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Unlocking Artificial Intelligence for Sustainable Energy Transition: A Fuzzy MCDM Assessment of Economic and Environmental Barriers

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ABSTRACT

The shift toward low-carbon energy systems at an international level necessitates new actions to address socio-economic and technical barriers. In this transition, artificial intelligence (AI) plays a main role by enhancing efficiency and decision-making across the entire energy sector. This study applies a fuzzy simple weight calculation (F-SIWEC) method to systematically assess the economic and environmental barriers to unlock AI for sustainable energy transition. Data was collected from four domain experts who evaluated eleven barriers, and the adopted method was then applied to determine the relative importance of each barrier. The findings indicate that the surging energy use associated with AI training and data centers along with the rapid rise in data center electricity demand constitutes the most significant overall barriers. Within the economic dimension, the high cost of AI services emerges as the most critical constraint. The study makes a meaningful contribution to the decision sciences and management literature by offering practical insights for policymakers and concludes by outlining clear avenues for future research.

1. Introduction

Throughout the century, increasing concern has appeared over the manner energy generated and used in human societies, especially through fossil fuels combustion due to their powerful connection with climate change [1]. Compared with the pre-industrial period, the global average temperature has already been increased by at least 1.3°C due to conventional usage of energy [2]. Climate change causes considerable threats to human being, comprising of recurrent harsh weather which endangers water accessibility, food security, and agricultural production [3]. It also aggravate socio-economic imbalances and speed the shortage related to biodiversity and ecosystems. As there is an increase of these impacts, there is an increased international call for pressing action to attain a durable energy transition.

Despite the recent speedy expansion of clean energy technologies, which has generated great hope for energy transition at an international level, considerable issues persist. Therefore, a transition pathway determined by a great electrification and great share of renewable energy (RE) is envisaged by policymakers

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and scientists [4]. Although some achievements have been made, there is a high possibility that these plans required several decades to be execute because of unsolved financial and technical issues [5].

Amid the energy transition related challenges, digital technologies are progressively appearing as a main pillar [6]. By using progressively produced energy data, they allow energy systems to become more proactive, adaptive, and efficient in overcoming sustainability and operational issues [7]. This increasing significance is shown in main initiatives such as International Energy Agency (IEA)'s digital demand-driven electricity networks (3DEN) program for emerging economies, the European Union (EU)'s digitalizing energy action programme, and the United Kingdom (UK)'s digital spine project.

Amidst the recommended digital technologies, artificial intelligence (AI) is progressively known as a main technology for developing the energy transition [8], due to its revolutionary influence across various study and application areas. In the past decade, deep learning has shown great effectiveness in computer vision and natural language processing areas [9], while AI for science has assisted data analysis, experimental design, and hypothesis generation [10]. In recent years, the increase of large language models (LLMs) and generative pre-trained transformers (GPT) has later extended AI's problem-solving abilities [11]. Additionally, the AI implementations across logistics, industry, healthcare, business, and finance sectors emphasize their larger scalability and versatility.

AI related studies in the energy sector has speedily increased, with publications rising approximately tenfold over the past decade. Actual research include areas such as discovery of novel energy materials [12], smart grid management [13], system optimization [14], system security and stability [15], demand and supply prediction [16]. However, as emphasized in recent research, the focalization of this research is progressively moving alongside advances in AI and the progressing needs of energy transition.

In this situation, two main questions arise: What is the actual state of AI research in the energy transition field and what barriers do previous studies reveal? Although, Wang, Li [17] identified economic and environmental barriers to AI deployment in the energy transition, their study doesn't rank them in order of critical importance, nor does they adopt a powerful managerial decision-making tool for such assessment. Given the proven effectiveness of multi-criteria decision-making (MCDM) methods in overcoming strategic problems [18, 19], this study advances the literature through the identification and prioritization of economic and environmental challenges to AI application in the energy transition using the Fuzzy SImple WEight Calculation (F-SIWEC).

The remaining of the study is as follows: literature review, problem definition, methodology, application, findings and discussion, managerial implications, and conclusions and recommendations.

2. Literature review

Two sub-sections have been defined as follows.

2.1 Studies related to AI deployment in energy transition

Various studies related to the AI deployment in energy transition have been conducted around the world. For instance, Liu, Fan [20] reviewed the advantages related to AI in designing and discovering latest material for electrochemical energy storage. Shoaei, Noorollahi [21] summarized the latest studies that adopted AI and machine learning in renewable energy system area. Entezari, Aslani [22] conducted a bibliographic study of the AI and ML techniques in energy related fields. Wang, Zhang [23] developed a new composite AI index through projection pursuit for renewable energy transition. Li, Xing [24] explored how the energy market progress under AI area. Gao, Ji [25] determined how the AI implementation and development can successfully foster the energy transition at city level. Wang, Wang [26] examines how is the AI impact on great quality energy development. Chishti, Xia [27] explored the AI, belt and road initiative (BRI), and Paris agreement (PA) on the transition of energy. Lee, Fang [28] determined the AI impact on energy transition at international level under digital economy. Wang [29] determined how AI promote energy transition in the organization for economic co-operation and development (OECD) countries. Zhao, Zhao [30] examined the AI-driven regional energy transition. Wang, Zhang [31] examined the AI impact on carbon emissions. Table 1 provides the AI deployment in energy transition studies.

Table 1
AI deployment in energy transition studies

Authors	**Objective**	**Methodology**	**Location**
Liu, Fan [20]	AI role on improving material design	Review	Global
Shoaei, Noorollahi [21]	AI and ML methods implementation on renewable energy systems (RES)	Review	Global
Entezari, Aslani [22]	Summarize AI and ML deployment in energy systems	Bibliographic review	Global
Wang, Zhang [23]	AI role in RE transition from financial development perspective	A multidimensional AI composite index	119 countries
Li, Xing [24]	Energy market evolution under AI era	Wavelet analysis	-
Gao, Ji [25]	AI impact on ET	Panel data analysis	China
Wang, Wang [26]	AI impact on energy quality development	SYS-GMM	China
Chishti, Xia [27]	AI, BRI, and PA impacts on energy transition	QVAR method	-
Lee, Fang [28]	AI impact on global energy transition	Assessment index system	Global
Wang [29]	AI and climate policy impact on energy transition	AAH	OECD countries
Zhao, Zhao [30]	AI impact on energy transformation development	Fixed effects and instrumental variable regressions	China
Wang, Zhang [31]	AI's impact on energy transition and carbon emissions	STIRPAT approach	Panel of 69 countries

Note: **AAH**- Augmenting Anderson and Hsiao; **QVAR**- Quantile Vector Autoregressive; **SYS-GMM**- System Generalized Method of Moments.

2.2 MCDM applications on energy transition related studies

Various studies have adopted MCDM approaches on the energy transition field [32]. For instance, Nuriyev and Nuriyev [33] adopted a fuzzy scenario framework to solve the task related to energy transition. Alyamani, Solangi [34] proposed a hybrid approach for the evaluation of parameters and strategies for durable energy transition. Seraj, Parvez [35] introduced a decision making technique for improving the performance of building tools in harsh climatic situations. Kamali Saraji and Streimikiene [36] applied a new evaluating framework to assess the European Union performance based on issues related to low-carbon energy transition. Nuriyev, Nuriyev [37] applied framework under Z-information for the development related to energy transition policy. Danielson, Ekenberg [38] introduced a participatory MCDA technique to the establishment of energy transition policy. Zubairu, Mohammed [39] explored and assess the supply chains sources of renewable energy to direct practitioners in the choice and investment of appropriate RE supply chains. Chen, Chai [40] adopted a data-driven multi-criteria framework to comprehensively assess energy transition pathways. Ali and Kim [41] explored the criteria and alternatives to consider for sustainable energy transition development. Jameel, Yasin [42] introduced a framework to prioritize renewable energy for durable development. **Table 2** indicates the MCDM applications of energy transition studies.

Table 2
Applications of MCDM approaches on energy transition studies

Authors	Objective	Methodology	Location
Nuriyev and Nuriyev [33]	Multi-period energy transition task assessment	Fuzzy-TOPSIS	Azerbaijan
Alyamani, Solangi [34]	Factors and strategies assessment for energy transition	SWOT, TOWS, FAHP, FVIKOR	Saudi Arabia
Seraj, Parvez [35]	Sustainable energy transition assessment in harsh climate situations	AHP, TOPSIS	-
Kamali Saraji and Streimikiene [36]	Evaluation of challenges related to low-carbon energy transition	FF, SWARA, MEREC	European Union countries
Nuriyev, Nuriyev [37]	Energy transition policy development	Z-environment	Azerbaijan
Danielson, Ekenberg [38]	Energy transition policy establishment	Participatory MCDA approach	Jordan
Zubairu, Mohammed [39]	RE supply chain assessment	AHP, TOPSIS	Oman
Chen, Chai [40]	Energy transition path evaluation through social media	Integrated natural language procedure approach with MCDM	-
Ali and Kim [41]	Energy transition selection	AHP	Indonesia
Jameel, Yasin [42]	RE prioritization for sustainable development	LIDFS, RANCOM, MEREC, MAUT	Global

Note: **AHP**-Analytical Hierarchy Process; **FF**-Fermatean Fuzzy; **LIDFS**- Linear Diophantine Fuzzy Sets; **RANCOM**- Ranking Comparison; **MEREC**- Method based on the Removal Effects of Criteria; **MAUT**- Multi-Attribute Utility Theory; **SWARA**- Stepwise Weight Assessment Ratio Analysis; **TOPSIS**- Technique for Order Preference by Similarity to Ideal Solution.

3. Problem definition

Table 3 outlines the economic and environmental barriers to unlock AI for sustainable energy transition based on the experts' opinions and previous studies.

Table 3
Assessment of Economic and Environmental Barriers

Barriers	Sub-barriers	References
Economic barriers (EC)	High cost of AI services (EC1)	[17]
	Dependence on economies of scale (EC2)	[43]
	Exclusion of smaller energy companies and independent operators (EC3)	[26]
	Long payback period of digital infrastructure investments (EC4)	Expert opinion
	Low customer willingness to participate in smart energy services (EC5)	Expert opinion
	Potential slowdown of the energy transition (EC6)	[17]
	Greenhouse gas emissions from digital technologies (EN1)	[44]

Environmental barriers (EN)	AI's share in national electricity demand (EN2)	Expert opinion
	Increased energy consumption of AI training and data centers (EN3)	[29]
	Rapid growth in data center energy demand (EN4)	[17]
	High carbon emissions from AI model training (EN5)	Expert opinion

4. Methodology

A novel subjective criteria weighting approach has been recently introduced by Puška, Nedeljković [45]: a SIWEC method, which make easier the procedure of finding criteria significance for experts (Es). The assessment of criteria are assessed separately in the absence of comparison and prioritization. Simple procedures and steps are adopted for computing the weights of criteria. Since it has been introduced, various sectors such as renewable energy adoption [46], green digital technology assessment [47], digital twins technology enhancement [48], railway infrastructure planning [49], tourism in cultural heritages [50], transport policy selection [51], durable logistics and transport systems [52], electric vehicle selection [53], tourism valorization [54], and African Continental Free Trade Area initiative potential assessment [55], and have adopted it. **Fig.1** indicates the flowchart of our methodology.

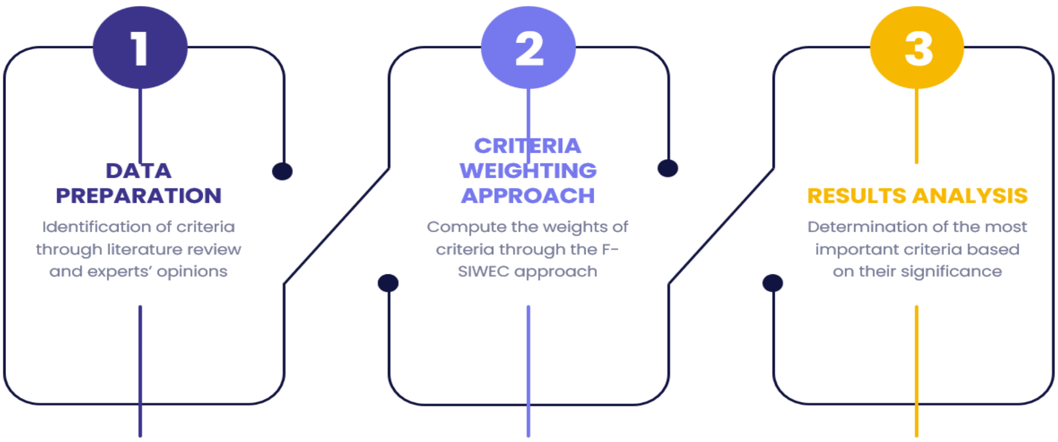

Fig.1. The flowchart of our methodology.

The steps of fuzzy SIWEC are shown as follows.

Step 1. Each criterion associated with importance is evaluated by experts by given linguistic variables (LVs) shown in **Table 4** to show the experts ideas.

Table 4
Fuzzy linguistic evaluation scale

Linguistic terms	Membership function
Absolutely bad (AB)	(1,1,1)

Very bad (VB)	(1,2,3)
Bad (B)	(2,3,4)
Medium-bad (MB)	(3,4,5)
Equal (E)	(4,56)
Medium-good (MG)	(5,6,7)
Good (G)	(6,7,8)
Extremely good (EG)	(7,8,9)
Absolutely good (AG)	(8,9,10)
Perfect (P)	(9,10,10)

Step 2. The opinions of experts assessed through LVs are transformed to triangular fuzzy numbers (TFNs) as lower, middle, and upper bounds shown in Eq. (1).

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

Step 3. There is an establishment of an original fuzzy decision matrix based on fuzzy numbers derived from the experts' evaluation. The indicated importance of a specific criterion is represented through each parameter, comprising of uncertainty obtained through the assessment of linguistics. This matrix shown in Eq. (2) is a base for calculating criteria weight via the SIWEC approach under fuzzy environment.

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

Step 4. Fuzzy values are normalized from decision matrix through their division by the greater upper bound ($\max x_{ij}^{u}$) observed through all criteria and experts in Eq. (3).

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

Step 5. The standard deviation (std.dev_j) are computed based on fuzzy numbers derived from experts. This computation shows consistency or variation in the evaluation of criteria, allowing the approach to emphasize criteria where experts' opinions show greater differentiation, a significant feature of the F-SIWEC technique for apprehending the related significance under uncertainty.

Step 6. The normalized fuzzy rating in Eq. (4) reflected through the multiplication of normalized fuzzy rating by associated values of standard deviation.

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

Step 7. The weighted fuzzy evaluation provided by all experts are summed to provide an aggregation fuzzy weighted values for each parameter. This generates an overall representation of each factor's importance, permitting both individual expert opinions and the uncertainty apprehend in previous steps. The outcomes are a combined fuzzy weight for each factor, which becomes a basis in obtaining the final importance rankings in Eq. (5).

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

Step 8. Each separate fuzzy value is divided by the total sum of all fuzzy values to obtain the normalized fuzzy weight for each parameter indicated in Eq. (6). During this process, it is significant to make sure that the lower bound is less or equal to the middle value. This can be done only if there is maintained logical order of fuzzy numbers.

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

Step 9. The final fuzzy weights of each criterion are retained through their de-fuzzified or fuzzy form into crisp values, according to the analytical requirements. Herein, de-fuzzified of fuzzy weights are adopted through an appropriate defuzzification technique to transform each fuzzy number inti an individual representative value, shown in Eq. (7).

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

5. Application

A three-step methodological approach based on the F-SIWEC procedure is adopted to establish data-driven assessment of economic and environmental barriers to AI adoption for energy transition. With the goal to generate a comprehensive guideline for the exploration of this study, 11 barriers under economic and environmental aspect has been found from experts' opinions and literature review. A panel of four experts comprising of AI practitioners, policymakers, and researchers in the energy sector, working towards sustainable development have been involved. Fuzzy weights are derived from a linguistic decision matrix based on expert evaluations of each barrier, as summarized in **Table 5**, which presents the initial judgments of the four experts.

Table 5
Linguistic decision-making matrix

	EC1	EC2	EC3	EC4	EC5	EC6	EN1	EN2	EN3	EN4	EN5
E1	E	B	VB	MB	AB	VB	G	EG	P	AG	AG
E2	E	B	VB	E	VB	AB	G	AG	AG	AG	EG
E3	MG	E	B	MG	VB	AB	MG	EG	P	AG	G
E4	G	MB	MB	MB	B	AB	MG	EG	P	P	G

In order to establish an original fuzzy decision matrix based on the opinions of the experts, the data are first normalized to guarantee comparability on a basic scale. Following the F-SIWEC approach, each TFN was divided by the highest upper-bound value across all strategies for each expert, mapping the values into the [0, 1] range. This normalization keeps the proportional relationships among the initial evaluations while removing scale-related bias. The resulting initial and normalized fuzzy decision matrices are presented in **Table 6** and represent the basis for obtaining strategies weights in the next stage.

Table 6
Normalized fuzzy decision-making matrix

	E1	E2	E3	E4
EC1	(0.4, 0.5,0.6)	(0.4, 0.5,0.6)	(0.5, 0.6,0.7)	(0.6, 0.7,0.8)
EC2	(0.2, 0.3,0.4)	(0.2, 0.3,0.4)	(0.4, 0.5,0.6)	(0.3, 0.4,0.5)
EC3	(0.1, 0.2,0.3)	(0.1, 0.2,0.3)	(0.2, 0.3,0.4)	(0.3, 0.4,0.5)
EC4	(0.3, 0.4,0.5)	(0.4, 0.5,0.6)	(0.5, 0.6,0.7)	(0.3, 0.4,0.5)
EC5	(0.1, 0.2,0.3)	(0.1, 0.2,0.3)	(0.1, 0.2,0.3)	(0.2, 0.3,0.4)
EC6	(0.1, 0.2,0.3)	(0.1, 0.1,0.2)	(0.1, 0.1,0.2)	(0.1, 0.1,0.2)
EN1	(0.6, 0.7,0.8)	(0.6, 0.7,0.8)	(0.5, 0.6,0.7)	(0.5, 0.6,0.7)
EN2	(0.7, 0.8,0.9)	(0.8, 0.9,1.0)	(0.7, 0.8,0.9)	(0.7, 0.8,0.9)

EN3	(0.9, 1.0,1.0)	(0.8, 0.9,1.0)	(0.9, 1.0,1.0)	(0.9, 1.0,1.0)
EN4	(0.8, 0.9,1.0)	(0.8, 0.9,1.0)	(0.8, 0.9,1.0)	(0.9, 1.0,1.0)
EN5	(0.8, 0.9,1.0)	(0.7, 0.8,0.9)	(0.6, 0.7,0.8)	(0.6, 0.7,0.8)

After normalization, the F-SEWIC method integrates expert consensus by multiplying each normalized fuzzy value by the corresponding standard deviation, thereby embedding opinion variability into the weighting process. This gives greater importance to strategy where expert views diverge, reflecting their contextual sensitivity. The adjusted values are then summed, as shown in **Table 7**, to produce the first-level fuzzy weights for each strategy while preserving uncertainty. During these calculations, the triangular fuzzy structure was maintained so that each weight satisfies the condition (lower bound ≤ mode ≤ upper bound).

Table 7
Obtaining final values of the criteria by using fuzzy SIWEC method

Barriers	$\tilde{s}_{ij}$	$\widetilde{w}_{ij}$
EC1	(0.46,0.56,0.66)	(0.07,0.09,0.13
EC2	(0.27,0.36,0.46)	(0.04,0.06,0.09)
EC3	(0.17,0.26,0.36)	(0.02,0.04,0.07)
EC4	(0.37,0.47,0.56)	(0.05,0.07,0.11)
EC5	(0.12,0.19,0.29)	(0.02,0.03,0.06)
EC6	(0.10,0.12,0.22)	(0.01,0.02,0.04)
EN1	(0.54,0.64,0.74)	(0.08,0.11,0.15)
EN2	(0.71,0.81,0.91)	(0.10,0.13,0.18)
EN3	(0.85,0.95,0.98)	(0.12,0.16,0.19)
EN4	(0.80,0.90,0.98)	(0.11,0.15,0.19)
EN5	(0.66,0.76,0.86)	(0.09,0.13,0.17)

The results displayed in **Fig. 1** for the defuzzified barriers' weights suggest a clear ranking regarding the perceived influence of the barriers to AI adoption for energy transition.

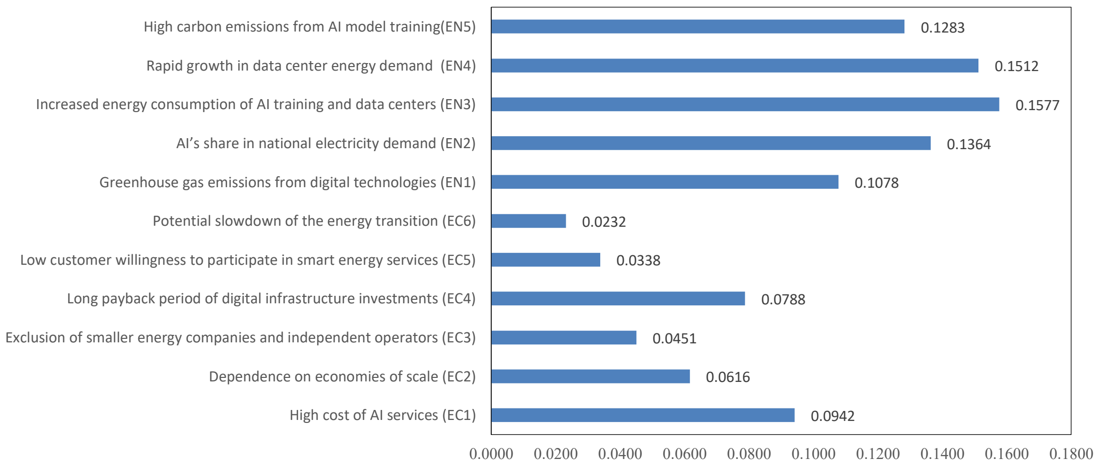

Fig. 1. Defuzzified value of the weights of barriers.

6. Findings and discussion

This study provides insights into the adoption of fuzzy simple weight calculation technique for thoroughly identifying and prioritizing the economic and environmental barriers to AI adoption to energy transition for sustainable development. Through the implemented technique, increased energy consumption of AI training and data centers (EN3) is the most critical barrier among all barriers, followed by the rapid growth in data center energy demand (EN4). Meanwhile the high cost of AI services (EC1) is the most critical barrier under economic category. The least critical barrier under all barriers remains the potential slowdown of the energy transition (EC6).

Various studies confirmed "*increased energy consumption of AI training and data centers (EN3)"* as the most critical barrier to AI adoption for energy transition. This confirms the study of Wang, Li [17] who emphasizes how this barrier contradicts the objectives of sustainability by rising of carbon emissions, costs and demand of electricity, especially less advanced countries with restricted carbon-intensive power systems. Additionally, the burden related to weak energy infrastructures can diminish the reliability of the system, redirect scarce resources, and eventually slow progress toward a clean and efficient energy transition.

The second most critical barrier is the "*rapid growth in data center energy demand (EN4)*". Wilson and Zimmerman [56] indicated that the AI training has caused a quick growth in data center energy consumption in the United States, and its greater energy consumption has become the main parameter in the 7% rise in electricity demand in the country in previous year, which was moderately just 5% in last decade. According to Boston Consulting Group, the energy consumption of such data centers may represents 7.5% in 2030. Ludvigsen [57] estimated the carbon footprint of training GPT-4 only to represent 14,994 metric tons CO2e.

Under economic category, "*high cost of AI services (EC1)*" is the most critical barrier to AI adoption for energy transition. This is explained by the fact that it restricts scalability and accessibility, particularly in less advanced countries with limited financial resources. The implementation of AI solutions necessitates considerable investment in the latest hardware, skilled personnel, data infrastructure, and continuous operational expenses, making them unreasonable for many energy providers and public institutions. This financial burden disappoints adoption and expands the gap between developed and under-developed energy systems, eventually impeding the successful integration of AI technologies required to promote a sustainable and efficient energy transition.

7. Managerial implications

The findings of the study provide some implications as follows. Policymakers should invest in low-carbon data center infrastructures and energy-efficient AI systems to reduce the dominant barrier of increasing energy consumption, including the employment of renewable-powered data centers and optimizing training algorithms. Targeted financial strategies like shared digital infrastructure, PPPs, and subsidies are important to handle the issues related to high costs of AI services and enhance accessibility for energy providers in less advanced countries. Capacity building should be promoted, and effective resources should be allocated to guarantee that the AI implementation improve, instead of burdening previous energy systems. In general, aligning AI investments with energy affordability, efficiency, and low-carbon targets is important for permitting a durable and scalable energy transition.

8. Conclusions and future recommendations

In this study, a fuzzy SIWEC methodology is used to evaluate the economic and environmental barriers to unlock AI for sustainable energy transition. For that, eleven barriers are identified based on experts' opinions and literature review. To collect the data, four experts are involved. The results indicated that energy intensity of AI training and data centers ranks as the most significant overall barrier, followed by the rapid rise in data center energy demand. Within the economic dimension, the high cost of AI services is the leading barrier, while the potential slowdown of the energy transition is identified as the least critical barrier overall. 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. Future studies should consider increasing the number of experts, conducting the study at national, regional, or continental levels. In addition, new methodology can be adopted using an integration of data envelopment analysis (DEA) and fuzzy logic [58]. Moreover, the methodology proposed in this paper can be further extended using frameworks such as hyper fuzzy sets [59] and super hyper fuzzy Sets [60].

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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