SCIENTIFIC OASIS

Management Science Advances

Journal homepage: www.msa-journal.org
eISSN: 3042-2205

Assessing the Role of Artificial Intelligence in Poverty Eradication (SDG1): A SWOT–Fuzzy SIWEC Framework

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ARTICLE INFO

Article history:
Received 7 February 2026
Received in revised form 2 April 2026
Accepted 30 April 2026
Available online 3 May 2026

Keywords:
Artificial intelligence; SWOT analysis; Poverty eradication; Sustainable development goal; F-SIWEC.

ABSTRACT

This study adopted a fuzzy-based strategic approach to assess the strengths, weaknesses, opportunities, and threats (SWOT) related to the role of artificial intelligence (AI) in eradicating poverty under Sustainable Development Goal (SDG 1). First, 17 SWOT factors are identified based on experts' opinions and a literature review. Then, data were collected from four domain experts, and a fuzzy simple weight calculation (F-SIWEC) is applied to determine the weight of SWOT factors. The findings reveal that the predictive capabilities of machine learning applied to satellite and aerial imagery (S2), along with the integration of passive data collection and AI-driven analytics for reliable poverty estimation (O5), serve as key enablers of poverty eradication. In contrast, the lack of effective data for measuring poverty in developing countries (W1) and the risk of automation exacerbating income inequality and widening the rich–poor gap (T2) constitute major barriers to achieving this goal. The study makes a meaningful contribution to the decision sciences and management literature by offering practical insights for policymakers in eradicating poverty and concludes by outlining clear avenues for future research.

1. Introduction

In 2015, the implementation of the 2030 Agenda by the United Nations represents a significant step toward sustainability at international level, indicated through 17 sustainable development goals (SDGs) and 169 related goals designed to handle interlinked socio-economic and environmental issues [1]. These goals together span important areas like resilience to climate, protection of environment, eradication of poverty, show the difficulty of sustainable development in a speedy transforming world. Within this situation, artificial intelligence (AI) has considerably appeared as a changing technological instrument with the ability to foster development towards these goals. Its

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https://doi.org/10.31181/msa31202648

implementation for durable development and societal advantage has attracted increased interest from both practitioners from industry and academic researchers [2].

However, the AI contribution to the SDGs is far from single direction. Previous studies highlight its dualistic nature, showing that while AI can considerably advance sustainability goals, it may also show new threats and unexpected drawbacks that could restrict development. In a comprehensive evaluation, Vinuesa *et al.* [3] evaluated the interconnection between AI technologies and all the SDG targets, summarizing that AI has the ability to assist the fulfilment of 134 goals. At the same time, it may negatively impact 59 goals, with some zones experiencing both permitting and restricting influences based on the development context. Extending on this line, Gupta *et al.* [4] offered clearer exploration at the indicator level, providing nuanced insights into the AI could shape specific dimensions of SDG performance. Liengpunsakul [5] determined how AI impact SD at both regional and international levels. Nasir *et al.* [6] adopted an automated approach to find out the overlaps and insights between SDGs and AI. Goralski and Tan [7] investigate how AI affect the work related to SDGs in the areas related to business, government policy and corporate practices. Truby [8] examines how practical pre-emptive regulatory measure can reduce scenarios of AI threatening the SDGs. Maghsoudi *et al.* [9] explores how the international public discourse on AI and its concordance with the SDGs is. Lampropoulos *et al.* [10] reviewed the AI role in reaching SDGs.

Studies adopting strengths, weaknesses, opportunities, and threats (SWOT) analyses to investigate the AI impact in eradicating poverty are few. Palomares *et al.* [11] presented the SWOT analysis of the AI impact on eradicating poverty (SDG1). However, their study did not assess and prioritize the most important factors that promote or impede this impact. additionally, their study lack a framework that combine 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 1.

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

To support this, a fuzzy simple weight calculation (F-SIWEC) method developed by Puška *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 challenges and threats to the application of AI for eradicating poverty. 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 eradicating poverty. 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

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

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

3. Problem Definition

Table 1 outlines the SWOT factors related to the assessment of AI for ending poverty (SDG-1) based on the opinions of experts and previous studies [3, 8, 27].

Table 1
SWOT analysis related to AI for ending poverty

Criteria	Sub-criteria	References
Strengths (S)	Integration of property data and digital transaction in regression techniques (S1)	[3, 8, 27] and experts' opinions
	Predictive power of machine learning upon satellite and aerial images (S2)	
	Deep Learning with mobile device data as a powerful domestic income predictor (S3)	
	Rise of new technologies in primary and industrial sectors across less advanced nations (S4)	
Weaknesses (W)	Lack of effective data to measure poverty in developing countries (W1)	
	Institution costs to actively collect data for measuring poverty (W2)	
	Determining appropriate thresholds for poverty level classification tasks (W3)	
	Institutional corruption and instability as obstacles to economic prosperity (W4)	
Opportunities (O)	AI and digital technologies support government decision-making against economic breach (O1)	
	Identifying how AI advances spread globally to ensure equal development (O2)	
	Digital labor and outsourcing for employment (O3)	
	Blockchain for transparent and corruption-free government processes (O4)	
	Passive data collection bridged with AI and data analysis for reliable poverty estimations (O5)	
Threats (T)	Higher economic disparity risk due to technologically globalized trade (T1)	
	Automation processes accentuate rich-poor breach and economic disparity (T2)	
	AI-driven automation could affect low-salary labor workforce (T3)	
	Dependence on other nations if no pathways for AI breakthroughs are identified nationwide (T4)	

4. Methodology

To evaluate the SWOT factors of AI in achieving SDG 1, this study adopts the fuzzy simple weight calculation method. Since its inception, the approach has been applied for localized supply chain networks [28], electric car choices [29], selection of competitive intelligence platforms [30], green digital twins [31], transportation policy choice [32], tourism in botanical gardens [33], China-Africa cooperation [34], railway infrastructure planning [35], sustainable supplier selection [36], organizational structure of an agro-food company [37], sustainable waste disposal technology selection [38].

This technique is robust in mitigating ambiguities and the subjective nature of expert opinions. The approach aggregates expert assessments using linguistic variables, transforms them into fuzzy numbers, and computes normalized weights to reflect the relative importance of each criterion. The specific steps of the methodology are outlined below:

Step 1. The relative significance of each criterion is evaluated by experts who provide judgments specifically within each SWOT category. By assigning linguistic variables ranging from 'very low' to 'very high,' these qualitative assessments capture the perceived importance of each parameter in determining the potential of AI to achieve SDG 1.

Step 2. The linguistic evaluations provided by experts are transformed into triangular fuzzy numbers (TFNs), characterized by lower, middle, and upper bounds. This conversion serves to capture the subjectivity inherent in the experts' opinions.

$$\tilde{x}_{ij} = \left(x_{ij}^{l}, x_{ij}^{m}, x_{ij}^{u}\right) \tag{1}$$

Step 3. The initial fuzzy decision matrix is prepared using the fuzzy numbers derived from expert assessments. Each entry represents the relative significance of a specific criterion, incorporating the uncertainty captured through linguistic evaluations. Consequently, this matrix serves as the fundamental basis for computing the criteria weights using the F-SIWEC technique.

$$\begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ . & . & \cdots & . \\ . & . & \cdots & . \\ . & . & \cdots & . \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{2}$$

Where $\tilde{x}_{ij}$ represents the ranking assigned by the decision-maker to a specific criterion, expressed as a fuzzy number.

Step 4. This step involves the normalization of the fuzzy values within the decision matrix. This is achieved by dividing each value by the maximum upper bound observed across all criteria and expert assessments ($\max x_{ij}^{u}$).

$$\tilde{n}_{ij} = \frac{x_{ij}^{l}}{\max x_{ij}^{u}}, \frac{x_{ij}^{m}}{\max x_{ij}^{u}}, \frac{x_{ij}^{u}}{\max x_{ij}^{u}} \tag{3}$$

Step 5. The standard deviation (std.dev_j) is calculated based on the fuzzy numbers derived from expert assessments. This metric represents consistency or variation within the criteria evaluation, enabling the approach to highlight parameters where expert judgments exhibit higher differentiation. This process constitutes a critical characteristic of the F-SIWEC technique for capturing the associated importance under ambiguity.

Step 6. A multiplication of normalized fuzzy rating by related values of standard deviation is made to reflect the normalized fuzzy rating.

$$\tilde{v}_{ij} = \tilde{n}_{ij} \times st.dev_j \tag{4}$$

Step 7. The fuzzy weighted values for each parameter are aggregated by summing the weighted fuzzy assessments provided by all experts. This process yields a comprehensive representation of each parameter's significance, incorporating both independent expert opinions and the ambiguity captured in the preceding steps. The result is an integrated fuzzy weight for each parameter, which forms the basis for determining the final significance rankings.

$$\tilde{S}_{ij} = \sum_{j=1}^{n} \tilde{v}_j \tag{5}$$

Step 8. The normalized fuzzy weight for each parameter is obtained by dividing each independent fuzzy value by the total sum of all fuzzy values. During this procedure, it is imperative to ensure that the lower bound remains less than or equal to the middle value. This condition is met only if the logical order of the fuzzy numbers is maintained.

$$\widetilde{w}_{ij} = \frac{S_{ij}^{l}}{\sum_{j=1}^{n} S_{ij}^{u}}, \frac{S_{ij}^{m}}{\sum_{j=1}^{n} S_{ij}^{m}}, \frac{S_{ij}^{u}}{\sum_{j=1}^{n} S_{ij}^{l}} \tag{6}$$

Step 9. The final fuzzy weights of each criterion may be retained in their fuzzy form or defuzzified into crisp values, depending on analytical requirements. In this study, the fuzzy weights are defuzzified using a suitable defuzzification approach to convert each fuzzy number into a unique representative value.

$$w_{jdef} = \frac{w_{ij}^{l} + 4 \times w_{ij}^{m} + w_{ij}^{l}}{6} \tag{7}$$

5. Application

To establish a comprehensive framework for analysis, this study identifies and categorizes the key AI-based factors influencing the achievement of SDG 1. These factors are systematically grouped into four main categories: strengths (S), weaknesses (W), opportunities (O), and threats (T), encompassing a total of seventeen distinct sub-criteria. Each expert assessed the criteria using a predefined linguistic scale, which was subsequently converted into TFN's to facilitate the fuzzy weight calculation. The derived criterion weights were then applied to evaluate and rank the SWOT categories and their corresponding sub-factors, establishing a clear priority for implementation. The linguistic scale used for this assessment is presented in Table 2, while Table 3 displays the linguistic decision-making matrix for the criteria.

Table 2
Fuzzy linguistic evaluation scale

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)

Table 3
Linguistic decision-making matrix

Criteria	Sub-criteria	E1	E2	E3	E4
Strengths (S)	(S1)	VH	VH	H	MH
	(S2)	EH	EH	VH	EH
	(S3)	VH	H	H	H
	(S4)	M	MH	MH	M
Weaknesses (W)	(W1)	EH	VH	VH	EH
	(W2)	MH	VH	MH	MH
	(W3)	M	ML	ML	VL
	(W4)	H	H	VH	H
Opportunities (O)	(O1)	VH	H	MH	VH
	(O2)	VL	VL	VL	ML
	(O3)	M	M	MH	M
	(O4)	ML	ML	ML	ML
	(O5)	EH	H	M	VH
Threats (T)	(T1)	MH	M	ML	ML
	(T2)	EH	MH	VH	EH
	(T3)	H	M	MH	H
	(T4)	VL	VL	VL	ML

Normalization of the initial fuzzy decision matrix was essential to establish a uniform comparative scale. This matrix was constructed from expert evaluations. Following the F-SIWEC methodology, we achieved this by simply dividing each fuzzy number by the maximum upper bound value across all criteria and responses. This procedure effectively rescales the data to the standardized [0, 1] range. Crucially, this action must retain the original relational significance of the expert judgments. The resulting normalized matrix mitigates potential scale discrepancies, ensuring a reliable foundation for subsequent criterion weight derivation. The finalized matrix (Table 4) now forms the direct input for our computational phase.

Table 4
Normalized fuzzy decision-making matrix

	S1	S2	S3	S4	σ_j
E1	(0.778,0.889,1.000)	(0.889,1.000,1.000)	(0.778,0.889,1.000)	(0.333,0.444,0.556)	0.221
E2	(0.778,0.889,1.000)	(0.889,1.000,1.000)	(0.667,0.778,0.889)	(0.444,0.556,0.667)	0.175
E3	(0.667,0.778,0.889)	(0.778,0.889,1.000)	(0.667,0.778,0.889)	(0.444,0.556,0.667)	0.151
E4	(0.444,0.556,0.667)	(0.889,1.000,1.000)	(0.667,0.778,0.889)	(0.333,0.444,0.556)	0.217

Following the normalization process, the F-SIWEC procedure proceeds by multiplying the normalized fuzzy values by the standard deviation computed for each SWOT factor, showed in Table 4. This operation directly incorporates the dispersion of expert opinions into the weight calculation, thereby amplifying the influence of factors that exhibit greater divergence in expert assessments. The resulting weighted fuzzy products are then aggregated across all experts for each individual factor, as presented in Table 5. This summation yields preliminary fuzzy weights, which collectively represent the integrated importance of each factor within a framework of uncertainty. Throughout this computational stage, the integrity of the TFN structure is meticulously preserved, ensuring that the fundamental condition (lower bound ≤ modal value ≤ upper bound) is consistently maintained.

Table 5
Obtaining final values of the strengths' factors by using fuzzy SIWEC method

	S1	S2	S3	S4
$\tilde{s}_{ij}$	(0.505,0.590,0.675)	(0.662,0.747,0.764)	(0.534,0.619,0.704)	(0.291,0.376,0.461)
$\widetilde{w}_{ij}$	(0.254,0.253,0.259)	(0.332,0.320,0.293)	(0.268,0.265,0.270)	(0.146,0.161,0.177)

The results of the defuzzified factor weights for the strengths category are presented in Table 6, revealing a clear hierarchy of priorities among the artificial intelligence-based strengths factors for addressing poverty alleviation.

Table 6
Defuzzified value of the weights of strengths

	S1	S2	S3	S4
w_j	0.254	0.318	0.267	0.161

Table 7 presents the final weights calculated for the sub-criteria using the F-SIWEC method. The analysis reveals a strategic roadmap for AI integration in poverty alleviation, prioritizing high-impact data sources and systemic risks.

Table 7
Sub-criteria weights using F-SIWEC method

Criteria	Sub-criteria	Weight	Rank
Strengths (S)	(S1)	0.254	3
	(S2)	0.318	1
	(S3)	0.267	2
	(S4)	0.161	4
Weaknesses (W)	(W1)	0.347	1
	(W2)	0.235	3
	(W3)	0.119	4
	(W4)	0.298	2
Opportunities (O)	(O1)	0.303	2
	(O2)	0.093	5
	(O3)	0.172	3
	(O4)	0.123	4
	(O5)	0.308	1
Threats (T)	(T1)	0.185	3
	(T2)	0.403	1
	(T3)	0.300	2
	(T4)	0.112	4

Figure 1 presents the ranking of the strengths. In Figure 1, predictive power of machine learning upon satellite and aerial images (S2, 0.318) is the most important factor, followed by deep Learning with mobile device data as a powerful domestic income predictor (S3) and integration of property data and digital transaction in regression techniques (S1). The least important strength factor is (S4) with 0.161, as a weight value.

Under the weaknesses category, lack of effective data to measure poverty in developing countries (W1, 0.347) is identified as the primary barrier, as indicated in Figure 2. Institutional corruption and instability as obstacles to economic prosperity (W4) is the second most critical weakness 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.

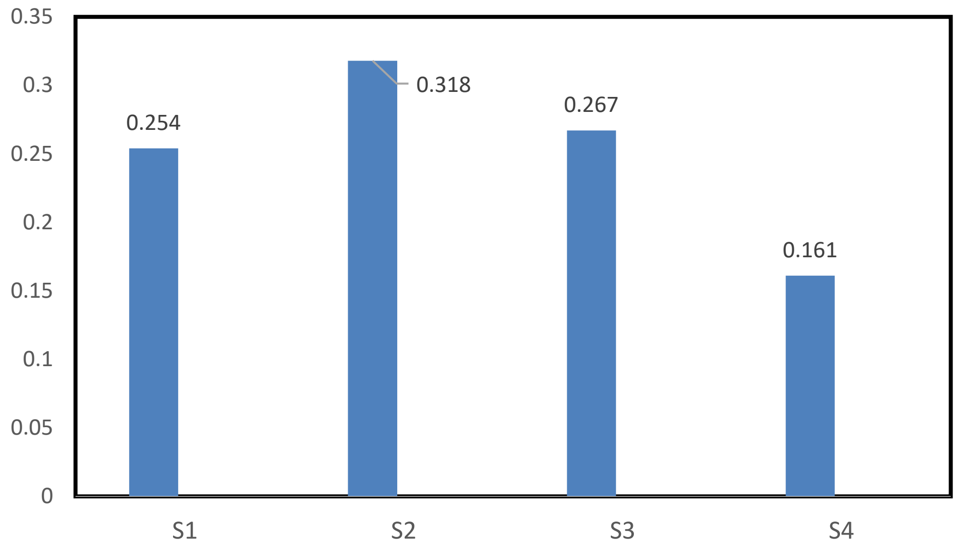

Fig. 1. Ranking of the strengths

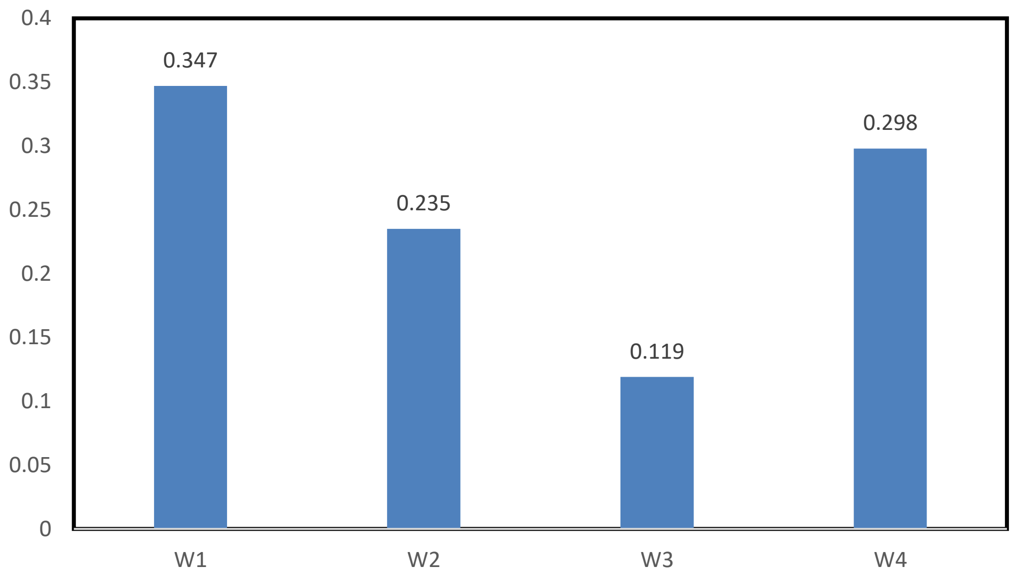

Fig. 2. Ranking of the weaknesses

Regarding opportunities, passive data collection bridged with AI and data analysis for reliable poverty estimations (O5, 0.308) and AI and digital technologies support government decision-making against economic breach (O1, 0.303) are the top important opportunities (Figure 3). Identifying how AI advances spread globally to ensure equal development (O2) is the least important opportunity behind digital labor and outsourcing for employment (O3) and blockchain for transparent and corruption-free government processes (O4), respectively.

In Figure 4, automation processes accentuating rich-poor breach and economic disparity (T2, 0.403) is the most critical threat followed by AI-driven automation affecting low-salary labor workforce (T3) and higher economic disparity risk due to technologically globalized trade (T1). Dependence on other nations if no pathways for AI breakthroughs are identified nationwide (T4) is the least critical threat.

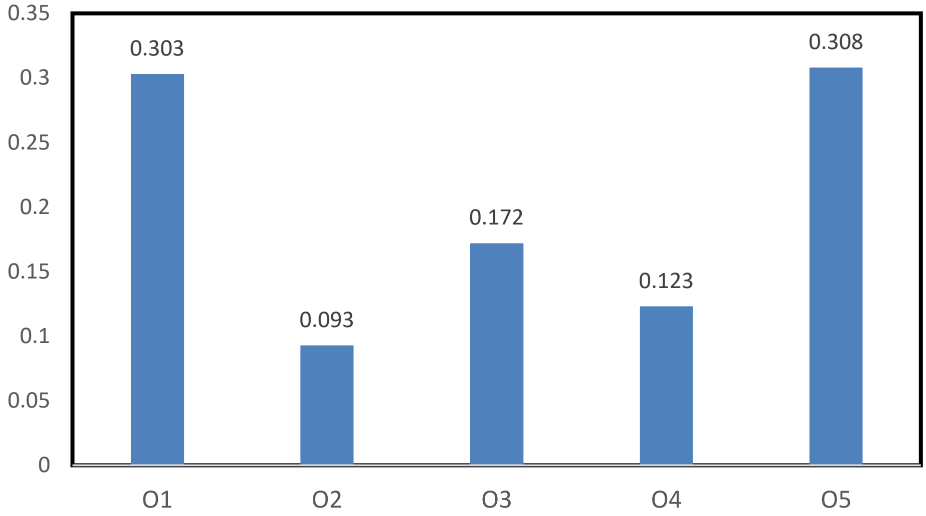

Fig. 3. Ranking of the opportunities

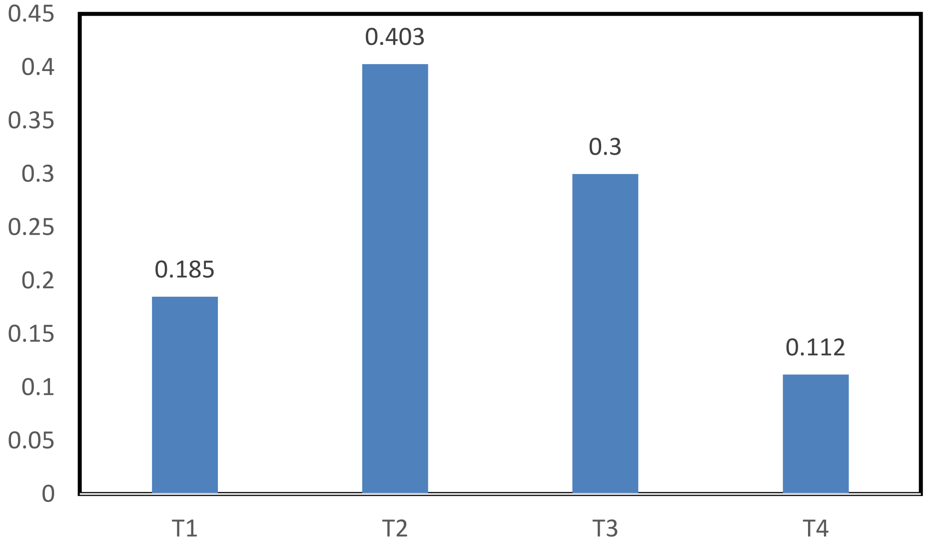

Fig. 4. Ranking of the threats

6. Comparative analysis

To validate the robustness and reliability of the prioritization hierarchy for AI-driven strategies in the context of SDG 1, a comparative analysis was performed using the fuzzy stepwise weight assessment ratio analysis (F-SWARA) [39] and the fuzzy criteria importance through intercriteria correlation (F-CRITIC) [40] methods. These techniques were selected to provide multi-dimensional validation; while F-SWARA captures the direct subjective expertise of the decision-makers, F-CRITIC extracts weights based on the objective contrast and correlation within the data matrix. As illustrated in the final results presented in Figure 5, both techniques yielded a consistent ranking order for 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 artifacts of a specific mathematical model.

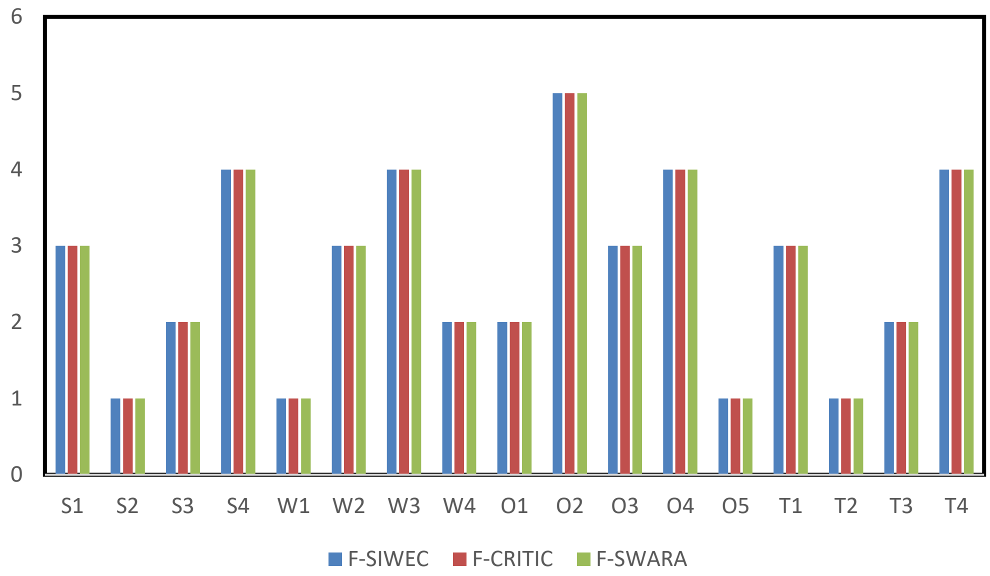

Fig. 5. Comparative analysis results

7. Sensitivity analysis

To ensure the reliability and stability of the criteria weights derived through the F-SIWEC method, a sensitivity analysis was conducted. It was designed to evaluate the robustness of the weight coefficients against potential expert bias. A "leave-one-out" cross-validation procedure was employed, wherein four distinct scenarios were simulated by iteratively excluding the evaluations of one expert from the aggregation process. This allows for a rigorous assessment of whether the final weight distribution is the result of a collective consensus or is disproportionately influenced by the subjective judgment of a single outlier.

The results for the strengths sub-criteria, as summarized in Table 8, demonstrate a high degree of structural stability. Across all simulated scenarios, S2 (Efficiency) consistently emerged as the most significant factor, maintaining the primary rank regardless of which expert's input was removed. While minor numerical fluctuation was observed in the weight coefficients in Scenario 4, where the exclusion of Expert 4 narrowed the margin between the top two factors; the ordinal ranking of the sub-criteria (S2 > S3 > S1 > S4) remained consistent. This indicates that the preference for S2 is deeply embedded in the collective data and is not an artifact of a specific individual’s evaluation, thereby validating the internal consistency of the F-SIWEC application.

Table 8
Sensitivity analysis of the Strengths sub-criteria weights

Scenario	S1 Weight (Rank)	S2 Weight (Rank)	S3 Weight (Rank)	S4 Weight (Rank)	Rank Order
Original (E1–E4)	0.2542 (3)	0.3179 (1)	0.2666 (2)	0.1613 (4)	S2 > S3 > S1 > S4
Excluding E1	0.2485 (3)	0.3248 (1)	0.2544 (2)	0.1723 (4)	S2 > S3 > S1 > S4
Excluding E2	0.2485 (3)	0.3248 (1)	0.2644 (2)	0.1623 (4)	S2 > S3 > S1 > S4
Excluding E3	0.2647 (2)	0.3218 (1)	0.2588 (3)	0.1547 (4)	S2 > S1 > S3 > S4
Excluding E4	0.2552 (3)	0.2831 (1)	0.2818 (2)	0.1799 (4)	S2 > S3 > S1 > S4

A similar trend of stability is evident in the analysis of the remaining criteria categories (Weaknesses, Opportunities, and Threats), as presented in Table 9. In the weaknesses and threats groups, the ranking of factors remained identical across all scenarios, reflecting a clear strategic consensus among the experts regarding the hierarchy of these factors. In the opportunities category, although a slight rank reversal occurred between O1 and O5 in Scenario 3, the variation was statistically marginal and did not disrupt the overall prioritization logic. These findings collectively suggest that the F-SIWEC model is highly robust to variations in expert input, providing a dependable foundation for strategic decision-making and ensuring that the final weights are representative of a stable, multi-expert perspective.

Table 9
Results of sensitivity analysis

Sub-Criteria	Original Result	(Excl. E1)	(Excl. E2)	(Excl. E3)	(Excl. E4)
W1	0.347 (1)	0.339 (1)	0.355 (1)	0.351 (1)	0.343 (1)
W2	0.235 (3)	0.231 (3)	0.222 (3)	0.245 (3)	0.242 (3)
W3	0.119 (4)	0.125 (4)	0.121 (4)	0.128 (4)	0.102 (4)
W4	0.298 (2)	0.305 (2)	0.302 (2)	0.276 (2)	0.313 (2)
O1	0.303 (2)	0.292 (2)	0.301 (2)	0.318 (1)	0.301 (2)
O2	0.093 (5)	0.095 (5)	0.091 (5)	0.090 (5)	0.096 (5)
O3	0.172 (3)	0.176 (3)	0.171 (3)	0.165 (3)	0.176 (3)
O4	0.123 (4)	0.126 (4)	0.122 (4)	0.121 (4)	0.123 (4)
O5	0.308 (1)	0.311 (1)	0.315 (1)	0.306 (2)	0.304 (1)
T2	0.403 (1)	0.398 (1)	0.415 (1)	0.399 (1)	0.400 (1)
T3	0.300 (2)	0.308 (2)	0.285 (2)	0.302 (2)	0.305 (2)
T1	0.185 (3)	0.180 (3)	0.189 (3)	0.188 (3)	0.183 (3)
T4	0.112 (4)	0.114 (4)	0.111 (4)	0.111 (4)	0.112 (4)

8. Discussion

In this study, a fuzzy SIWEC approach is adopted to evaluate the AI role in eradicating the poverty through a SWOT analysis. Via the framework, the most important factors that either enable or impede this eradication are provided: predictive power of machine learning upon satellite and aerial images (S2), lack of effective data to measure poverty in developing countries (W1), passive data collection bridged with AI and data analysis for reliable poverty estimations (O5), and automation processes accentuating rich-poor breach and economic disparity (T2).

Various studies confirmed the crucial importance of "predictive power of machine learning upon satellite and aerial images (S2)" on AI role for attaining SDG1. It permits cost effective, accurate, and scalable evaluation of poverty indications in areas where conventional collection of data is restricted or deficient. Through the extraction of great resolution spatial features, machine learning techniques can adequately predict socio-economic situations and pinpoint exposed people. The "lack of effective data to measure poverty in developing countries (W1)" is the most critical weakness for this AI role under the same context. In many less-developed countries, there is frequently inconsistent, deficient, and sparse poverty related data because of restricted institutional capacity, deficient data infrastructures, and greater costs of data collection. This erodes the generalizability, fairness, and performance of AI models, causing biased predictions and unreliable policy suggestions.

Under opportunity category, the "passive data collection bridged with AI and data analysis for reliable poverty estimations (O5)" is the most important factor. This permits continual, cost-efficient, and real-time poverty monitoring without depending just on conventional surveys. Passive data sources can be systematically apprehended at huge scale and examined through AI to reveal patterns associated with access to services, mobility, and income levels. Regarding threat category, the "automation processes accentuating rich-poor breach and economic disparity (T2)" is the most critical one. This is because it risks larging the gap between rich and poor by unequally advantaging technological advanced areas, capital owners, and skilled workers, while displacing low-skilled labor in poor communities. As manual and routine jobs are progressively automated, many people in less-advanced countries, who depend on such employments, encounter job losses and diminishes income advantages without appropriate reskilling pathways.

8. Managerial Implications

Various significant managerial implications are offered for decision-makers to implement a strategic and balanced framework for leveraging AI for poverty eradication through the capitalization of powerful predictive abilities while overcoming crucial data limitations and reducing socio-economic risks. At first, policymakers and practitioners should focus on investing in powerful data infrastructure, promote the incorporation of passive data sources with latest analytics, and guarantee data quality, inclusiveness, and governance. Second, proactive active actions such as inclusive innovation policies, reskilling of workforce, and ethical AI schemes need to be adopted to prevent the widening of inequality produced by automation. By aligning technological deployment with social equity goals, managers can improve the sustainability, fairness, and effectiveness of AI-driven poverty reduction measures.

9. Conclusions and Future Recommendations

In this study, a fuzzy SIWEC methodology is used to evaluate the strengths, weaknesses, opportunities, and threats (SWOT) related to AI role for eradicating poverty. For that, 13 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, 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 [41]. 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 complexed Pythagorean fuzzy sets [42], pentagonal intuitionistic fuzzy numbers [43], circular complex picture fuzzy sets [44], and other types of fuzzy sets [45].

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.

Acknowledgement

This research was not funded by any grant.

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