The average closeness coefficient is 0.432 for AI and 0.568 for HI.

ORIGINALITY/VALUE: The study compares AI and HI optimisation modelling strategies for sustainability governance in a mathematically explicit, uncertainty-aware manner. It contributes to diverse areas of risk management research and provides a decision-making framework for industries seeking solutions to address sustainability governance challenges.

RESEARCH LIMITATIONS: The study employs benchmark numerical scenarios rather than field observations; however, it provides a transparent comparative framework for future empirical testing.

PRACTICAL IMPLICATIONS: Public institutions need to avoid one-size-fits-all automation and instead deploy AI where meaningful human oversight is provided.

KEYWORDS: *Artificial Intelligence; Sustainability Governance; Human Intelligence; Environmental, Social and Governance; Optimisation Modelling Strategies; Fuzzy TOPSIS.*

INTRODUCTION

Artificial Intelligence (AI) has long been recommended as a driver of the Sustainable Development Goals (SDGs), enabling better forecasting, resource allocation, and institutional responsiveness. Machine intelligence is conceptually rooted in Turing (1950), and AI can, with adequate governance frameworks, help underpin the SDGs. In contrast, researchers have expressed concerns that AI systems operating without contextual judgement or ethical control may deepen opacity, bias, energy consumption and governance asymmetries in AI development (Floridi *et al.*, 2018; Jobin *et al.*, 2019; Sriram *et al.*, 2022; Vinuesa *et al.*, 2020; Dwivedi *et al.*, 2021; Van Wynsberghe, 2021). Therefore, the central policy question is no longer whether to use AI, but where it should lead, where humans should lead, and how these forms of intelligence can be rigorously contrasted.

This question matters even more in the context of sustainability problems. Such problems never contain only a single objective. A sustainable solution has to be technically sound, socially legitimate, and ethical (defensible and robust under incomplete information). It is for this reason that governance systems for water, agriculture, energy, and procurement are often still reliant on human insight even when AI-based analytics are available. Recent work shows that AI can aggregate information more effectively than human actors in certain domains (Shin *et al.*, 2023). However, in contexts where tacit knowledge and best-practice moral reasoning matter (Chanda, 2024; Islami and Mulolli, 2024), social interpretation (Alawamleh *et al.*, 2024) or institutional legitimacy is at stake, humans still outperform machines.

The literature further reveals that sustainable AI needs to be approached simultaneously from both perspectives: as a facilitator of sustainability, fittingly encapsulated in the term ‘AI for sustainability’, and as an application with environmental and ethical burdens that require close monitoring and management (Van Wynsberghe, 2021; Bossert and Hagendorff, 2023; Bolte and Van Wynsberghe, 2025). For example, an AI that appears to be effective in a narrow technical sense is weak if it introduces greater energy burdens, extracts more knowledge from minority populations or reduces accountability. This promotes a comparative, rather than a celebratory, lens for sustainability decisions related to governance.

As this comparison involves linguistic, vague and imprecise features, fuzzy mathematics is employed. Judgement criteria that require careful application of context or ethics, or that rely on human interpretation, may render a classical crisp-scoring approach too rigid. In fuzzy sets, linguistic judgements are numerically represented while maintaining uncertainty and vagueness (Zadeh, 1965; Bellman and Zadeh, 1970; Chen, 2000). The versatility of this method has been utilised in the domain of cognition-based fuzzy mathematics (Yogeesh, 2018; Yogeesh *et al.*, 2025). This research builds on this rationale by contrasting the application of AI and Human Intelligence (HI) within sustainability governance.

This study makes four contributions. First, it establishes a formal mathematical framework for estimating the trade-off between AI and HI under uncertainty. Second, it compares five benchmark sustainability problems with different technical structures and socio-ethical densities. Third, it produces crossover thresholds that illustrate changes in ranking order, as technical efficiency receives greater weight in the rankings. Fourth, it provides a concise governance interpretation. AI is best at structured optimisation; HI excels, by wide margins, at context-rich arbitration; hybrid governance represents the most robust institutional design.

Research Questions (RQs)

RQ1: How do AI and HI differ in solving sustainability problems that combine technical efficiency, ethical judgement and contextual interpretation?

RQ2: Which benchmark sustainability-governance scenarios provide stronger comparative suitability for AI, and which scenarios provide stronger comparative suitability for HI?

RQ3: How can triangular fuzzy numbers, fused Analytic Hierarchy Process (AHP)-entropy weights and fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) be used to quantify the trade-off between AI-driven and HI-driven decision pathways?

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RQ4: How does the technical-weight emphasis parameter change the ranking of AI and HI across renewable energy dispatch, water allocation governance, climate-smart agriculture, circular waste logistics and Environmental, Social and Governance (ESG)-oriented public procurement?

RQ5: What practical governance guidance can be derived for designing hybrid AI-HI sustainability decision systems under uncertainty?

Contribution of the Current Study

The present work adds mathematical rigour to sustainability and AI governance research by providing a method for comparing AI and HI rather than treating them as general-purpose competitors. It proposes a benchmark fuzzy TOPSIS approach that includes both technical criteria, such as accuracy, speed, and scalability, and governance criteria, including explainability, context sensitivity, ethical judgement, and robustness under data scarcity. It also includes numerical evidence for scenario postulation, along with threshold points at which AI should lead, HI should lead, and hybrid oversight is appropriate. This contribution is beneficial to public institutions, private sustainability decision-makers and researchers who require accountable decision support under uncertainty.

LITERATURE REVIEW

Current literature makes a case for AI as a tool for sustainable development through optimisation, prediction and pattern recognition. The literature links practical applications of AI to progress towards the SDGs (Vinuesa *et al.*, 2020; Mei *et al.*, 2025), green marketing (Mei *et al.*, 2025), disclosure of AI and ESG scores (Bogdan *et al.*, 2025), and supply chain monitoring powered by AI for the purposes of managing ESG risk (Hong and Kim, 2025; Qi and Yu, 2025; Capodagli *et al.*, 2025). However, this literature is often about performance, rather than relative governance fit. For example, a fast and scalable AI system may be institutionally weak if its recommendations cannot be explained to the impacted communities.

A second stream addresses ethics and governance of AI. The main issues here are fairness, transparency, accountability and human control (Floridi *et al.*, 2018; Jobin *et al.*, 2019; Pošćić, 2024; Bellaby, 2026; Dumitriu, 2026). These studies illustrate that governance failure is not just a function of model error, but also of the lack of a clear accountability trail. That is why human judgement remains essential in public-interest decisions. Human input should not be regarded as a residual factor but as a constitutive necessity for high-

quality decision-making, requiring organisational meaning, moral framing, and contextual interpretation (Chanda, 2024; Islami and Mulolli, 2024).

Finally, the last stream explores sustainable AI more directly. This perspective on the role of AI is echoed by Van Wynsberghe (2021), who distinguishes between AI for sustainability and the sustainability of AI, while Bossert and Hagendorff (2023) extend this discussion to broader ethical costs. Bolte and Van Wynsberghe (2025) claim that sustainable AI is about a structural turn, not a narrow checklist. Kudina *et al.* (2026) show that environmental sustainability is achievable only through clearer normative reasoning that goes far beyond what current instances allow. Although these studies are pivotal, most discuss AI and HI in broad qualitative terms without indicating how well groups of this type compare across various sustainability tasks through a compact numerical framework.

The fourth stream of research does not develop human-centred design as such, but develops soft tools for uncertainty. When human judgement and other ambiguous criteria cannot be avoided, fuzzy logic and fuzzy multi-criteria decision-making (MCDM) have been extensively applied (Zadeh, 1965; Bellman and Zadeh, 1970; Chen, 2000; Pérez-Briceño *et al.*, 2025). These methods are especially relevant when the comparison includes intangible criteria such as explainability or ethical adequacy. However, a clear, comprehensive comparative study that specifically contrasts AI and HI in sustainability problem-solving remains limited.

Research Gap

Existing scholarship indicates that AI can help with sustainability and that HI remains essential, but it gives limited numerical guidance on which intelligence should dominate which sustainability problem. This study addresses that gap through a benchmark fuzzy comparative model.

RESEARCH METHODS

Benchmark Scenarios and Criteria

Five benchmark scenarios are selected to represent distinct sustainability-governance tasks:

1. renewable energy dispatch;
2. water allocation governance;

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3. climate-smart agriculture;
4. circular waste logistics; and
5. ESG-oriented public procurement.

These scenarios are not claimed as field observations, but rather as benchmark numerical cases designed to represent realistic governance tensions. The comparison uses eight benefit criteria: accuracy, speed, scalability, explainability, context sensitivity, ethical judgement, carbon efficiency and robustness under data scarcity. The criteria deliberately include both technical and human-centred dimensions, as shown in Table 1.

Table 1: Evaluation Criteria and Fused Weights

<i>Code</i>	<i>Criterion</i>	<i>Type</i>	<i>Weight</i>
C1	Accuracy	Benefit	0.18
C2	Speed	Benefit	0.14
C3	Scalability	Benefit	0.12
C4	Explainability	Benefit	0.12
C5	Context sensitivity	Benefit	0.14
C6	Ethical judgement	Benefit	0.14
C7	Carbon efficiency	Benefit	0.08
C8	Robustness under data scarcity	Benefit	0.08

Source: Authors' computation

Fuzzy Representation

For alternative i , criterion j and scenario s , the performance score is expressed as a triangular fuzzy number:

$$\tilde{x}_{ijs} = (l_{ijs}, m_{ijs}, u_{ijs}),$$

Where l_{ijs} , m_{ijs} and u_{ijs} denote the lower, modal, and upper assessments, respectively. The linguistic-to-fuzzy mapping is given in Table 2.

Table 2: Linguistic Scale Used in the Numerical Study

<i>Linguistic term</i>	<i>Triangular fuzzy number</i>
Very low (VL)	(0.00, 0.00, 0.15)
Low (L)	(0.05, 0.25, 0.45)
Medium (M)	(0.30, 0.50, 0.70)

<i>Linguistic term</i>	<i>Triangular fuzzy number</i>
High (H)	(0.55, 0.75, 0.90)
Very high (VH)	(0.80, 0.95, 1.00)

Source: Authors' computation

To facilitate interpretation, a centroid defuzzification operator is also used:

$$\chi(\tilde{a}) = \frac{l + m + u}{3}.$$

Weight Fusion

The final criterion weights combine expert-prioritised AHP weights and entropy-based discrimination weights. Let w_j^{AHP} be the expert weight and w_j^E the entropy weight.

$$w_j = \lambda w_j^{AHP} + (1 - \lambda) w_j^E, \quad 0 \leq \lambda \leq 1.$$

In the above fusion formula, w_j represents the final fused weight assigned to criterion C_j . The term w_j^{AHP} represents the expert-prioritised AHP weight for criterion C_j , whereas w_j^E represents the entropy-based discrimination weight obtained from the spread of the numerical ratings. The parameter lambda (λ), where $0 \leq \lambda \leq 1$, controls the relative contribution of expert governance judgement, and $1 - \lambda$ controls the contribution of data-driven entropy. The index $j = 1, 2, \dots, 8$ denotes the eight evaluation criteria. Therefore, the fused weight is a convex combination of expert preference and objective score dispersion, and the final weights are used in the weighted fuzzy TOPSIS matrix after normalisation.

In this study, λ is set to 0.6, giving slightly greater importance to expert governance judgement than to purely data-driven dispersion.

Following Shannon (1948), the entropy component is computed as follows:

$$e_j = -k \sum_{i=1}^m p_{ij} \ln(p_{ij}), \quad d_j = 1 - e_j, \quad w_j^E = \frac{d_j}{\sum_{j=1}^n d_j},$$

where $k = 1/\ln(m)$ and p_{ij} is the normalised score proportion of the alternative i on criterion j .

In the entropy expression, e_j denotes the entropy value of criterion C_j , p_{ij} denotes the normalised proportion of alternative i on criterion j , m denotes the number of compared alternatives in the entropy calculation, and $k = 1/\ln(m)$ is the scaling constant. A criterion receives a stronger entropy contribution when it discriminates more clearly between AI and HI across the benchmark evaluations.





Fuzzy TOPSIS Model

All criteria are treated as benefits. Normalisation is given by:

$$\tilde{r}_{ijs} = \left(\frac{l_{ijs}}{u_{js}^+}, \frac{m_{ijs}}{u_{js}^+}, \frac{u_{ijs}}{u_{js}^+} \right),$$

Where u_{js}^+ is the maximum upper bound across alternatives for the criterion j in scenario s .

The weighted fuzzy value becomes:

$$\tilde{v}_{ijs} = w_j \otimes \tilde{r}_{ijs}.$$

Let A^+ and A^- denote the fuzzy positive-ideal and negative-ideal solutions. The vertex distance between fuzzy numbers $a=(l_1, m_1, u_1)$ and $b=(l_2, m_2, u_2)$ is given as:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2}{3}}.$$

Hence, the separation measures are

$$D_i^+ = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{A}_j^+), \quad D_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{A}_j^-),$$

and the closeness coefficient is given as:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad 0 \leq CC_i \leq 1.$$

A higher closeness coefficient indicates greater comparative suitability in this study.

Sensitivity Analysis

A technical-weight emphasis parameter, alpha (α), is introduced to determine when AI overtakes HI. $T=\{C1, C2, C3\}$, $H=\{C4, C5, C6, C8\}$. Carbon efficiency is fixed at 0.08. Thus,

$$\sum_{j \in T} w_j = 0.92\alpha, \quad \sum_{j \in H} w_j = 0.92(1 - \alpha), \quad w_{C7} = 0.08.$$

The AI advantage function is given as:

$$\Phi_s(\alpha) = CC_{AI,s}(\alpha) - CC_{HI,s}(\alpha).$$

The crossover threshold α_s^* is defined by the zero of the AI-advantage function.

NUMERICAL RESULTS

Figure 1 below summarises the analytical structure used in the study.

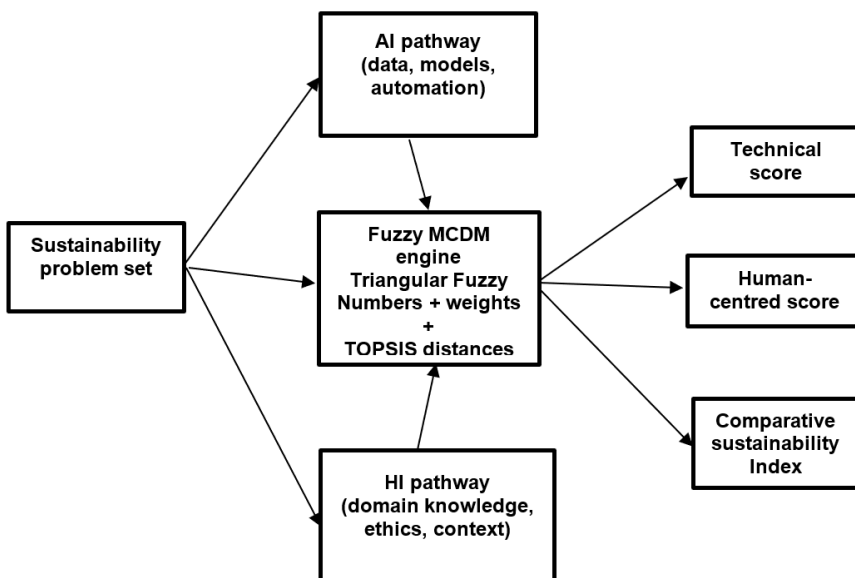


Figure 1: Comparative Analytical Framework Linking AI and HI Pathways with Fuzzy

Source: Authors' construction

MCDM Evaluation

In Figure 2, the membership functions for the five linguistic labels are shown. The graphical overlap most accurately represents the uncertainty expected from real-world governance assessments.

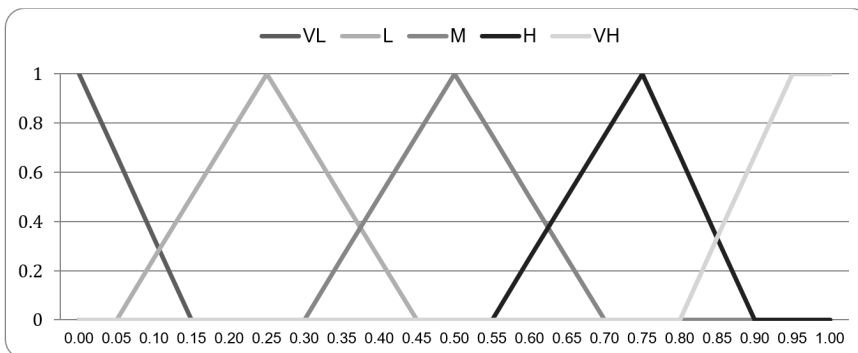


Figure 2: Membership Functions for the Linguistic Performance Scale

Source: Authors' computation





For example, consider the accuracy metric in renewable energy dispatch. AI fuzzy rating = (0.82, 0.89, 0.96). HI fuzzy rating = (0.61, 0.68, 0.75). Based on a maximum upper bound of 0.96, the normalised values are:

$$\tilde{r}_{AI} = (0.854, 0.927, 1.000), \quad \tilde{r}_{HI} = (0.635, 0.708, 0.781).$$

With weight $w_1 = 0.18$, the weighted normalised numbers become as shown below:

$$\tilde{v}_{AI} = (0.154, 0.167, 0.180), \quad \tilde{v}_{HI} = (0.114, 0.128, 0.141).$$

The above calculations illustrate AI’s advantage on the accuracy criterion in the renewable energy dispatch scenario. Note that the overall ranking is based on all eight criteria.

For Table 3, the high-level (compact) scenario codes are abbreviated as follows:

CC= Closeness Coefficient; RED = Renewable Energy Dispatch; WAG = Water Allocation Governance; CSA = Climate-Smart Agriculture; CWL = Circular Waste Logistics; and ESGP = ESG Public Procurement.

Table 3: Scenario-Wise Comparative Results

Code	AI technical mean	HI technical mean	AI human-centred mean	HI human-centred mean	AI CC	HI CC	Winner
RED	0.913	0.497	0.528	0.775	0.532	0.468	AI
WAG	0.847	0.570	0.555	0.822	0.432	0.568	HI
CSA	0.817	0.603	0.540	0.855	0.343	0.657	HI
CWL	0.893	0.523	0.570	0.780	0.541	0.459	AI
ESGP	0.793	0.597	0.525	0.882	0.310	0.690	HI

Source: Authors’ computation

The above results show a clear pattern based on the listed values. AI ranks higher in renewable energy dispatch and circular waste logistics. These tasks are highly structured and reward speed, scalability and computational accuracy. HI ranks higher in water allocation governance, climate-smart agriculture and ESG-oriented public procurement. These tasks require local interpretation, fairness negotiation, institutional sensitivity and context-aware ethical judgement.

The average closeness coefficients across all five scenarios are 0.432 for AI and 0.568 for HI. This does not imply that HI is globally more efficient. Rather, it implies that the chosen sustainability problems are sufficiently governance-heavy for human judgement to retain greater overall value. Figure 3 presents the scenario-wise coefficients graphically.

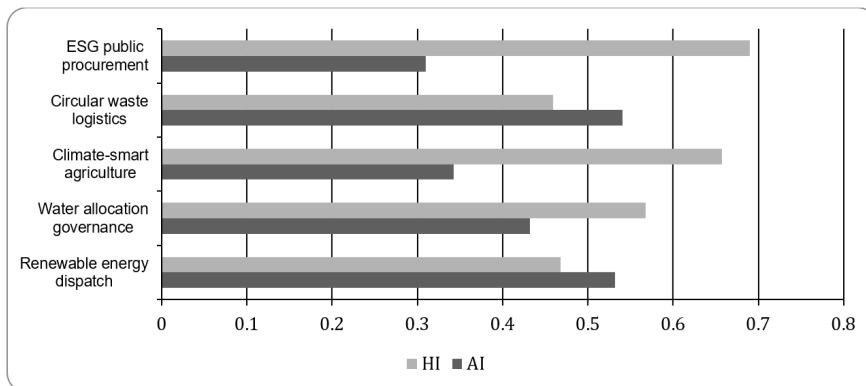


Figure 3: Fuzzy TOPSIS Closeness Coefficients for AI and HI Across the Five Benchmark Scenarios

Source: Authors' computation

Figure 3 also clarifies that AI and HI are not far apart in the two AI-winning scenarios. Renewable energy dispatch yields closeness coefficients of 0.532 for AI and 0.468 for HI, while circular waste logistics yields 0.541 for AI and 0.459 for HI. In contrast, the HI advantage is stronger in agriculture and procurement, especially in the latter where explainability, fairness and contextual judgement dominate.

Sensitivity analysis deepens the comparison. As alpha increases, greater weight is placed on technical criteria. The complete mapping of the AI-advantage function is represented in Figure 4.

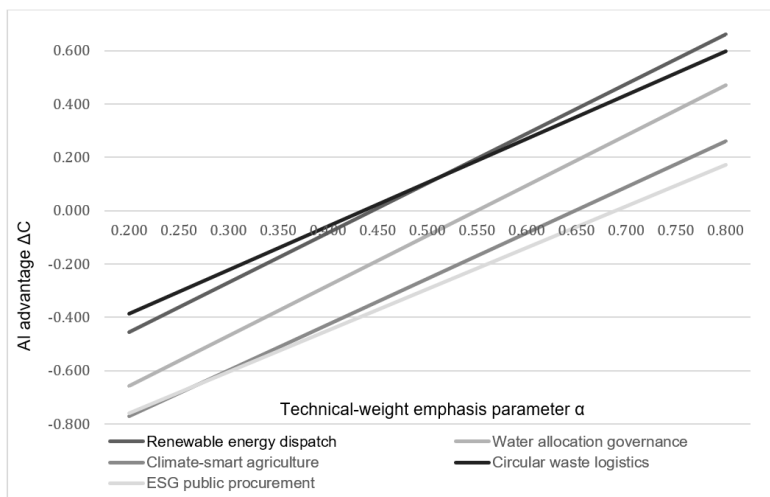


Figure 4: Sensitivity of Comparative Ranking to Technical-Weight Emphasis: Positive

Source: Authors' computation

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Values Favour AI; Negative Values Favour HI

The crossover thresholds are reported in Table 4.

Table 4: Sensitivity-based Crossover Thresholds

Scenario	Crossover threshold α^*	Interpretation
RED	0.445	AI requires only moderate technical emphasis
WAG	0.550	HI remains stronger unless technical emphasis becomes high
CSA	0.648	HI remains stronger unless technical emphasis becomes high
CWL	0.436	AI requires only moderate technical emphasis
ESGP	0.690	HI remains stronger unless technical emphasis becomes high

Source: Authors' computation

The crossover thresholds provide important insights into decision dominance under varying technical-weight conditions. At $\alpha=0.44$, circular waste logistics has crossed its threshold of 0.436, whereas renewable energy dispatch has not yet crossed its threshold of 0.445. Both scenarios become AI-dominant only when α exceeds 0.445. Water allocation governance crosses the threshold at a moderate-to-high level of technical emphasis. In climate-smart agriculture and ESG-oriented public procurement, human-centred criteria remain structurally decisive, and AI overtakes only when very high weight is assigned to the technical criteria.

An example of a criterion-level advantage map is shown in Table 5.

Table 5: Criterion-Level AI Minus HI Advantage Map by Scenario. Positive Cells Favour AI and Negative Cells Favour HI

Criterion	Renewable energy dispatch	Water allocation governance	Climate-smart agriculture	Circular waste logistics	ESG public procurement
Accuracy	+0.21	+0.07	+0.03	+0.17	-0.02
Speed	+0.52	+0.38	+0.30	+0.47	+0.30
Scalability	+0.52	+0.38	+0.33	+0.47	+0.31
Explainability	-0.21	-0.21	-0.26	-0.18	-0.26
Context sensitivity	-0.28	-0.27	-0.29	-0.20	-0.16
Ethical judgement	-0.34	-0.33	-0.37	-0.31	-0.42
Carbon efficiency	-0.09	-0.15	-0.21	-0.13	-0.19
Robustness	-0.16	-0.26	-0.34	-0.15	-0.39

 Favours HI  Favours AI  Neutral

Source: Authors' computation

The internal structure of the rankings is confirmed in Table 5. Across all five scenarios, AI performs better in speed and scalability. It also performs better in accuracy in four scenarios, while HI has a marginal accuracy advantage in ESG public procurement (ESGP). Across the remaining criteria, HI consistently performs strongly in explainability, context sensitivity, ethical judgement, and robustness under data scarcity. Carbon efficiency in this benchmark is typically higher for HI, suggesting a non-negligible environmental cost of deploying data-intensive AI.

ANALYSIS AND DISCUSSION

RQ1 is answered by the comparison of AI and HI across technical and human-centred criteria. The results show that AI generally has a stronger advantage on accuracy, speed and scalability, while HI has a stronger advantage on explainability, context sensitivity, ethical judgement and robustness under data scarcity. Hence, the difference between AI and HI is not general superiority but task-dependent suitability. RQ2 is answered through the scenario-wise closeness coefficients: AI is stronger in renewable energy dispatch and circular waste logistics, whereas HI is stronger in water allocation governance, climate-smart agriculture and ESG-oriented procurement. RQ3 is answered by the modelling sequence itself; triangular fuzzy numbers retain uncertainty in linguistic evaluation, AHP-entropy fusion balances expert governance judgement with data dispersion, and fuzzy TOPSIS converts the weighted performance matrix into comparable closeness coefficients. RQ4 is answered by the sensitivity and crossover analysis: RED and CWL cross at moderate alpha levels, while WAG, CSA and ESGP require higher technical emphasis before AI can overtake HI. RQ5 is therefore answered through the governance interpretation that AI should lead structured and information-rich optimisation tasks, HI should lead ethically dense and context-sensitive decisions, and hybrid AI-HI systems should be preferred where technical efficiency and legitimacy must be balanced.

The numerical findings provide affirmation of a simple but significant insight: sustainability governance is not a one-off decision context. Structured optimisation and normative contention in governance represent different epistemic classes. AI should assume the primary operational role in the first class, while HI should remain at the centre of the second class.

This distinction should be relevant for the current debate over AI-enabled governance. The corporate and public sectors are rapidly adopting AI, as it seems fast, scalable, and impartial. But speed and scale do not eliminate the need to justify decisions. In short, when water is scarce and must be divided among different users, when farmers face uncertain climatic risks, or when procurement has implications for labour conditions and community

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equity, the person making the decision needs to justify why one option is more equitable and legitimate than another. However, that justification burden remains inherently dependent upon human judgement (Floridi *et al.*, 2018; Pošćić, 2024; Bellaby, 2026).

The findings also refute overly simplistic arguments that AI directly renders human decision-makers obsolete. Human judgement does not disappear when AI enters the system; it shifts to model design (algorithm creation), parameter selection, threshold setting for positive and negative cases (false positives and false negatives), exception handling, and accountability review. This corroborates contemporary findings that the greatest synergy between AI and HI occurs when the former augments, rather than substitutes for, human judgement (Shin *et al.*, 2023; Chanda, 2024; Islami and Mulolli, 2024). For example, in management and public governance, the optimal blend is typically not AI versus HI but instead AI with sufficient human oversight.

In addition to the theoretical contribution of this study to sustainable AI, the study addresses carbon efficiency more explicitly within its rigorous framework. An organisation that automates its governance challenges with AI will incur additional energy overheads and increased digital dependency. As guided by Bossert and Hagendorff (2023), sustainable AI governance is not a one-size-fits-all proposition, and it requires choosing and limiting where, why, when, and how AI is used. Taken together, sustainability in AI does not mean adopting AI everywhere (Kudina *et al.*, 2026; Van Wynsberghe, 2021; Bossert and Hagendorff, 2023). This is especially salient in low-resource governance scenarios, where high computational intensity is not environmentally or fiscally sustainable.

The challenges of human capital and ethical capacity are also covered in the study. AI adoption will shift work away from routine tasks towards oversight, interpretation, and responsible implementation, which may contribute more to organisational value than automation or simple task and process replacement (Qi and Yu, 2025; Joseph *et al.*, 2026; Najam Shaikh *et al.*, 2025). This is not just a last-resort option; HI also becomes an asset for governance. Similarly, Yogeesh (2018) argues that leadership and pedagogical judgement are essential in human-development contexts, which are easily transferable to sustainability governance, where trust and legitimacy are the primary outputs.

CONCLUSIONS

The work developed a fuzzy number-based framework for comparing AI and HI while addressing sustainability issues. In addition, triangular fuzzy numbers, fused weights, and fuzzy TOPSIS were used to establish the main finding that AI is better at data-rich, structured tasks. At the same time, HI is superior in context-rich, ethically dense tasks.

Across the five benchmark scenarios, HI has the higher average closeness coefficient; however, the ranking changes systematically as greater weight is assigned to the technical criteria.

Three policy conclusions follow. First, public institutions should be wary of uncritical scaling up of AI for sustainability governance. Second, AI should be used where structure, repetition and data abundance predominate. Third, HI should be retained for decisions requiring social legitimacy, contextual interpretation and ethical balancing. Thus, the most appropriate governance design is a hybrid: AI for analysis and outcome prediction, HI for adjudication and an accountable final decision.

The key limitation is that the benchmark numerical scenarios are not based on primary field observations. Future studies can generalise the model using real-world public-sector, agricultural or organisational-performance datasets and analyse AI, HI, and hybrid intelligence as distinct decision-making approaches. Despite this limitation, the present study offers explicitly mathematically grounded reasoning for deciding when AI should take the lead over human decision-makers, and vice versa, and why both actors in sustainability governance are required.

ETHICAL STATEMENT

This study is based on benchmark numerical scenarios, published literature and the authors' computations. It does not involve human participants, animal subjects, clinical intervention, private institutional records or personally identifiable data. Therefore, formal ethical clearance was not required. The assumptions, criteria, fuzzy scales and computational procedures are reported transparently so that future researchers can replicate, adapt, or empirically validate the framework.

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