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Assessment of Solar Energy Technologies in Meeting the 2030 Agenda and Sustainable Development Goals Under an Interval-Valued Fermatean Fuzzy Environment

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ABSTRACT

Renewable energy sources, particularly solar energy, play a vital role in achieving the 2030 Agenda and Sustainable Development Goals (SDGs) in Africa. While not explicitly addressed in the Millennium Development Goals (MDGs), renewable energy, including solar energy technologies, indirectly contributed to MDG targets in Africa. Nevertheless, the absence of quantifiable assessments regarding the impacts of solar energy technologies, potentially attributed to their limited implementation in the developing world, motivates this paper to evaluate their potential impact in Africa. The analysis, based on a two-level criteria framework and utilizing the interval-valued Fermatean fuzzy analytical hierarchy process methodology, identifies the top three potential impacts as the reduction of CO_2 emissions, monetary savings, and the diminishment of air pollution.

1. Introduction

A significant majority of the African population, particularly in rural areas (over 70%), lacks electricity access, relying on traditional biomass [1]. Establishing access to the national power grid in peri-urban and rural areas is challenging due to high costs and slow development [2]. The increasing energy demand in Africa, driven by population growth, poses a major obstacle to sustainable economic growth. With rising energy demand and prices, coupled with the necessity to combat global warming, renewable energy sources (RES) are globally recognized as a crucial solution [3-6]. Renewable energy (RE), harnessed from natural sources like sunlight and wind, is quickly gaining traction as a global alternative to conventional fossil fuels, including in Africa.

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Mitigating energy challenges involves replacing harmful fuels with cleaner options. Africa's wealth of natural resources offers practical and cost-effective solutions, yielding socio-economic and environmental benefits. Eastern and Northern Africa boast significant potential for solar and wind energy, while Central Africa has less potential. Moreover, certain African countries show promise in adopting various RE technologies [7].

Solar energy (SE), the most abundant and RES, is clean and cost-effective as the price continues to drop. While Africa has significant solar potential, cost-effective transmission requires a more than 50% reduction in investment costs [8]. SE provides efficient electricity generation with a minimal environmental impact, offering large-scale energy storage solutions for rural areas [9]. The successful integration of SE into Africa's energy mix for sustainable growth depends on government strategies and policies [10].

Advanced developing countries, such as China and India, dominate the global solar markets, holding the first and third positions, respectively [11]. China stands out as the largest solar market. The global solar PV market, valued at $150 billion in 2022, is projected to surpass $383.78 billion by 2032, with an anticipated compound annual growth rate (CAGR) of 9.90% from 2023 to 2032. Despite the rapid global and regional growth in the solar market, the majority of African countries, excluding South Africa, are trailing behind.

RE, particularly SE, is vital for addressing global challenges like sustainable development, food insecurity, poverty, and climate change [12]. Although not explicitly mentioned in the UN Millennium Development Goals (MDGs), RE indirectly contributed to MDG targets in Africa [13]. However, weak implementation of solar projects, limited participation in Clean Development Mechanism (CDM) initiatives, and a lack of institutional capacity hindered progress in African countries [14, 15]. Unlike the MDGs, the 2030 agenda, specifically sustainable development goal (SDG) 7, recognizes the crucial role of the energy sector in achieving global goals, emphasizing access to affordable, reliable, sustainable, and modern energy for all. In this paper, the potential impacts of SE in meeting the SDGs are examined in the African context.

2. Literature Review

Various methodologies have been utilized in research to investigate different aspects of REs, particularly SE. These methodologies include IRN-LBWA-CODAS [16], HFLTS-CRITIC [6], QNSLF DEMATEL-TOPSIS [17], CBF-VIKOR [18], IVPF-WASPAS [19], GIS-DANP-MABAC [20]. In addition to these, alternative approaches have been proposed, such as SF-AHP [21], SFCMM [22], SWOT-FAHP [23], AHP-FTOPSIS [24], and AHP-FTOPSIS [25].

SE research in Africa has been conducted in countries such as Nigeria [26], Cameroon [27], Ghana [28], Ethiopia [29], Kenya [30], Tanzania [31], and Morrocco [32], accompanied by an extensive study spanning various regions [33-39]. Despite these efforts, a limited number of researchers have established connections between SE and SDGs in the African context, with references to this linkage found in works by Adenle [12], among others [12, 40, 41]. Notably, Adenle [12] is one of the few researchers who have evaluated SE technologies in Africa and the associated challenges in aligning with the 2030 agenda and SDGs. However, their study lacks a specific assessment of the potential impacts (benefits) of SE in contributing to SDGs through the application of multi-criteria decision-making (MCDM) methods in the African context.

To overcome the limitations of previous research, a comprehensive evaluation of the potential impacts of SE on SDGs necessitates a managerial perspective that explicitly considers multiple criteria for more effective decision-making outcomes [42-64]. MCDM techniques, known for their ability to address complex problems and incorporate diverse criteria, are well-suited for this task [9, 57, 65-86].

3. Methodology

The research methodology employed in this study involved a series of consecutive steps. Initially, an extensive review of existing literature was conducted to establish a two-level criteria hierarchy, encompassing the potential impacts of SE in achieving the SDGs. Following this, experts were consulted to categorize and refine these criteria. The IVFF-AHP method was then utilized to ascertain the relative weights of the two-level criteria, involving the creation of a pairwise comparison matrix.

3.1. Criteria determination

Analyzing the intricacies associated with the potential impacts of SE in achieving the SDGs entails a nuanced decision-making process that spans various dimensions. The incorporation of numerous variables demanding attention complicates the identification of these impacts. To tackle this challenge, a comprehensive literature review was undertaken to pinpoint the most relevant criteria, with a specific emphasis on the SDGs. The potential factors identified as criteria underwent further refinement through consultations with a panel of experts. The inner level (Level-2) illustrating the potential impacts of SE in meeting the SDGs is detailed in **Table 1** for analysis.

Table 1
Level-2 criteria list

Criteria	Sub-criteria	References
Social (SO)	Poverty reduction contribution (SO1)	[12, 87-89]
	Quality of health services improvement (SO2)	
	Electrification improvement (SO3)	
	Leaning environment and quality of education improvement (SO4)	
	Capacity and knowledge sharing amelioration at rural household level (SO5)	
	Adequate sanitation and safe drink water assessment (SO6)	
Economic (EC)	Employment opportunities establishment (EC1)	[12, 87-89]
	Monetary savings (EC2)	
Environmental (EN)	Air pollution diminishment (EN1)	[12, 87-89]
	CO_2 emission diminishment (EN2)	

3.2. Interval-valued Fermatean fuzzy AHP method

The IVFF-AHP approach, as presented by Alkan and Kahraman [90], extends the analytic hierarchy process (AHP) to tackle issues related to MCDM techniques. The fundamental steps of the IVFF-AHP method are delineated as follows.

Step 1. Establishing a hierarchical framework involves identifying primary and subsidiary criteria. Assume that $C_j (j = 1,2, \ldots, m)$ be a category of m criteria with $w_j = (w_1, w_2, \ldots, w_m)$, where $w_j > 0$ and $\sum_{j=1}^{m} w_j = 1$ as the vector of the criteria weights. Let ψ^t the reputation (weight) of experts t and k is the number of experts where $\sum_{t=1}^{k} \psi^t = 1$.

Step 2. The IVFF pairwise comparison matrix $Z = (z_{ij})_{m\times m}$ is established based on experts' opinions via 1-5 scale approach such equal importance-EI (1), medium high importance-MHI (2), high importance-HI (3), very high importance-VHI (4), and categorically high importance-CHI (5).

$$Z = \begin{bmatrix} 1 & z_{12} & \cdots & z_{1m} \\ z_{21} & 1 & \cdots & z_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & \cdots & 1 \end{bmatrix} \text{ where } z_{ij} = \langle [\mu_{ij}^L, \mu_{ij}^U], [v_{ij}^L, v_{ij}^U] \rangle \tag{1}$$

Step 3. The consistency ratio (CR) for each pairwise comparison (PC) matrix (Z) is determined using Saaty's classical consistency procedure.

Step 4. The aggregation of expert opinions is accomplished via IVFFWG operator [90-92].

Let $A_{ij}^t = ([\mu_{ij}^{Lt}, \mu_{ij}^{Ut}], [v_{ij}^{Lt}, v_{ij}^{Ut}])$ be the PC of criteria i and j by expert t.

$$\text{IVFFWG}(A_{ij}^1, A_{ij}^2, \ldots, A_{ij}^k) = \left(\begin{array}{c} \left[\prod_{t=1}^{k} (\mu_{ij}^{Lt})^{\psi^t}, \prod_{t=1}^{k} (\mu_{ij}^{Ut})^{\psi^t}\right], \\ \left[\sqrt[3]{\left(1 - \prod_{t=1}^{k} \left(1 - (v_{ij}^{Lt})^3\right)^{\psi^t}\right)}, \sqrt[3]{\left(1 - \prod_{t=1}^{k} \left(1 - (v_{ij}^{Ut})^3\right)^{\psi^t}\right)}\right] \end{array} \right) \tag{2}$$

Step 5. The differentiation in the computation matrix $\mathrm{D} = (\mathrm{d_{ij}})_{\mathrm{m\times m}}$ between the lower and upper points involves the two degrees of functions through Eqs (3) and (4):

$$d_{ij}^L = (\mu_{ij}^L)^3 - (v_{ij}^U)^3 \tag{3}$$

$$d_{ij}^U = (\mu_{ij}^U)^3 - (v_{ij}^L)^3 \tag{4}$$

Step 6. The computation of the interval generative matrix $S = (s_{ij})_{m\times m}$ is done via Eqs. (5) and (6):

$$s_{ij}^L = \sqrt[3]{1000^{d_{ij}^L}} \tag{5}$$

$$s_{ij}^U = \sqrt[3]{1000^{d_{ij}^U}} \tag{6}$$

Step 7. The obtention of uncertainty value $T = (t_{ij})_{m\times m}$ of the z_{ij} as follows.

$$t_{ij} = 1 - (\mu_{ij_U}^3 - \mu_{ij_L}^3) - (v_{ij_U}^3 - v_{ij_L}^3) \tag{7}$$

Step 8. The uncertainty levels are multiplied with $S = (s_{ij})_{m\times m}$ matrix to find the matrix of unnoted weights $R = (r_{ij})_{m\times m}$ by Eq. (8):

$$r_{ij} = \left(\frac{s_{ij}^L + s_{ij}^U}{2}\right) t_{ij} \tag{8}$$

Step 9. The normalized priority weights w_i is calculated as follows.

$$w_i = \frac{\sum_{j=1}^{m} r_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{m} r_{ij}} \tag{9}$$

4. Application

In this research, ten potential impacts of SE on meeting SDGs in Africa were identified and categorized into three aspects. To ensure the effective evaluation of the proposed framework, three experts with a minimum of 10 years of experience and a master's degree or higher were selected for data collection.

4.1. Criteria determination

Step 1. Initially, the weights for level-1 criteria were determined. In this process, experts scrutinized the environmental (EN), economic (EC), and social (SO) criteria.

Step 2. To conduct a pairwise comparison (PC) of the level-1 criteria, experts were instructed to employ the 1-5 scale approach. The resulting pairwise comparisons made by the experts for the criteria are detailed in Table 2.

Table 2
PC for main criteria

Criteria	E1	CR=0.4%		E2	CR=0%		E3	CR=5.6%	
	SO	EN	EC	SO	EN	EC	SO	EN	EC
SO	EI	CHI	HI	EI	VHI	SMI	EI	SMI	HI
EN	CLI	EI	SMI	VLI	EI	SMI	SLI	EI	HI
EC	LI	SLI	EI	SLI	SLI	EI	LI	LI	EI

Note: E-expert.

Step 3. The consistency of each matrix was examined, and all were deemed consistent, as per the consistency ratio (CR) values calculated and outlined in Table 2.

Step 4. Subsequently, experts' opinions were combined, considering their reputations, to establish criteria weights through the IVFF-AHP method. The consolidated evaluation matrix for level-1 criteria is illustrated in Table 3.

Table 3
Aggregated PC matrix for level-1 criteria

	Social				Environmental				Economic			
	μ_L	μ_U	v_L	v_U	μ_L	μ_U	v_L	v_U	μ_L	μ_U	v_L	v_U
SO	0.500	0.500	0.500	0.500	0.000	0.000	0.779	0.846	0.243	0.332	0.663	0.743
EN	0.000	0.000	0.320	0.432	0.500	0.500	0.500	0.500	0.628	0.691	0.295	0.336
EC	0.427	0.527	0.377	0.467	0.430	0.510	0.431	0.515	0.500	0.500	0.500	0.500

Step 5. The matrix representing the differences between lower and upper values was generated and displayed in Table 4.

Table 4
Difference matrix for level-1 criteria

	Social		Environmental		Economic	
SO	0.000	0.000	-0.607	-0.473	-0.397	-0.255
EN	-0.080	-0.032	0.000	0.000	0.198	0.305
EC	-0.023	0.093	-0.056	0.052	0.000	0.000

Step 6. The generative matrix for intervals was created and is provided in Table 5.

Table 5
Interval generative matrix for level-1 criteria

	Social		Environmental		Economic	
SO	1.000	1.000	0.246	0.336	0.400	0.555
EN	0.830	0.927	1.000	1.000	1.580	2.019
EC	0.946	1.239	0.877	1.128	1.000	1.000

Step 7. The calculation of uncertainty values for each criterion was performed and presented in Table 6.

Step 8. Weights in their unnormalized form were computed using information from both Table 5 and Table 6. The unnormalized weights are outlined in Table 7.

Table 6
Uncertainty levels for level-1 criteria

	Social	Environmental	Economic
SO	1.000	0.865	0.857
EN	0.951	1.000	0.893
EC	0.882	0.890	1.000

Table 7
Unnormalized weights of level-1 criteria

	Social	Environmental	Economic
SO	1.000	0.252	0.410
EN	0.836	1.000	1.608
EC	0.964	0.893	1.000

Step 9. Ultimately, the weights are standardized, and the weights for the criteria are established. The findings in Figure 1 show that the environmental (EN) criterion is the most significant, followed by the economic (EC) criterion, with the social (SO) criterion ranked last.

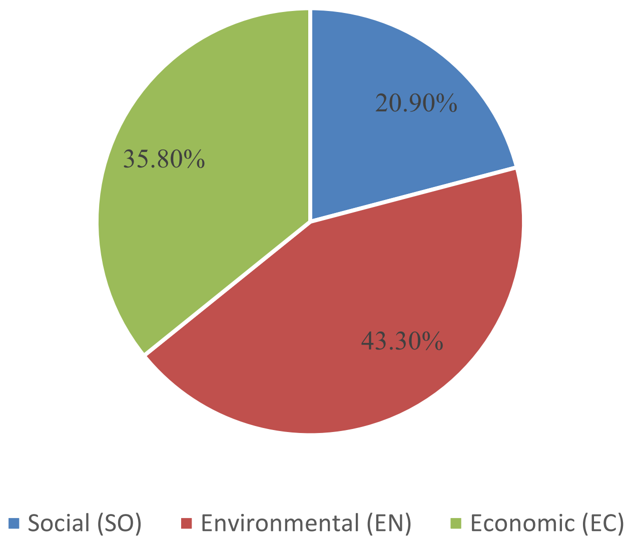

Fig.1. Level-1 criteria rank

Subsequently, the identical experts were enlisted to assess the internal levels of criteria. In this regard, they formulated pairwise comparison (PC) matrices for level-2 criteria using their expertise. Tables 8, 9, and 10 showcase the matrices for the pairwise comparisons of level-2 criteria corresponding to the three primary criteria, respectively.

Table 8
PC matrices for level-2 social criteria

			E1	CR=8.6%		
	SO1	SO2	SO3	SO4	SO5	SO6
SO1	EI	VLI	LI	LI	VLI	VLI
SO2	VHI	EI	LI	SLI	LI	SLI
SO3	HI	HI	EI	HI	HI	SMI
SO4	HI	SMI	LI	EI	SMI	LI
SO5	VHI	HI	LI	SLI	EI	SLI
SO6	VHI	SMI	SLI	HI	SMI	EI
			E2	CR=2.1%		
	SO1	SO2	SO3	SO4	SO5	SO6
SO1	EI	SLI	CLI	CLI	SLI	SLI
SO2	SMI	EI	LI	CLI	EI	SLI
SO3	CHI	HI	EI	SLI	HI	EI
SO4	CHI	CHI	SMI	EI	VHI	SMI
SO5	SMI	EI	LI	VLI	EI	LI
SO6	SMI	SMI	EI	SLI	HI	EI
			E3	CR=6.3%		
	SO1	SO2	SO3	SO4	SO5	SO6
SO1	EI	SLI	LI	SLI	LI	LI
SO2	SMI	EI	LI	SLI	SLI	LI
SO3	HI	HI	EI	SMI	SMI	VHI
SO4	SMI	SMI	SLI	EI	SLI	SLI
SO5	HI	SMI	SLI	SMI	EI	LI
SO6	HI	HI	SLI	SMI	HI	EI

Note: SO-Social.

Table 9
PC matrices for level-2 economic criteria

	E1 CR=0%		**E2 CR=0%**		**E3 CR=0%**	
	EC1	**EC2**	**EC1**	**EC2**	**EC1**	**EC2**
EC1	EI	VLI	EI	LI	EI	SLI
EC2	VHI	EI	HI	EI	SMI	EI

Note: EC-Economic.

Table 10
PC matrices for level-2 environmental criteria

	E1 CR=0%		**E2 CR=0%**		**E3 CR=0%**	
	EN1	**EN2**	**EN1**	**EN2**	**EN1**	**EN2**
EN1	EI	LI	EI	LI	EI	SLI
EN2	HI	EI	HI	EI	SMI	EI

Note: EN-Environmental.

After confirming the consistency of the level-2 comparison matrices, criteria weights for the inner level were recalculated using the IVFF-AHP steps. Figures 2, 3, and 4 show the criteria weights assigned by individual experts at level-2 within each level-1 category. Analysis of Figure 2 highlights electrification improvement and quality of healthcare services improvement as the top two most critical criteria in the social aspect. In the economic dimension (Figure 3), monetary savings takes precedence, while in the environmental aspect (Figure 4), the most beneficial criterion is the reduction of CO2 emissions.

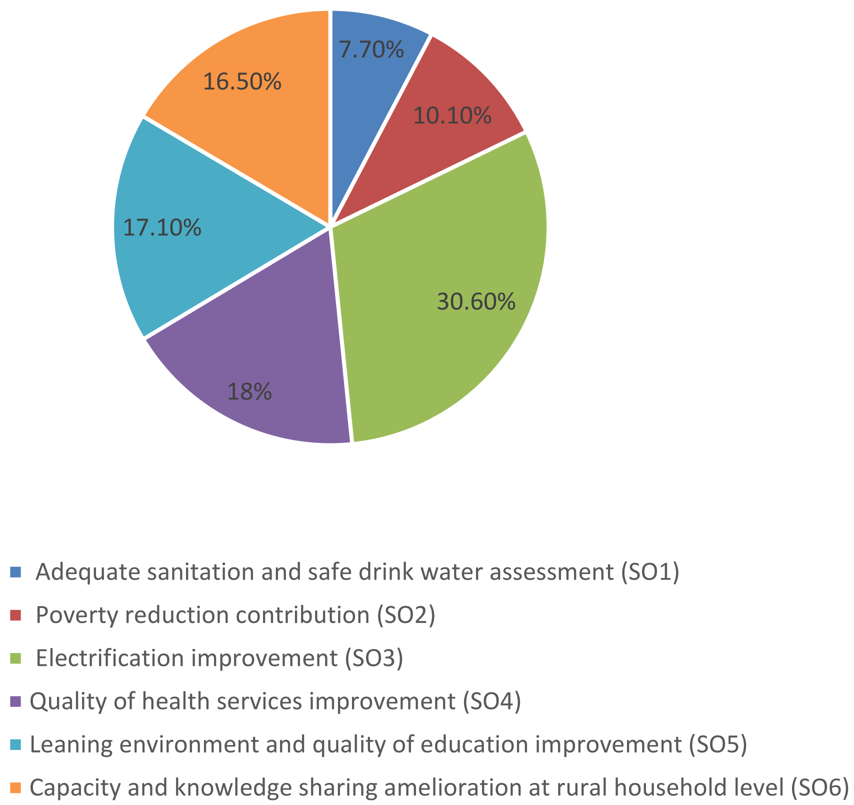

Fig.2. Level-2 sub-criteria rank under social aspect

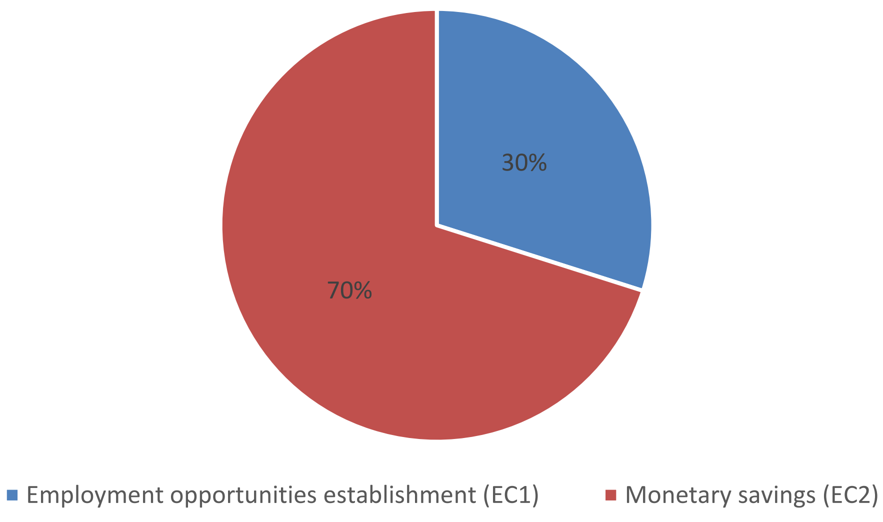

Fig.3. Level-2 sub-criteria rank under economic aspect

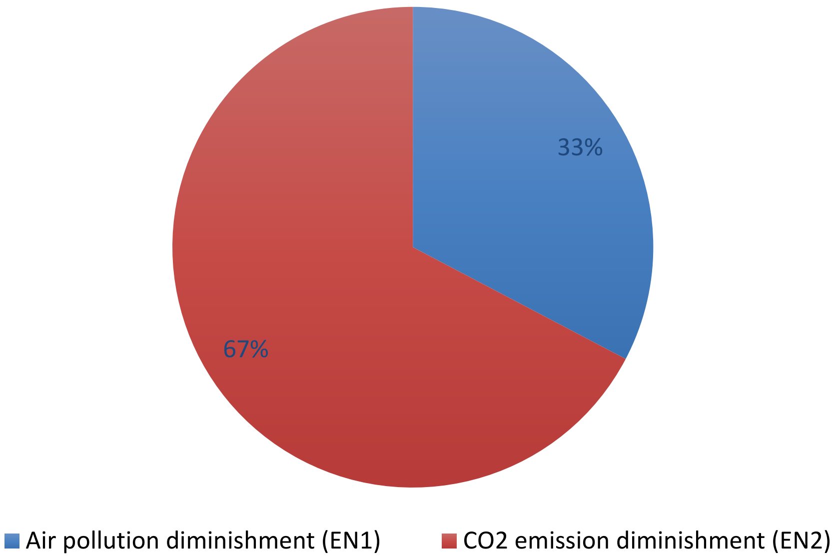

Fig.4. Level-2 sub-criteria rank under environmental aspect

In level-2 (Figure 5), sub-criteria weights are determined by multiplying them with the weights of level-1 criteria. Notably, among all level-2 criteria, the most significant sub-criterion is the reduction of CO2 emissions, aligning with its classification under the crucial environmental aspect at level-1. Following closely are monetary savings and air pollution diminishment, with final weights of 25.09% and 14.16%, respectively. This ranking underscores the pivotal role of environmental and economic aspects in advancing the 2030 agenda and SDGs, emphasizing the importance for decision-makers to consider these factors. Establishing employment opportunities under the economic aspect holds the fourth position, highlighting its significance. Conversely, the criterion assessing adequate sanitation and safe drinking water, categorized under the social aspect, is regarded as the least important. Nonetheless, it is advised to address all criteria for the attainment of the 2030 agenda and SDGs, given their collective significance.

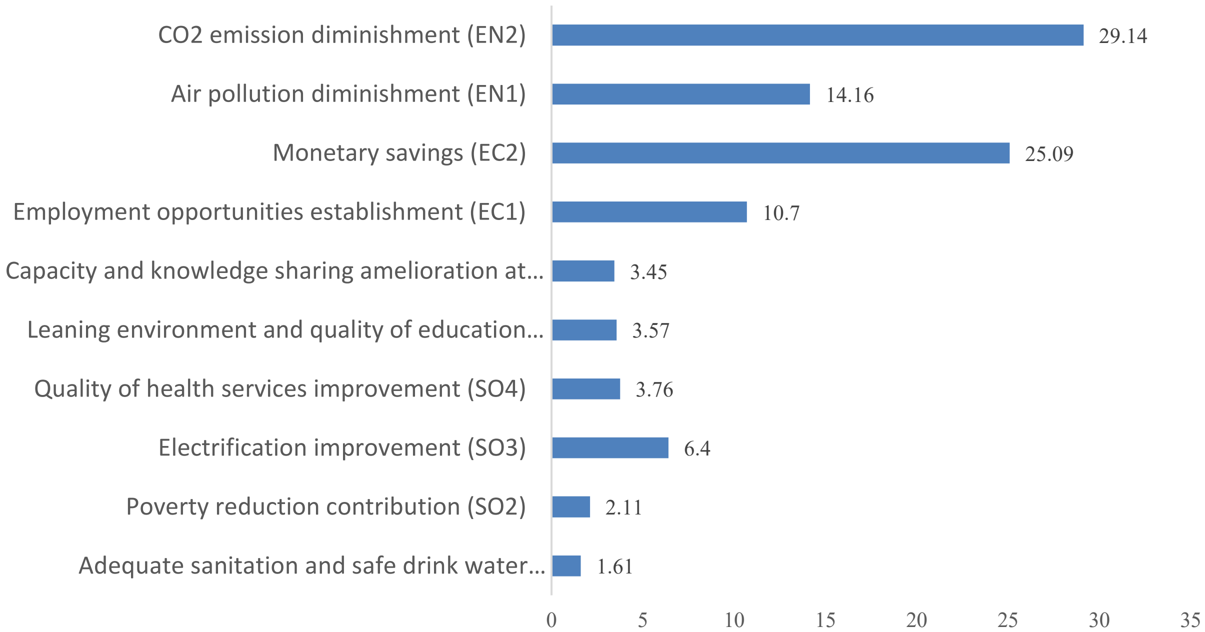

Fig.5. All sub-criteria rank under level-2

5. Conclusion

This study's main goal is to evaluate how solar energy technologies can contribute to achieving the 2030 agenda and SDGs. It is crucial for governments planning to invest in these technologies to understand their fundamental impacts. The study conducts a thorough analysis to identify and accurately assess these impacts. By examining existing literature and consulting three experts, the study uses the IVFF-AHP methodology to assign relative weights to these impacts. The findings reveal that the top three potential impacts of solar energy technologies are the reduction of CO2 emissions, monetary savings, and the diminishment of air pollution. The insights from this study can guide informed decision-making in Africa, helping efficiently allocate resources to solar energy technologies for the successful attainment of the 2030 agenda and sustainable development goals.

Author Contributions

Conceptualization, B.M.B.; methodology, B.M.B. and I. B.; software, B.M.B. and I. B.; validation, I. B. and Q. Y.; formal analysis, B.M.B., I. B., and Q. Y.; investigation, B.M.B., I. B., and Q. Y.; resources, Q. Y.; data curation, B.M.B. and I. B.; writing—original draft preparation, B, M.B., L, J.M., and M. R.; writing—review and editing, B, M.B., L, J.M., and M. R.; visualization, L, J.M., and M. R.; supervision, L, J.M., and M. R.; project administration, Q. Y. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

There is no data in this study.

Conflicts of Interests

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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