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Advancing Environmental Sustainability through Artificial Intelligence: A Fuzzy SWOT–LOGSTA-Based Strategic Analysis

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ABSTRACT

Sustainability has become a major global priority, highlighting goals such as achieving net-zero emissions by 2050, reducing waste, and promoting the use of recycled materials. In response, companies are working to lower carbon emissions and improve resource efficiency. Artificial intelligence (AI) offers strong potential to address these challenges. This study adopted a fuzzy based strategic approach to assess the strengths, weaknesses, opportunities, and threats (SWOT) related to AI role for environmental sustainability. First, 12 SWOT factors are identified based on experts' opinions and literature review. Then, a fuzzy logarithm normalization and standard deviation (F-LOGSTA) is applied to determine the weight of SWOT factors. The findings indicated that governance, energy use, and economic risks are the most influential factors for promoting environmental sustainability through AI. This study advances understanding of AI in sustainability by offering insights for researchers, practitioners, and policymakers, supporting further work at the nexus of AI and sustainable development.

1. Introduction

Raising the issue about climate change and environmental damage has recently emphasized the critical necessity for durable practices via industrial sector. The importance of this necessity has been amplified by political measures to reduce global emissions, like the Green Deals of the European Union. The objective of this deal is to the greenhouse gas (GHGs) emissions reduction and climate neutrality achievement by 2050. Furthermore, the deals have the sub-objective of GHGs reduction by at least 50% below 1990 levels by 2030 [1].

Previous studies identified efficiency, sufficiency, and consistency as the three important strategies to achieve the goals [2]. While the sufficiency related strategy centers on the reduction of consumption by modifying the manner of living so that it encourages more durable levels of resource employment, the efficiency strategy highlights the effective usage of resources to rise productivity and diminish waste. The consistency related strategy, in turn, establishes a good interconnection of technology and nature to produce an eco-friendly circular economy [3]. Although it is observed that considerable improvements can be offered by both sufficiency and consistency related strategies in most of cases, more successful or practical

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technological techniques are required in some areas to be appropriate for an eco-friendly future in the medium term [4].

With the development of large language models, artificial intelligence (AI) is becoming progressively necessary in the actual society. Because of this development, there has recently a great improvement of AI capabilities, and new approaches of its application have appeared. Therefore, it is beneficial to evaluate the actual advances and restrictions for its application, such as for sustainability. In that regard, AI enhances the effectiveness of sustainability attempts in diverse sectors. The AI related approaches maximize environmental impact evaluation [5], diminish GHGs emissions [6], and increase the efficiency of resource [7]. The benefit of AI is especially important given the necessity for enhanced productivity in many sectors due to the predicted rise in the population at a global level [8]. To better apprehend this benefit, our study will assess how AI can be used to handle related challenges concerning the management of the ecosystem and climate change mitigation.

In emerging fields such as AI for sustainability, Greif, Kimmig [9] performed a strengths, weaknesses, opportunities, and threats (SWOT) analysis, assisting in the clarification of actual insights and future research necessities. However, their study did not provide the most important factors that promote or impede AI for environmental sustainability. Moreover, they did not provide a framework that integrate both qualitative analysis and multi-criteria decision method (MCDM), which have been recently largely adopted [10, 11]. In contrast, the present study goes beyond previous literature by developing an integrated SWOT-MCDM framework tailored to assessment of the actual role of AI in promoting environmental sustainability. Specifically, the study seeks to answer the following research questions: (1) What are the key strengths, weaknesses, opportunities, and threats influencing the actual role of AI in promoting environmental sustainability? (2) How can an integrated SWOT-MCDM framework enhance decision-making for the actual role of AI in promoting environmental sustainability?

To support this, a logarithm normalization and standard deviation (LOGSTA) developed by Stevic, Ulutas [12] is extended under fuzzy environment in this study to assess the SWOT factors. The objective of the study is to find out the most important strengths and opportunities as well as the most critical challenges and threats to the application of AI for sustainability environment. The originality of the study lies in the combination of SWOT analysis and MCDM within a single framework, explicitly tailored to the AI role for environmental sustainability. The remaining study is organized in various sections: literature review, problem definition, methodology, application, discussion, managerial insights, and conclusions and future recommendations.

2. Literature review

Various studies related to AI for environmental sustainability have been conducted around the world. For instance, Nti, Cobbina [13] provided an AI review to assist enhance considerably towards reaching environmental sustainability in water, transportation, energy, and biodiversity related studies. Kirikkaleli, Ali [14] assessed the asymmetric and long-term effects of AI investment and green electricity on environmental quality in the United States (US). Kaswan and Kumar [15] emphasized the most critical issues that impede the effective AI deployment in environmental sustainability. Dewasiri, Rathnasiri [16] evaluated various AI technologies for environmental sustainability in the healthcare sector. Raihan, Paul [17] evaluated the environmental sustainability issues via technological innovations in the energy sector. Kumari and Pandey [18] determined how AI can be adopted for climate change and environmental sustainability. Abonamah, Hassan [19] developed a feasible AI adoption tool to assist industry leaders from energy sector promote sustainability management. Uriarte-Gallastegi, Arana-Landín [20] explores energy management and its influence on efficiency and emissions via a multi-case study of various projects across different sectors. Wang and Zhang [21] explores how AI-enabled adaptive supply chains impact environmental, social, and governance (ESG) performance in energy sector considering the crucial role of innovation and collaboration and the moderating role of proactive sustainability measures.

3. Problem definition

Table 1 outlines the SWOT factors related to the assessment of AI for environmentally sustainability based on the opinions of experts and previous studies [9, 22].

Table 1
SWOT analysis related to AI for environmental sustainability

Criteria	Sub-criteria	Reference
Strengths (S)	Separability (S1)	[9, 22] and experts' opinions
	Speed (S2)	
	Complexity (S3)	
Weaknesses (W)	Explainability (W1)	
	Energy use (W2)	
	Data bias (W3)	
Opportunities (O)	Mitigate climate change impacts (O1)	
	Governance (O2)	
	Scientific value (O3)	
Threats (T)	Regulation (T1)	
	Cybersecurity (T2)	
	Economic risks (T3)	

4. Methodology

The proposed Fuzzy-LOGSTA method extends the objective weighting logic of the original LOGSTA method [12] into a fuzzy environment. This approach handles uncertainty and vagueness associated with expert linguistic assessments using Triangular Fuzzy Numbers (TFNs). The method assigns weights to criteria based on the contrast intensity (standard deviation) of their logarithmic normalized values. A higher weight indicates a higher degree of variance among the experts' opinions regarding a specific criterion. The computational procedure consists of the following five steps:

Step 1: Construct the Fuzzy Decision Matrix. Let $X = \{x_1, x_2, \dots \dots \dots, x_m\}$ be the set of criteria and $E = \{e_1, e_2, \dots \dots, e_k\}$ be the set of experts. The linguistic evaluations provided by the experts are converted into TFNs, denoted as $\tilde{x}_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right)$, where $a_{ij} \leq b_{ij} \leq c_{ij}$. This forms the initial fuzzy decision matrix $\widetilde{D} = \left[\tilde{x}_{ij}\right]_{k\times m}$.

Step 2: Fuzzy Logarithmic Normalization. To normalize the data and reduce the impact of extreme values, a logarithmic transformation is applied to the TFNs. The normalized fuzzy value $\tilde{r}_{ij}$ is calculated as shown in Eq. (1).

$$\tilde{r}_{ij} = \frac{ln\left(\tilde{x}_{ij}\right)}{\oplus_{p=1}^{k} ln\left(\tilde{x}_{ij}\right)} \tag{1}$$

Where $ln\left(\tilde{x}_{ij}\right) = \left(ln\left(a_{ij}\right), ln\left(b_{ij}\right), ln\left(c_{ij}\right)\right)$. The division of two fuzzy numbers $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$ is performed as $\frac{\tilde{A}}{\tilde{B}} = \left(\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1}\right)$.

Step 3: Calculation of Fuzzy Mean and Standard Deviation. For each criterion j, the fuzzy mean $\tilde{\bar{r}}_j$ of the normalized values is computed as shown in Eq. (2).

$$\tilde{\bar{r}}_j = \frac{1}{k} \otimes \left(\oplus_{i=1}^{k} \tilde{r}_{ij}\right) \tag{2}$$

Subsequently, the Fuzzy Standard Deviation $\tilde{\sigma}_j$ is calculated to measure the dispersion (contrast intensity) of the experts' opinions using Eq. (3).

$$\tilde{\sigma}_j = \sqrt{\frac{1}{k} \otimes \left(\oplus_{i=1}^{k} \left(\tilde{r}_{ij} \ominus \tilde{\bar{r}}_j\right)^2\right)} \tag{3}$$

Step 4: Determination of Fuzzy Weights. The fuzzy weight $\widetilde{\omega}_j$ for each criterion is obtained by normalizing the fuzzy standard deviations using Eq. (4). This ensures that the sum of the weight equals 1 (in a fuzzy sense).

$$\widetilde{\omega}_j = \frac{\tilde{\sigma}_j}{\bigoplus_{i=1}^{m} \tilde{\sigma}_j} \tag{4}$$

Step 5: Defuzzification. To obtain crisp values that can be used in subsequent decision-making processes, the fuzzy weights $\widetilde{\omega}_j = \left(\omega_{jl}, \omega_{jm}, \omega_{ju}\right)$ are defuzzified using the Center of Gravity method in Eq. (5).

$$W_j = \frac{\omega_{jl} + \omega_{jm} + \omega_{ju}}{3} \tag{5}$$

The final crisp weights W_j are then ranked to determine the importance of each criterion. Linguistic variables are converted into Triangular Fuzzy Numbers (TFNs) to enable the calculation phase. The 1–9 scale showed in Table 2 is employed to satisfy the domain requirements of the subsequent logarithmic transformation.

Table 2
Logarithmic transformation scale

Linguistic Term	Abbreviation	Triangular Fuzzy Number
Extremely Low	EL	(1, 1, 2)
Very Low	VL	(1, 2, 3)
Medium Low	ML	(2, 3, 4)
Medium	M	(3, 4, 5)
Medium High	MH	(4, 5, 6)
High	H	(6, 7, 8)
Very High	VH	(7, 8, 9)
Extremely High	EH	(8, 9, 9)

5. Application

The integration of Artificial Intelligence (AI) into environmental sustainability strategies represents a complex MCDM problem that includes technical uncertainties and conflicting strategic objectives. A case study is conducted focusing on the strategic evaluation of AI's role in promoting environmental sustainability. An overall evaluation framework has been developed using a SWOT framework that provides a list of key strengths, weaknesses, opportunities, and threats based on a review of current literature and expert opinion. This case study serves to illustrate the practical applicability and robustness of the proposed Fuzzy LOGSTA method in determining the relative importance of these factors under conditions of vagueness and expert subjectivity.

The required data collection process involves a panel of four domain experts (E1-E4). These experts were tasked with evaluating twelve specific sub-criteria spanning the four SWOT dimensions using the logarithmic scale presented in Table 2. Table 3 shows the initial decision matrix, where the rows represent the sub-criteria and the columns correspond to the fuzzy evaluations provided by each expert.

Table 4 presents the initial fuzzy decision matrix transformed into TFNs. Each entry in the matrix represents the fuzzy evaluation of a specific SWOT sub-criterion by an individual expert, quantifying the degree of importance assigned to each factor. The matrix serves as the major input for the Fuzzy LOGSTA algorithm, encapsulating the inherent subjectivity and varying levels of consensus among the decision-makers regarding the strategic impact of AI on environmental sustainability.

Table 3
Initial matrix

	E1	E2	E3	E4
S1	ML	M	ML	ML
S2	VH	H	H	H
S3	VH	H	VH	VH
W1	EL	EL	VL	EL
W2	VH	H	H	MH
W3	M	MH	MH	M
O1	EH	VH	EH	VH
O2	M	MH	ML	M
O3	MH	M	M	M
T1	ML	VL	ML	VL
T2	M	M	ML	M
T3	H	MH	H	MH

Table 4
TFN's matrix

Criterion	E1	E2	E3	E4
S1	(2,3,4)	(3,4,5)	(2,3,4)	(2,3,4)
S2	(7,8,9)	(6,7,8)	(6,7,8)	(6,7,8)
S3	(7,8,9)	(6,7,8)	(7,8,9)	(7,8,9)
W1	(1,1,2)	(1,1,2)	(1,2,3)	(1,1,2)
W2	(7,8,9)	(6,7,8)	(6,7,8)	(4,5,6)
W3	(3,4,5)	(4,5,6)	(4,5,6)	(3,4,5)
O1	(8,9,9)	(7,8,9)	(8,9,9)	(7,8,9)
O2	(3,4,5)	(4,5,6)	(2,3,4)	(3,4,5)
O3	(4,5,6)	(3,4,5)	(3,4,5)	(3,4,5)
T1	(2,3,4)	(1,2,3)	(2,3,4)	(1,2,3)
T2	(3,4,5)	(3,4,5)	(2,3,4)	(3,4,5)
T3	(6,7,8)	(4,5,6)	(6,7,8)	(4,5,6)

Step 1: Fuzzy Logarithmic is normalized using equation below.

$$\tilde{r}_{ij} = \frac{\widetilde{ln}(\tilde{x}_{ij})}{\sum \widetilde{ln}(\tilde{x}_{ij})}$$

$ln(2,3,4) = (0.69,1.10,1.39) * ln(3,4,5) = (1.1,1.39,1.61)$

Then summation of logs for S1

$$Lower(L): 0.69 + 1.10 + 0.69 + 0.69 = 3.17, Middle(M): 1.1 + 1.39 + 1.10 + 1.10 = 4.69, Upper(U): 1.39 + 1.61 + 1.39 + 1.39 = 5.78$$

$\tilde{S}_{S1} = (3.17,4.69,5.78)$

Step 2: The individual fuzzy logarithmic values calculated in Step 1 are divided by the total sum vector $\tilde{S}_{S1} = (3.17,4.69,5.78)$ to obtain the normalized values $\tilde{r}_{ij}$. This step converts the raw ratings into relative performance scores within a $[0,1]$ interval.

$$\tilde{r}_{11} = \frac{(0.69,1.10,1.39)}{(3.17,4.69,5.78)}$$

$$Lower: 0.69/5.78 = 0.12, Middle = 1.10/4.69 = 0.23, Upper = 1.39/3.17 = 0.44$$

$$\tilde{r}_{11} = (0.12,0.23,0.44)$$

Step 3: The fuzzy mean $\tilde{r}_{ij}$ is computed by aggregating all normalized values for a specific criterion. This represents the average normalized importance rating assigned by the expert panel.

Summing up the normalized values: $(0.12,0.23,0.44) + (0.19,0.30,0.51) + \cdots$

$$Sum = (0.55,0.99,1.83)$$
$$\tilde{\tilde{r}}_{S1} = \frac{(0.55,0.99,1.83)}{4} = (0.14,0.25,0.46)$$

Step 4: The fuzzy standard deviation $\tilde{\sigma}_j$ measures the contrast intensity (dispersion) of the expert opinions. A higher deviation indicates greater disagreement among experts, which translates to a higher weight in the LOGSTA method.

$$\tilde{\sigma}_{S1} = (0.04,0.05,0.07)$$

Step 5: To obtain a usable crisp value, the fuzzy standard deviation is defuzzified using the center of gravity method. This averages the lower, middle, and upper bounds.

$$W_{S1} \frac{0.041 + 0.052 + 0.067}{3} = \frac{0.160}{3} = 0.053$$

Table 5 summarizes the computational outcomes of the proposed method, presenting the calculated fuzzy weights alongside the crisp weights obtained through the center of Gravity defuzzification method. The results establish a distinct hierarchy of priorities, with the sub-criterion O2 (Governance) attaining the highest weight (W=0.169), followed by W2 (Energy use) and T3 (Economic risks). This ranking quantifies the relative influence of each SWOT factor, providing the necessary weighted parameters for the final decision-making process.

Table 5
Final Criteria Weights and Ranking via Fuzzy LOGSTA

Main Criteria	Sub-Criteria	Fuzzy Weight (l, m, u)	Crisp Weight (W⁻)	Rank
Strengths	S1	(0.041, 0.052, 0.067)	0.053	10
	S2	(0.028, 0.036, 0.049)	0.038	12
	S3	(0.045, 0.058, 0.075)	0.059	9
Weaknesses	W1	(0.048, 0.061, 0.079)	0.063	8
	W2	(0.112, 0.142, 0.178)	0.144	2
	W3	(0.071, 0.089, 0.112)	0.091	6
Opportunities	O1	(0.031, 0.040, 0.054)	0.042	11
	O2	(0.134, 0.168, 0.205)	0.169	1
	O3	(0.052, 0.065, 0.082)	0.066	5
Threats	T1	(0.055, 0.069, 0.088)	0.071	4
	T2	(0.050, 0.063, 0.081)	0.065	7
	T3	(0.098, 0.124, 0.156)	0.126	3

Table 6 presents the results of the fuzzy LOGSTA method applied individually to each SWOT category to determine local weights. By analyzing each SWOT category independently, this approach emphasizes the relative importance of sub-criteria within each category. As a result, the weights presented for each main criterion sum to unity, allowing decision-makers to identify the most critical factor specific to internal strengths, weaknesses, and external strategic factors.

Table 6
Local Weights and Ranking via Fuzzy LOGSTA

Main Criteria	Sub-Criteria	Fuzzy Weight (l, m, u)	Crisp Weight (W^-)	Rank
Strengths	S1	(0.18, 0.28, 0.42)	0.29	3
	S2	(0.28, 0.42, 0.58)	0.43	1
	S3	(0.22, 0.30, 0.42)	0.31	2
Weaknesses	W1	(0.10, 0.15, 0.23)	0.16	3
	W2	(0.48, 0.62, 0.75)	0.62	1
	W3	(0.20, 0.28, 0.39)	0.29	2
Opportunities	O1	(0.12, 0.18, 0.27)	0.19	3
	O2	(0.52, 0.66, 0.78)	0.65	1
	O3	(0.18, 0.25, 0.35)	0.26	2
Threats	T1	(0.25, 0.35, 0.48)	0.36	2
	T2	(0.18, 0.25, 0.35)	0.26	3
	T3	(0.32, 0.44, 0.58)	0.45	1

Fig.1 presents the ranking of the strengths. In Fig. 1, speed (S2) factor is considered as the most important strength with a weight value of 0.43 followed by complexity (S3) which has a weight value of 0.31. The least important strength factor is separability (S1) with 0.29, as a weight value.

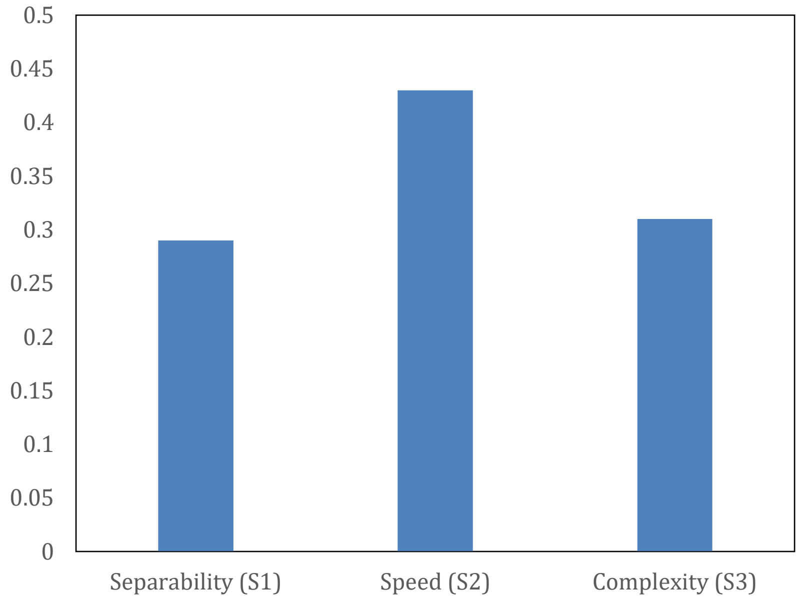

Fig.1. Ranking of the strengths.

Fig. 2 indicates the significance of the three weaknesses factors. According to it, energy use (W2), with 0.62 weight value, is the most critical weakness that impedes the AI adoption for environmental sustainability. Data bias (W3) is the second most critical weakness with a weight value of 0.29. The explainability (W1) is the least critical weakness for AI adoption in this context. The ranking of weaknesses is as follows: W2> W3> W1.

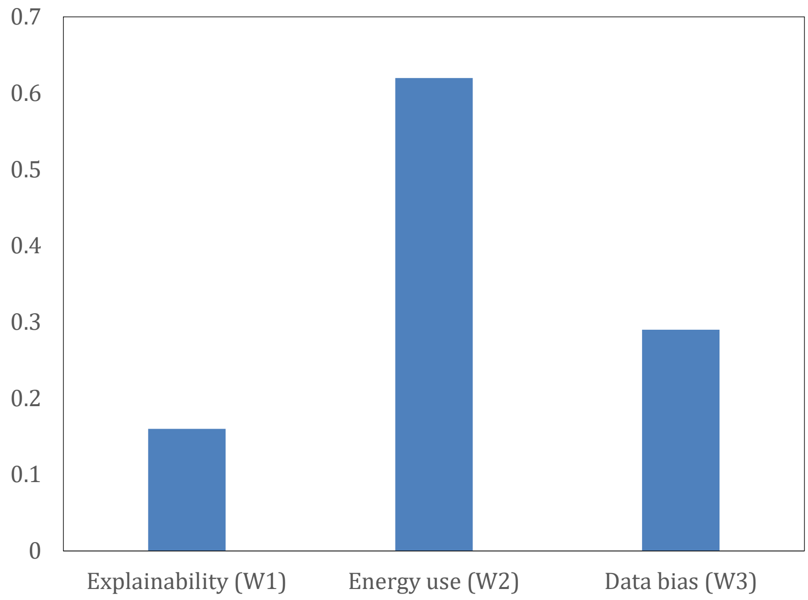

Fig.2. Ranking of the weaknesses.

In Fig.3, the importance of the three opportunity factors assessed by the experts are clearly elucidated. Governance (O2) is the most important opportunity factor with a weight value of 0.65, followed by scientific value (O3) which occupy the second position with a weight value of 0.26. Mitigate climate change impacts (O1) is the least important opportunity factor with a weight value of 0.19. The ranking of opportunities is as follows: O2> O3> O1.

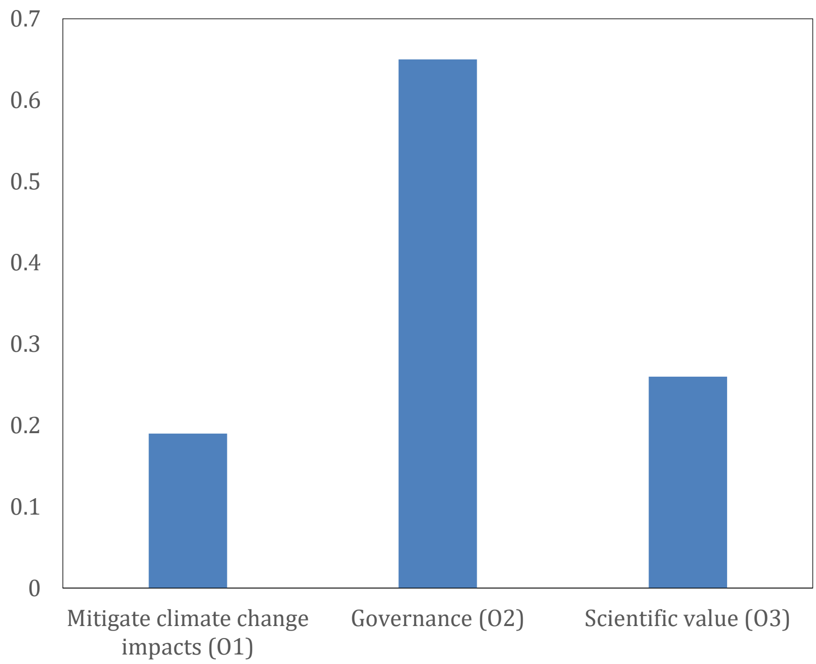

Fig.3. Ranking of the opportunities.

Fig.4 indicates the severity of the three threat factors. From the results, it is shown that economic risks (T3) is the most critical threat for this adoption with a weight value of 0.45, followed by regulation (T1), with a weight value of 0.36. Cybersecurity (T2) is the least critical threat. The ranking of the weaknesses is as follows: T3> T1> T2.

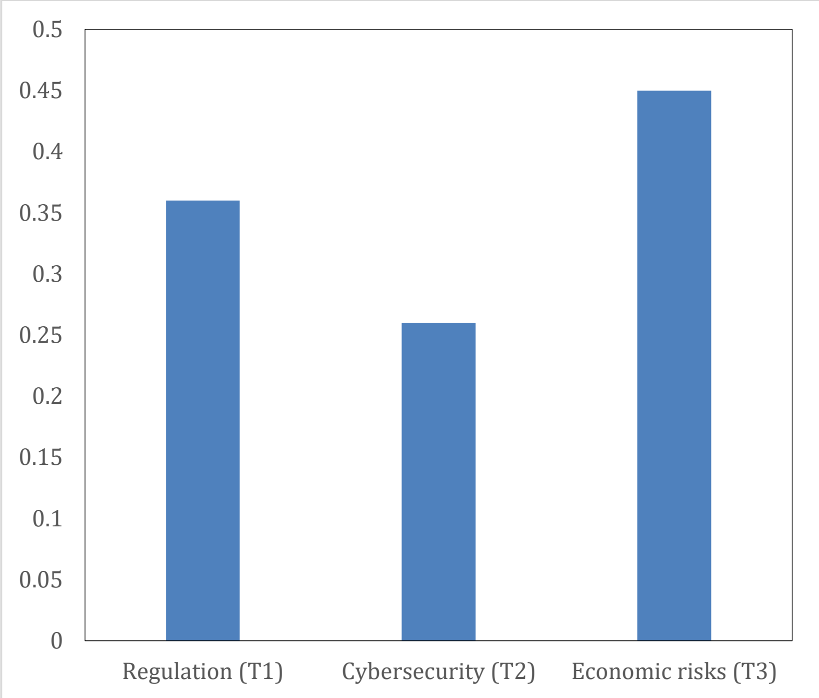

Fig.4. Ranking of the threats.

6. Comparative analysis

To validate the robustness and consistency of the proposed approach, a comparative analysis was conducted utilizing three fuzzy MCDM methods: F-TOPSIS, F-ARAS, and F-SIWEC. The weighting process for the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) involved aggregating the linguistic ratings provided by the experts across the sub-criteria (S1–T3) into composite triangular fuzzy numbers via the arithmetic mean. These fuzzy values were subsequently defuzzified utilizing the center of gravity method and normalized to derive the final crisp weights ($\boldsymbol{w_j}$). The analysis revealed a distinct hierarchy of importance, with O1 (Mitigate climate change consequences) securing the highest weight of 0.139, a reflection of the high consensus regarding its impact. This was followed closely by S3 (Speed) (0.129) and S2 (Complexity) (0.121).

Table 7
F-TOPSIS evaluation of the sub-criteria

Sub-Criteria	Fuzzy Weight $\tilde{w}_j$	De-fuzzified Weight $\boldsymbol{w'_j}$	Normalized Crisp Weight $\boldsymbol{w_j}$
S1	(2.25, 3.25, 4.25)	3.25	0.054
S2	(6.25, 7.25, 8.25)	7.25	0.121
S3	(6.75, 7.75, 8.75)	7.75	0.129
W1	(1.00, 1.25, 2.25)	1.50	0.025
W2	(5.75, 6.75, 7.75)	6.75	0.113
W3	(3.50, 4.50, 5.50)	4.50	0.075
O1	(7.50, 8.50, 9.00)	8.33	0.139
O2	(3.00, 4.00, 5.00)	4.00	0.067
O3	(3.25, 4.25, 5.25)	4.25	0.071
T1	(1.50, 2.50, 3.50)	2.50	0.042
T2	(2.75, 3.75, 4.75)	3.75	0.063
T3	(5.00, 6.00, 7.00)	6.00	0.100

The Fuzzy Additive Ratio Assessment (F-ARAS) method was employed as a comparative weighting approach in Table 8, utilizing the exact same aggregated fuzzy importance vectors $\acute{\boldsymbol{I}}_{\boldsymbol{j}}$ derived from the four experts' evaluations. The F-ARAS fuzzy weight $\widetilde{\boldsymbol{w}}_{\boldsymbol{j}}$ was calculated as the ratio of each criterion's $\acute{\boldsymbol{I}}_{\boldsymbol{j}}$ to the optimal fuzzy importance vector $\acute{\boldsymbol{I}}_{\boldsymbol{0}}$ =(10,10,10). Following defuzzification and normalization, the final crisp weights $\boldsymbol{w}_{\boldsymbol{j}}$ obtained from F-ARAS were found to be consistent with those derived for F-TOPSIS. This calculation confirms that O1 (Mitigate climate change consequences) maintains the dominant importance, validating the derived criterion hierarchy across multiple robust fuzzy weighting techniques.

Table 8

Obtaining final values of the criteria by using fuzzy ARAS method

Sub-Criteria	**Fuzzy Importance $\acute{I}_j$**	**Fuzzy Weight $\widetilde{w}_j$**	**Defuzzified Weight $d(w_j)$**	**Final Crisp Weight w_j**
S1	(2.25, 3.25, 4.25)	(0.038, 0.054, 0.071)	0.054	0.054
S2	(6.25, 7.25, 8.25)	(0.104, 0.121, 0.138)	0.121	0.121
S3	(6.75, 7.75, 8.75)	(0.113, 0.129, 0.146)	0.129	0.129
W1	(1.00, 1.25, 2.25)	(0.017, 0.021, 0.038)	0.025	0.025
W2	(5.75, 6.75, 7.75)	(0.096, 0.113, 0.129)	0.113	0.113
W3	(3.50, 4.50, 5.50)	(0.058, 0.075, 0.092)	0.075	0.075
O1	(7.50, 8.50, 9.00)	(0.125, 0.139, 0.150)	0.138	0.139
O2	(3.00, 4.00, 5.00)	(0.050, 0.065, 0.083)	0.066	0.067
O3	(3.25, 4.25, 5.25)	(0.054, 0.069, 0.087)	0.07	0.071
T1	(1.50, 2.50, 3.50)	(0.025, 0.041, 0.058)	0.041	0.042
T2	(2.75, 3.75, 4.75)	(0.046, 0.061, 0.079)	0.062	0.063
T3	(5.00, 6.00, 7.00)	(0.083, 0.098, 0.116)	0.099	0.1

The application of the Fuzzy Simple Weight Calculation (F-SIWEC) provided in Table 9 further validation of the criterion hierarchy by normalizing the aggregated fuzzy scores derived from the expert evaluations. As presented in Table 9, the results underscore the prominence of O1 (Mitigate climate change consequences), which attained the highest weight of 0.137. This is followed closely by the Strengths criteria S3 (Speed) and S2 (Complexity), with weights of 0.129 and 0.120, respectively. In contrast, W1 (Explainability) was assigned the lowest weight of 0.026. The ranking generated by F-SIWEC exhibits a strong correlation with the results of F-TOPSIS and F-ARAS, reinforcing the consistency of the consensus-based approach while highlighting the distinct perspective offered by the variance-based Fuzzy LOGSTA method.

Table 9

Obtaining final values of the criteria by using fuzzy SIWEC method

Sub-Criteria	$\tilde{s}_{ij}$	$\widetilde{w}_{ij}$	**Defuzzified value**
S1	(2.25, 3.25, 4.25)	(0.032, 0.054, 0.088)	0.055
S2	(6.25, 7.25, 8.25)	(0.088, 0.121, 0.170)	0.12
S3	(6.75, 7.75, 8.75)	(0.095, 0.130, 0.180)	0.129
W1	(1.00, 1.25, 2.25)	(0.014, 0.021, 0.046)	0.026
W2	(5.75, 6.75, 7.75)	(0.081, 0.113, 0.160)	0.112
W3	(3.50, 4.50, 5.50)	(0.049, 0.075, 0.113)	0.075
O1	(7.50, 8.50, 9.00)	(0.105, 0.142, 0.186)	0.137
O2	(3.00, 4.00, 5.00)	(0.042, 0.067, 0.103)	0.068
O3	(3.25, 4.25, 5.25)	(0.046, 0.071, 0.108)	0.071
T1	(1.50, 2.50, 3.50)	(0.021, 0.042, 0.072)	0.043
T2	(2.75, 3.75, 4.75)	(0.039, 0.063, 0.098)	0.064
T3	(5.00, 6.00, 7.00)	(0.070, 0.100, 0.144)	0.1

The results in Fig. 5 demonstrate a fundamental divergence between the Fuzzy LOGSTA method and the comparative approaches (F-TOPSIS, F-ARAS, F-SIWEC). The latter methods prioritize criteria based on magnitude, ranking O1 (Mitigate climate change) highest due to the consensus on its critical importance. In contrast, Fuzzy LOGSTA prioritizes criteria based on variance. It assigns lower weights to O1 not because it is unimportant, but because its importance is already universally agreed upon. Conversely, Fuzzy LOGSTA highlights O2 (Governance) and W2 (Energy use) as top priorities because these factors exhibit the highest levels of expert disagreement, signaling them as areas of strategic uncertainty requiring immediate attention.

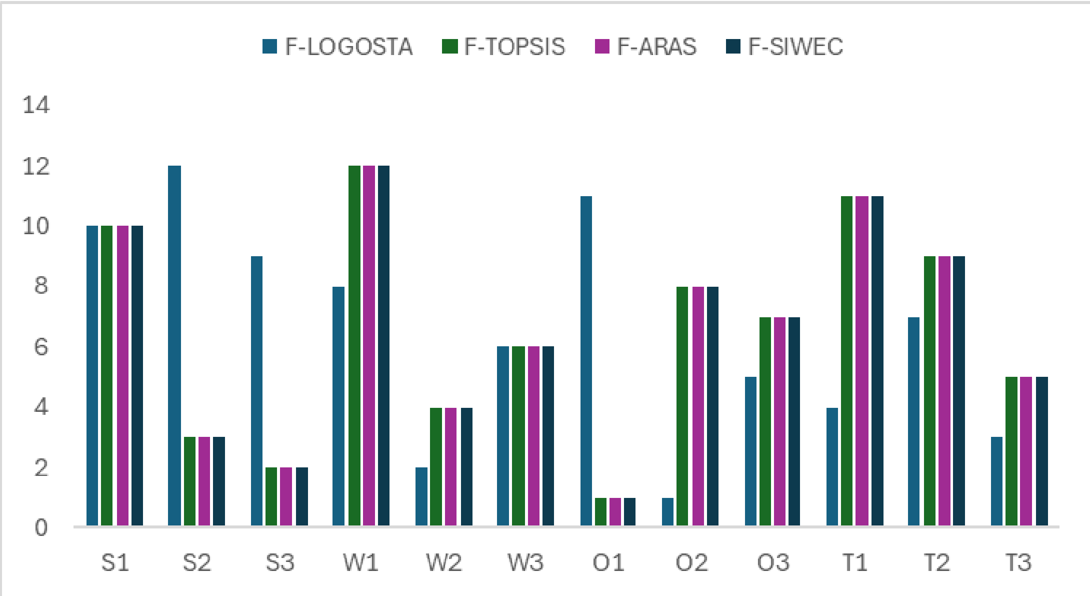

Fig. 5. Comparative analysis of the results.

7. Discussion

This study provides insights into the establishment of a SWOT-fuzzy LOGSTA framework for thoroughly analysing the internal and external factors of AI adoption for environmental sustainability. Via the framework, the most important factors that either enable or impede this adoption are provided: governance (O2), energy use (W2), and economic risks (T3). Various studies confirmed the crucial importance of "governance (O2)" on AI role for environmental sustainability. Tariq [23] indicated how this factor guarantees the successful implementation of AI for environmental sustainability. While AI enhance resource management and environmental monitoring, its adoption also raises issues associated with cybersecurity, transparency, and data protection. Powerful governance frameworks comprising of institutional oversight, ethical guidelines, and regulatory policies are therefore important for reducing these risks and align AI establishment with sustainability targets. In this situation, governance make sures that the benefits evaluated in the SWOT analysis can be translate into feasible and socially responsible environmental outcomes.

The "energy use (W2)" is the second most important factor for this AI role under the same context. Kirikkaleli, Ali [14] confirms this by showing how the AI's environmental effect is strongly associated with its greater energy consumption. Despite the fact that sustainability can be supported by the AI through efficient resource management, climate modelling, and energy optimization, its systems operation and development, particularly data centers necessitate considerable electricity and computational power. This demand of energy may rise the emissions of carbon and neutralize some of the environmental advantages that AI aims to reach. Therefore, overcoming the issues related to energy efficiency via sustainable data centers, renewable energy incorporation, and greener algorithms becomes inevitable to guarantee that AI contributes favourably to environmental sustainability rather than aggravating environmental burdens.

The third most important factor from this analysis is the "*economic risks (**O3**)*" factor. Gaur and Kumar [24] confirms this finding because huge financial investments necessitated for AI development and deployment may produce considerable economic uncertainties for governmental institutions. Although AI enhance environmental efficiency and management, its implementation frequently includes greater costs related to advanced infrastructure, skilled worforce, data collection, and continual technological upgrades. These financial challenges can restrict the availability of AI technologies, especially in developing economies and may disappoint stakeholders from investing in durable-oriented AI solutions. Therefore, the management of economic risks via financial incentives, assisted policies, and strategic investment planning is important to guarantee that AI-driven sustainability measures remain economically viable and largely adopted.

8. Managerial implications

Various significant managerial implications are offered for institutions, policymakers and technology producers looking to promote AI for environmental sustainability. At first, the powerful governance frameworks can be implemented by decision-makers through adequate ethical standards and regulations to guarantee the clear deployment of AI technologies. Secondly, the greater energy consumption issues can be overcome by managers through the adoption of greener algorithms, promotion of energy-efficient AI systems, and encouragement of renewable energy incorporation in data centers to diminish environmental footprint of AI implementations. At end, economic risks can be mitigated through establishment of supportive capacity building, provision of financial incentives, and strategic investment planning to make easier larger implementation of AI-based sustainability initiatives in less-advanced countries. These actions can aid guarantee that AI contributes substantially and sustainably to durable development and environmental management.

9. Conclusions and recommendations

In this study, a fuzzy LOGSTA methodology is used to evaluate the strengths, weaknesses, opportunities, and threats (SWOT) related to AI role for environmental sustainability. For that, 12 SWOT factors are identified based on experts' opinions and literature review. To collect the data, four experts were involved. The results indicated that governance, energy use, and economic risks are the most influential factors for promoting environmental sustainability through AI. While the study has made some contributions, it has some limitations. First, a small number of experts participated. Second, the study is conducted at global level, thus the findings cannot be generalized because every country or region may have specific characteristics. Third, the study relies primarily on expert judgment and qualitative assessments, which may introduce a degree of subjectivity into the evaluation process. Future studies should consider increasing the number of experts, conducting the study at national or regional levels, incorporating larger expert panels to enhance robustness. In addition, new methodology can be adopted using an integration of data envelopment analysis (DEA) and fuzzy logic [25]. Moreover, we should consider the clustering approach as a future research direction given the variety of regions with various characteristics across the globe. In addition, the methodology proposed in this paper can be further extended using frameworks such as, Hyper fuzzy sets [26] and circular Complex Picture Fuzzy Sets [27] and other recent fuzzy sets [28, 29, 30].

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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