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Fuzzy SWARA and Its Application to Prioritize the Artificial Intelligence-Based SWOT Factors for Achieving SDG 2 (Zero Hunger)

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ABSTRACT

This study adopts a fuzzy-based strategic approach to assess the strengths, weaknesses, opportunities, and threats (SWOT) associated with the role of artificial intelligence (AI) in achieving Sustainable Development Goal 2 (SDG 2: Zero Hunger). First, sixteen SWOT factors are identified through a comprehensive literature review and expert consultation. Subsequently, data were collected from four domain experts, and the Fuzzy Stepwise Weight Assessment Ratio Analysis (F-SWARA) method was applied to determine the relative importance of the identified SWOT factors. The findings reveal that the prediction of famine and crop-related issues using satellite and socioeconomic data (S2), together with AI-driven passive data for poverty insights (O5), are the most influential enablers of achieving zero hunger. In contrast, the shortage of relevant data for measuring poverty (W1) and the widening of the rich–poor gap due to automation (T1) constitute the major barriers to achieving this goal. The study contributes to the decision science and management literature by providing practical insights for policymakers seeking to accelerate progress toward SDG 2 and concludes by outlining several promising directions for future research.

1. Introduction

In 2015, the 2030 Agenda has been implemented by the United Nations. It represents a considerable step toward sustainability globally, through 17 sustainable development goals (SDGs) and 169 related goals [1]. It is designed to handle interlinked socio-economic and environmental issues. The goals comprise of climate resilience, environmental protection, ending hunger, showing the complexity of sustainable development (SD) in a quickly changing world. Within this context, artificial intelligence (AI) has significantly emerged as a transforming technological tool with the capacity of fostering development towards these goals. Its execution for sustainable development

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and societal benefit has attracted significant interest from both practitioners from industry and academic researchers [2].

However, the role of AI in achieving SDGs is not unidirectional. Existing studies highlight its dual nature, indicating that although AI can significantly accelerate sustainability goals, it can also show new threats and unintended drawbacks that may restrict development. In a comprehensive evaluation, Lampropoulos *et al.,* [3] reviewed the AI role in reaching SDGs. Maghsoudi *et al.,* [4] explores how the international public discourse on AI and its concordance with the SDGs is. Truby [5] examines how practical pre-emptive regulatory measures can reduce scenarios of AI threatening the SDGs. Goralski and Tan [6] investigate how AI affects the work related to SDGs in the areas related to business, government policy and corporate practices. Nasir *et al.,* [7] adopted an automated approach to find out the overlaps and insights between SDGs and AI. Liengpunsakul [8] determined how AI impact SD at both regional and international levels. Gupta *et al.,* [9] offered clearer exploration at the indicator level, providing nuanced insights into the AI that could shape specific dimensions of SDG performance. Vinuesa *et al.,* [10] evaluated the interconnection between AI technologies and all the SDG targets, summarizing that AI has the ability to assist the fulfilment of 134 goals.

Studies adopting strengths, weaknesses, opportunities, and threats (SWOT) analyses to investigate the AI impact in ending hunger are few. Palomares *et al.,* [11] presented the SWOT analysis of the AI impact on ending hunger (SDG 2). However, their study did not assess and prioritize the most important factors that promote or impede this impact. Additionally, their study lacks a framework that combines both qualitative analysis and multi-criteria decision analysis (MCDM) methods. In response to these gaps, the present study advances previous literature by applying a SWOT-MCDM framework tailored to the prioritization of the AI -based SWOT factors for achieving SDG 2.

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 ending hunger? (2) How can an integrated SWOT-MCDM framework enhance decision-making for the actual role of AI in ending hunger?

To support this, a fuzzy SWARA method developed by Keršuliene et al*.,* [12] is adopted 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 weaknesses and threats to the application of AI for ending hunger. 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 ending hunger. The remaining study is organized in various sections: literature review, problem definition, methodology, application, discussion, conclusions and future recommendations.

2. Literature review

Numerous studies related to SWOT analysis of AI applications are conducted. For instance, Suhara *et al.,* [13] determines how AI can be implemented in models related to digital business from SWOT analysis. Panja [14] explored it for educational purposes. Rony *et al.,* [15] examines the advantages and inconvenience of AI technologies, highlight areas for improvement, and pinpoint potential threats that may hinder their effective incorporation in nursing care. Abubakari *et al.,* [16] evaluated the AI potential from Islamic religious education perspective. Bouraima and Badi [17] adopted a fuzzy based strategic approach to evaluate the role of AI in environmental sustainability from SWOT analysis. Brandas *et al.,* [18] presented it with respect to project management. Noguerol *et al.,* [19] analyze the actual status of AI (Machine learning), applied to radiology from the SWOT analysis point of view. Attoh-Mensah *et al.,* [20] used it in personalized rehabilitation. Ali *et al.,* [21] conducted it in the AI application of Pakistani university libraries.

Other studies have adopted SWOT analysis with respect to SDGs. For instance, Talaat *et al.,* [22] analyze the role of integrating AI and renewable energy in attaining SDGs. Fazal *et al.,* [23] applied a qualitative approach to emphasize the importance of AI in reaching great levels of financial inclusion. Amuda and Alabdulrahman [24] examine AI for food generation among smallholder farmers in Nigeria. Leal Filho *et al.,* [25] adopt the AI to execute SDGs at university level. Mhlanga [26] examines the potential impacts of AI and FinTech on the progress of SDGs.

3. Problem definition

Table 1 outlines the SWOT factors related to the assessment of AI for eradicating hunger (SDG-2) based on the opinions of experts and previous studies [27-29].

Table 1
SWOT analysis related to AI for eradicating hunger

Criteria	Sub-criteria	References
Strengths (S)	Partnerships with tech firms enable better AI solutions (S1)	[27-29] and experts' opinions
	Predict famine and crop issues using satellite and socio-economic data (S2)	
	Optimize Water-Energy-Food Nexus for food security (S3)	
Weaknesses (W)	Shortage of relevant data to measure poverty (W1)	
	Institution costs for active data collection (W2)	
	Determining appropriate thresholds for poverty classification (W3)	
	Institutional corruption and instability (W4)	
Opportunities (O)	AI-driven government decision-making against economic breach (O1)	
	Track AI progress for equitable development (O2)	
	Digital labor and outsourcing for employment (O3)	
	Transparent government procedure via blockchain (O4)	
	AI-driven passive data for poverty insights (O5)	
Threats (T)	Automation widens rich-poor gap (T1)	
	AI automation threatens low-wage jobs (T2)	
	Globalized trade increases inequality (T3)	
	Dependence on foreign AI breakthroughs (T4)	

4. Methodology

To evaluate the SWOT factors of AI in achieving SDG 2, this study adopts the stepwise weight assessment ratio analysis (F-SWARA) method under fuzzy environment. Since its inception, the approach has been applied for bryophyte extinction analysis [30], choice of parking in logistics operations [31], business evaluation [32], influential factors of pyrolysis procedure [33], poverty alleviation strategies [34], organizational antifragility [35], and risk assessment [36]. This technique enables decision-makers to systematically assign criterion weights based on expert judgments regarding the relative importance of evaluation criteria. Its fuzzy extension incorporated triangular fuzzy numbers (TFN) to capture the vagueness inherent in expert evaluations.

The procedural steps of the F-SWARA method are systematically delineated as follows.

Step 1. Ranking of criteria. Experts establish a hierarchical ranking of the evaluation criteria according to their anticipated significance levels. The criteria are arranged in descending order of importance, commencing with the most critical criterion and concluding with the least significant one.

Step 2. Determination of comparative importance. Beginning with the second criterion in the ranked sequence, experts articulate the comparative importance of criterion j relative to the preceding criterion (j-1). This assessment employs linguistic variables that are subsequently transformed into TFNs $(\widetilde{S_j})$, representing the comparative importance of the average value. The fuzzy linguistic scale commonly utilized in F-SWARA applications is presented in Table 2.

Table 2
Fuzzy linguistic scale for comparative importance assessment

Linguistic terms	Membership function
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)

When multiple experts are involved, the geometric mean of their individual judgments is computed to obtain an aggregated comparative importance value for each criterion.

Step 3. Computation of fuzzy coefficients. The fuzzy coefficient $\tilde{k}_j$ is calculated using Eq. (1).

$$\tilde{k}_j = \begin{cases} \tilde{I} & j = 1 \\ \tilde{s}_j + \tilde{I} & j > 1 \end{cases} \tag{1}$$

Where $\tilde{I} = (1,1,2)$ and the addition operation follows fuzzy arithmetic principles.

Step 4. Calculation of fuzzy recalculated weights. The fuzzy recalculated weight $\tilde{q}_j$ is determined through Eq. (2).

$$\tilde{q}_j = \begin{cases} \tilde{I} & j = 1 \\ \frac{\tilde{q}_{j-1}}{\tilde{k}_j} & j > 1 \end{cases} \tag{2}$$

Where division is performed according to fuzzy number operations.

Step 5. Derivation of fuzzy criterion weights. The fuzzy relative weight $\widetilde{w}_j$ for each criterion is computed using Eq. (3).

$$\widetilde{w}_j = \frac{\tilde{q}_j}{\sum_{k=1}^{n} \tilde{q}_k} \tag{3}$$

Where $\widetilde{w}_j = \left(w_j^l, w_j^m, w_j^u\right)$ represents a triangular fuzzy number (TFN) comprising lower, modal, and upper values, and n denotes the total number of evaluation criteria.

Step 6. Defuzzification. To obtain crisp criterion weights for subsequent analyses, the fuzzy weights $w_j$are defuzzified using the centre-of-area (COA) method, also known as the centroid defuzzification technique, as expressed in Eq. (4).

$$w_j = \frac{w_j^l + w_j^m + w_j^u}{3} \tag{4}$$

5. Application

To construct a robust analytical framework, this study identifies and categorizes the key AI-enabled factors that influence the realization of SDG 2 (Zero Hunger). Sixteen factors are systematically organized into four SWOT dimensions. Each expert evaluated the relative importance of these sub-criteria using a predefined linguistic scale, which was subsequently transformed into TFNs to enable fuzzy weight calculations via the F-SWARA method. The derived fuzzy weights were then defuzzified to obtain crisp criterion weights, allowing for the prioritization of both the SWOT categories and their individual sub-factors. This prioritization establishes a clear implementation roadmap for leveraging AI in hunger eradication efforts. The linguistic scale employed for the assessments is presented in Table 2, while Table 3 provides the linguistic decision-making matrices for all criteria.

Table 3
Linguistic decision-making matrix

Criteria	Sub-criteria	E1	E2	E3	E4
Strengths (S)	(S1)	M	ML	MH	MH
	(S2)	VH	VH	H	EH
	(S3)	H	MH	H	M
Weaknesses (W)	(W1)	H	MH	H	H
	(W2)	ML	M	M	MH
	(W3)	ML	VL	VL	VL
	(W4)	MH	M	H	M
Opportunities (O)	(O1)	H	MH	H	MH
	(O2)	MH	M	ML	M
	(O3)	ML	VL	VL	ML
	(O4)	MH	M	MH	MH
	(O5)	H	VH	H	VH
Threats (T)	(T1)	H	VH	EH	H
	(T2)	M	MH	MH	H
	(T3)	H	MH	H	H
	(T4)	ML	VL	M	M

The F-SWARA calculations for the strengths sub-criteria are presented in Table 4, where the fuzzy comparative importance $\tilde{s}_j$ values reflect the relative superiority of each higher-ranked criterion over the subsequent one. Starting from the most important strength (S2), the coefficient $\tilde{k}_j$ is derived by adding unity to $\tilde{s}_j$, yielding fuzzy values that gradually increase as the comparisons proceed. The recalculated weights $\tilde{q}_j$ are obtained by sequentially dividing the previous $\tilde{q}_{j-1}$ by $\tilde{k}_j$, producing a decreasing sequence from (1.000, 1.000, 1.000) for S2 to (0.482, 0.537, 0.601) for S1.

Table 4
Calculations for the Strengths sub-criteria

	Comparative importance $\tilde{s}_j$	Coefficient $\tilde{k}_j$	Recalculated weight $\tilde{q}_j$	Fuzzy weight $\tilde{w}_j$
S2	---	(1.000,1.000,1.000)	(1.000,1.000,1.000)	(0.388,0.443,0.507)
S3	(0.30,0.38,0.46)	(1.300,1.380,1.460)	(0.685,0.725,0.769)	(0.266,0.321,0.390)
S1	(0.28,0.35,0.42)	(1.280,1.350,1.420)	(0.482,0.537,0.601)	(0.187,0.238,0.305)

Finally, the results of the defuzzified factor weights for the strengths category are presented in Table 5, revealing a clear hierarchy of priorities among the AI-based strengths factors for attaining zero hunger objective.

Table 5
Defuzzified value of the weights of strengths

	S1	S2	S3
w_j	0.228	0.446	0.326

Table 6 presents the final weights calculated for the sub-criteria using the F-SWARA method. The analysis reveals a strategic roadmap for AI integration in poverty alleviation, prioritizing high-impact data sources and systemic risks.

Table 6
Sub-criteria weights using F-SWARA method

Criteria	Sub-criteria	Weight
Strengths (S)	(S1)	0.228
	(S2)	0.446
	(S3)	0.326
Weaknesses (W)	(W1)	0.366
	(W2)	0.226
	(W3)	0.128
	(W4)	0.363
Opportunities (O)	(O1)	0.243
	(O2)	0.163
	(O3)	0.103
	(O4)	0.193
	(O5)	0.303
Threats (T)	(T1)	0.339
	(T2)	0.233
	(T3)	0.288
	(T4)	0.144

Figure 1 presents the ranking of the strengths. In Figure 1, the prediction of famine and crop issues using satellite and socio-economic data (S2, 0.446) is the most important factor, followed by the optimization of water-energy-food nexus for food security (S3). The least important strength factor is the partnerships with tech firms enable better AI solutions (S1) with 0.228, as a weight value.

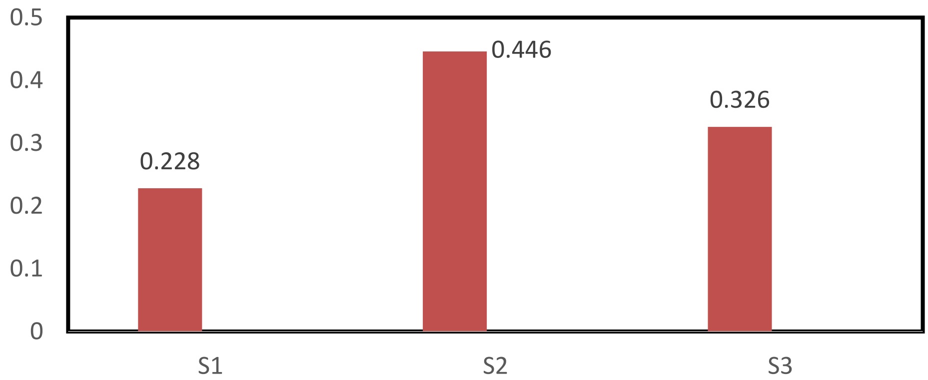

Fig. 1. Ranking of the strengths

Under the weaknesses category, shortage of relevant data to measure poverty (W1, 0.366) is identified as the primary weakness, as indicated in Figure 2. Institutional corruption and instability (W4) are the second most critical weaknesses followed by institution costs to actively collect data for measuring poverty (W2). Determining appropriate thresholds for poverty level classification tasks (W3) is the least critical weakness.

Regarding opportunities, AI-driven passive data for poverty insights (O5, 0.303) and AI-driven government decision-making against economic breach (O1, 0.243) are the top important opportunities (Figure 3). Digital labor and outsourcing for employment (O3) are the least important opportunity behind tracking AI progress for equitable development (O2) and transparent government procedure via blockchain (O4), respectively.

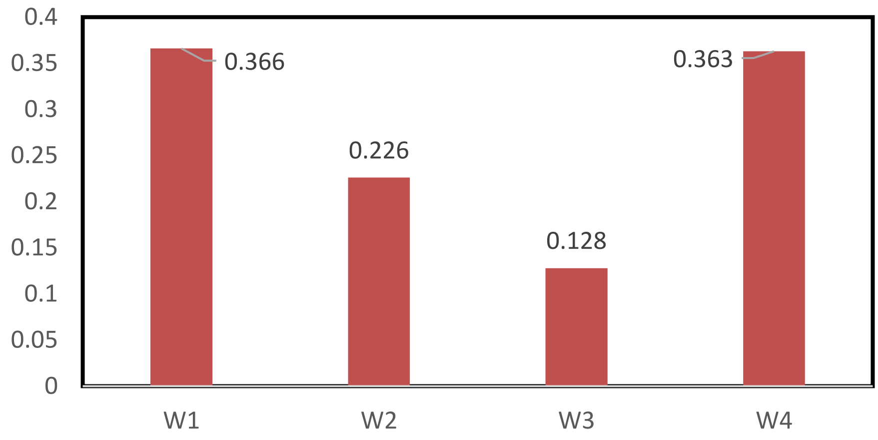

Fig. 2. Ranking of the weaknesses

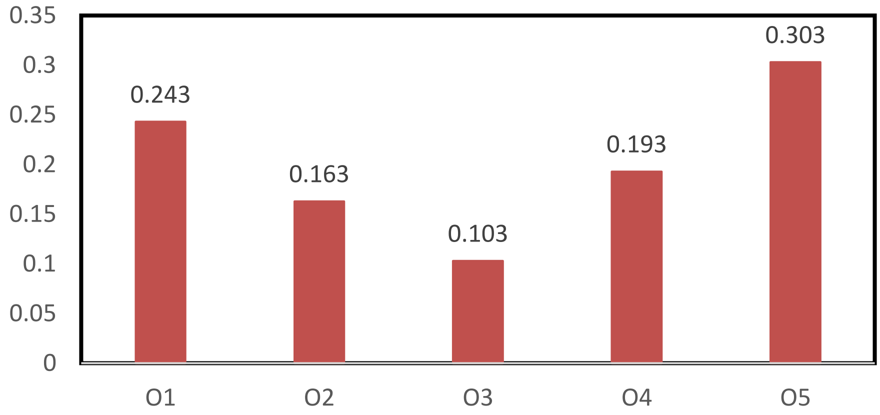

Fig. 3. Ranking of the opportunities

In Figure 4, automation widens rich-poor gap (T1, 0.339) is the most critical threat followed by globalized trade increases inequality (T3) and AI automation threatens low-wage jobs (T2). Dependence on foreign AI breakthroughs (T4) is the least critical threat.

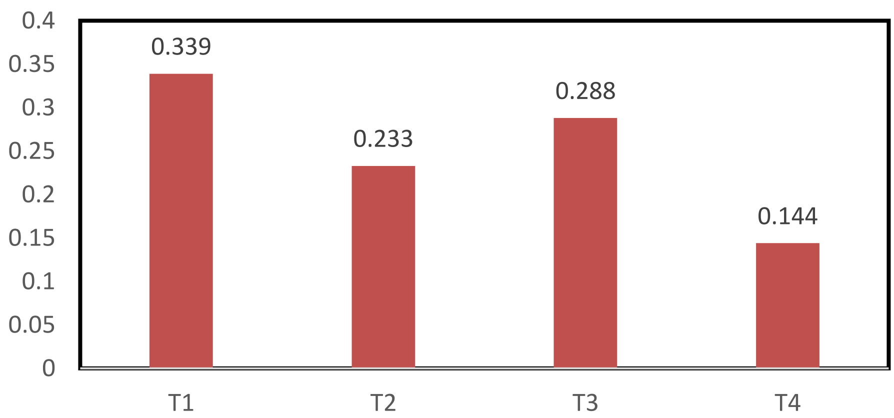

Fig. 4. Ranking of the threats

6. Comparative analysis

To validate the robustness and reliability of the prioritization hierarchy for AI-driven strategies in the context of SDG 2 (Zero Hunger), a comparative analysis was performed using two alternative weighting methods: fuzzy simple weight calculation (F-SIWEC) and fuzzy simple additive weighting

(F-SAW). These techniques were selected to provide a multi-dimensional validation: both F-SIWEC and F-SAW derive weights by directly aggregating and normalizing the fuzzy importance ratings provided by the expert panel, albeit with different defuzzification and normalization procedures. As illustrated in the final results presented in Table 7, all three techniques yielded a consistent ranking order for almost all sub-criteria across the four SWOT categories. This mathematical convergence provides compelling evidence for the stability of the established hierarchy. The high degree of rank correlation confirms that the identified priorities are not artefacts of a specific mathematical model.

Table 7
Comparative analysis using F-SIWEC and F-SAW

Criteria	Sub-criteria	F-SWARA		F-SIWEC		F-SAW	
		Weight	Rank	Weight	Rank	Weight	Rank
Strengths (S)	S1	0.228	3	0.233	3	0.237	3
	S2	0.446	1	0.455	1	0.442	1
	S3	0.326	2	0.312	2	0.321	2
Weaknesses (W)	W1	0.366	1	0.369	1	0.366	1
	W2	0.226	3	0.222	3	0.225	3
	W3	0.128	4	0.122	4	0.127	4
	W4	0.363	2	0.286	2	0.282	2
Opportunities (O)	O1	0.243	2	0.244	2	0.242	2
	O2	0.163	4	0.159	4	0.162	4
	O3	0.103	5	0.098	5	0.101	5
	O4	0.193	3	0.192	3	0.192	3
	O5	0.303	1	0.306	1	0.303	1
Threats (T)	T1	0.339	1	0.346	1	0.338	1
	T2	0.233	3	0.229	3	0.232	3
	T3	0.288	2	0.286	2	0.287	2
	T4	0.144	4	0.139	4	0.143	4

7. Discussions

In this study, a fuzzy SWARA approach is adopted to evaluate the AI role in reaching zero hunger goals through a SWOT analysis. Via the framework, the most important factors that either enable or impede this ending are provided: prediction of famine and crop issues using satellite and socio-economic data (S2), shortage of relevant data to measure poverty (W1), AI-driven passive data for poverty insights (O5), and automation widens rich-poor gap (T1).

Various studies confirmed the crucial importance of “prediction of famine and crop issues using satellite and socio-economic data (S2)” on AI role for attaining SDG2. This permits early recognition of agricultural risks and food insecurity before they increase into crises. Through the incorporation of satellite imagery and socio-economic parameters, the identification of regions at risk can be done with greater precision and timeliness. This careful insight assisted targeted measures like optimization of food distributions, resilience of climate farming strategies, and efficiency of resource allocation. The shortage of relevant data to measure poverty (W1) is the most critical weakness for this AI role under the same context. It prevents adequate identification of exposed people and true scale of food insecurity. In the absence of authentic, appropriate, and disaggregated information on income, available food, and living situations, policymakers and organizations cannot successfully target measures, provide resources, or design adequate agricultural and social assistance programs. This information gap results in unsuccessful distribution of aid, misinformed decisions, and the dismissal of most-at risk communities.

Under opportunity category, the “AI-driven passive data for poverty insights (O5)” is the most important factor. It permits continuous, real-time apprehension of food insecurity without depending on expensive and infrequent surveys. By leveraging data produced from usage of mobile phones, transaction patterns, and other digital traces, AI can uncover hidden poverty dynamics, detect sudden shocks, and map exposed populations with great spatial and temporal resolution. This produces a great opportunity to supplement conventional data resources, enhance the accuracy of poverty evaluations, and assist timely, targeted measures like food aid, subsidies, and agricultural assistance.

Regarding threat category, the automation widens rich-poor gap (T1) is the most critical one. It can advantage skilled workers and capital owners while displacing low-skilled labor, particularly in food and agriculture related fields. With the transformation and reduction of jobs, exposed people may encounter loss in income, food access reduction, food insecurity and poverty deepening. Moreover, unequal access to latest technologies and digital infrastructure farther concentrates gains productivity in already advantaged regions and groups. This increasing inequality erodes inclusive economic growth and restricts their capacity to secure adequate nutrition, ultimately posing a considerable barrier to ending hunger sustainably.

8. Conclusions and recommendations

In this study, a fuzzy SWARA methodology is used to evaluate the strengths, weaknesses, opportunities, and threats (SWOT) related to AI role for ending zero hunger. For that, 14 SWOT factors are identified based on experts' opinions and literature review. To collect the data, four experts were involved. The results indicated that the most important factor under each category. While the study has made some contributions, it has some limitations. First, the study is conducted at global level, thus the findings cannot be generalized because every country or region may have specific characteristics. Second, a small number of experts participated. 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 [37]. 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 [38, 39] and circular Complex Picture Fuzzy Sets [40, 41].

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Conflicts of Interest
Authors declare no conflicts of interest.

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