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Fermatean Fuzzy Decision-Analytics-Based Assessment of Policy Mechanisms for Promoting Electric Mobility

Mouhamed Bayane Bouraima [1,2*]

[1] Organization of African Academic Doctors (OAAD), Off Kamiti Road, Nairobi, Kenya
[2] International School of Technical Education, Sichuan College of Architectural Technology, Sichuan, China

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ABSTRACT

Electric mobility (e-mobility) has emerged as a promising pathway for reducing greenhouse gas emissions, improving energy security, and supporting sustainable transportation systems. However, its widespread adoption in Africa remains constrained by economic, infrastructural, and regulatory challenges, making the prioritization of effective policy mechanisms a complex decision-making problem. This study adopts the Fermatean Fuzzy Stepwise Weight Assessment Ratio Analysis (FF-SWARA) method to systematically evaluate the policy mechanisms required to accelerate e-mobility adoption under uncertainty. By incorporating Fermatean fuzzy sets, the proposed framework effectively captures the ambiguity and subjectivity inherent in expert judgments, resulting in a more robust and reliable assessment process. Data were collected from four domain experts who evaluated seven policy mechanisms, and the FF-SWARA method was employed to determine their relative importance. The findings indicate that improving energy availability is the most influential policy mechanism, followed by implementing innovative fiscal incentives and strengthening emission standards while restricting the importation of used internal combustion engine (ICE) vehicles. These results emphasize that successful e-mobility deployment in Africa requires a coordinated approach that simultaneously addresses energy infrastructure, financial incentives, and regulatory reforms. The study contributes to the decision sciences and sustainable transportation literature by demonstrating the applicability of the FF-SWARA method to strategic policy evaluation in emerging economies. From a practical perspective, the findings provide policymakers with a transparent and systematic framework for prioritizing investments and designing evidence-based policies that support the transition toward cleaner and more sustainable transportation systems. The study also identifies limitations and suggests future research directions, including the integration of additional multi-criteria decision-making methods and the validation of the proposed framework across different regional and national contexts.

* *Corresponding author.*
E-mail address: mouba121286@yahoo.fr

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1. Introduction

The first sentence Electric vehicles (EVs) are modifying global transportation as countries attempt to enhance the efficiency of energy, diminish the pollution of air, and attenuate climate change. Their widespread deployment is necessary for attaining various United Nations (UN) Sustainable Development Goals (SDGs). In 2024, global EV sales increased by 25% compared to the previous year, reaching approximately 17 million units, with approximately 95% of registrations centers in China, Europe, and the United States [1]. This powerful uptake in the Global North is mainly due to an adequate structured policy scheme, comprising manufacturer subsidies, tax exemptions, and purchase incentives, which assist EV production, battery development, renewable energy integration, and charging infrastructure [2]. In contrast, the African EV market is still embryonic, restricted by absence of a completed structured and adequate policy environments, resulting in insistent low adoption rates [3].

EV represents a main constituent in the international decarbonization strategy for transportation sector [4]. As a consequence, the slow EV adoption in Africa endangers undermining transportation decarbonization on the continent and restricting Africa's subscription to emission reduction targets at international level [1]. This worry is especially significant given that 53 African nations have submitted their climate action programmes [5], targeting a 40% reduction in carbon dioxide (CO2) emissions by 2030. The expansion of electric mobility can considerably diminish mortality related to air pollution and lower transportation-related greenhouse gas (GHGs) emissions [6]. It can also diminish the dependence on fossil fuels and produce cost savings by reducing spending on traditional fuel for internal combustion engine vehicles. Additionally, electric mobility creates job opportunities across charging infrastructure, maintenance, manufacturing, and assembly of EVs, and related constituents [7]. The continent's huge reserves of important raw materials farther position it to play an important role in the global EV and battery value chain [8].

The achievement of these benefits mainly depends on the presence of transparent, complete, and adequate policy frameworks. Some African countries, comprising of Ethiopia, Cape Verde, and Rwanda have implemented policies aimed at accelerating EV adoption, where many others are still at embryonic stages of planning and execution. Additionally, various electric mobility initiatives are appearing across the continent, including South Africa's attempts to electrify minibus taxi fleets [9], and Ethiopia's prohibition on the importation of internal combustion engine (ICE) vehicles [10]. However, the durability and success of these initiatives depend on powerful regulatory and legislative support.

Various dimensions have been explored in the actual literature related to electric mobility in Africa, comprising decarbonization measures [11], energy transition preparedness [12], barriers to paratransit electrification [13], adoption patterns [14], country-distinct EV transition case studies in South Africa [15], and Ghana [16]. Despite these contributions, extensive continent-wide assessments of EV adoption policies remain insufficient. Although Nnene, Oyelohunnu [17] carried a systematic review of policy related documents across all African countries to assess the existence of electric mobility policies, their study did not prioritize these policies according to their degree of significance. Moreover, it did not adopt a multi-criteria decision-making (MCDM) framework able of overcoming decision-making uncertainties and complexities [18, 19]. Therefore, a clear research gap exists in the literature: there is an absence of MCDM-based study that identify and prioritize electric mobility policy mechanisms from a managerial perspective within the African context.

To address this gap, the present study comprehensively identifies and prioritizes electric mobility policy mechanisms in Africa to assist the transition toward sustainable transportation. Unlike traditional survey-based or quantitative approaches commonly used in past studies, this study applies a Fermatean fuzzy framework using a linguistically scaled excel questionnaire. Data was collected from four EV experts, enabling a structured evaluation of policy mechanisms grounded in Africa's socio-economic and institutional context. The applied fuzzy framework avoids direct transfer of assumptions from advanced countries and offers policy-relevant insights tailored to local realities.

The main contributions and novelties of this study are summarized as follows:

i. Contextual aspect: This study offers an MCDA-based analysis specifically focused on assessment and prioritization of electric mobility policy mechanisms in Africa, addressing the limited availability of comprehensive African-focused electric mobility policy evaluations.
ii. Theoretical aspect: The study advances decision science literature and sustainable transportation by considering electric mobility policy mechanisms as an ambiguous-driven multi-criteria decision problem using fuzzy logic theory.
iii. Methodological aspect: The study adopts a fuzzy Fermatean MCDM framework assisted by linguistically scaled expert assessment, permitted enhanced handled of uncertainty, hesitation, and complicated trade-offs in contrast to traditional quantitative and fuzzy techniques.
iv. Managerial and policy contribution: The study offers a structured prioritization of EV policy mechanisms, providing actionable guidance for development agencies, transportation authorities, and policymakers to craft successful electric mobility strategies and optimize resource allocation.
v. Practical relevance: By involving expert-based linguistic assessments tailored to Africa's institutional and socio-economic conditions, the findings support evidence-based policymaking for promoting sustainable transportation transition across the continent.

The remaining study is organized in various sections. Section 2 Literature review, Section 3 Problem definition, Section 4 Methodology, Section 5 Application, Section 6 Managerial implications, and Section 7 Conclusions and future recommendations.

2. Literature review

Two sub-sections have been defined.

2.1 Studies Related to Electric MOBILITY around the World

Various studies have been conducted related to electric mobility [20]. For instance, Zhang *et al.,* [21] propose a real-time recommendation approach for battery-swapping stations (BSSs) based on deep reinforcement learning to improve the service quality and operational efficiency of battery swapping for electric micro-mobility vehicles (EMVs). Hosseini *et al.,* [22] established a new framework for assessing shared electric mobility hubs in Dublin. Liao *et al.,* [23] investigated people's choices to adopt multiple shared electric mobility options to replace their current modes, while also analyzing how preferences for using electric mobility hubs differ among these user groups. Zhang *et al.,* [24] examines the choices of users related to battery-swapping in electric micro-mobility vehicles. Zhang *et al.,* [25] adopted a reinforcement learning technique to optimize battery-swapping system management. Budnitz *et al.,* [26] conduct a comparative analysis of local transport policy development across multiple cities in diverse national and socio-economic contexts, highlighting how a broad set of factors shape decision-making processes and future transport planning strategies. Xi *et al.,* [27] introduce a model in which each mobility-as-a-Service (E-MaaS) platform acts as a leader that strategically optimizes its operational decisions to maximize profits while considering the expected participation behavior of travelers. Yang *et al.,* [28] establish an event driven simulation design for replicating the daily operational dynamics of electric autonomous mobility-on-demand (EAMoD) systems. Wang *et al.,* [29] analyze the asymmetric effects of e-mobility technology investments on EV adoption across ten leading economies with the highest research and development (R&D) spending in e-mobility. Huang *et al.* [30] examine how investments in e-mobility technologies affect carbon emission levels in the ten economies with the largest R&D expenditures in this sector. Table 1 presents the studies related to e-mobility.

Table 1
Studies related to e-mobility

Authors	Objective	Methodology
Zhang *et al.,* [21]	Capturing dynamic correlation between EMVs and BSSs	LSTM-DGAT module
Hosseini et al., [22]	Evaluating shared electric mobility	DEA, Negative binominal regression
Liao *et al.,* [23]	Assessing people's choice to mode substitution caused by electric mobility	Mixed logit models
Zhang *et al.,* [24]	Discern battery-swapping preferences	Mixed Hybrid Choice model
Zhang *et al.,* [25]	Optimization of battery-swapping systems management	Reinforcement learning model
Budnitz *et al.,* [26]	Determine how local policy processes can promote inclusive transitions to urban electric mobility	Expert interview
Xi *et al.,* [27]	Strategizing sustainability and profitability in electric-MaaS	Multi-leader multi-follower game model
Yang *et al.,* [28]	Fleet sizing and charging infrastructure design for EAMoD systems	Discrete event simulation model
Wang *et al.,* [29]	Exploring e-mobility technology budgets-EV adoption nexus	Refined Quantile-on-Quantile approach
Huang *et al.,* [30]	Exploring e-mobility technology budgets	Quantile-on-Quantile approach

Note: DEA- Data envelopment analysis; DGAT- Dynamic Graph Attention Network; LSTM- Long Short-Term Memory.

2.2 Application of MCDM Applications to Related Electric Mobility Studies

Various studies have applied MCDM approaches for e-mobility studies. For instance, Pala [31] explores several powertrain architectures according to various criteria, offering a decision forecasting on the best architecture. Roy *et al.,* [32] implemented an extensive optimization methodology including various, durable, spatial utility criteria to optimize the placement of electric vehicle charging stations (EVCS). Şimşek *et al.,* [33] proposed a decision support system for optimizing the EV related choice. Parmar *et al.,* [34] present a hybrid approach to assess and rank barriers related to electric vehicle sharing services (EVSS). Bi *et al.,* [35] established an expansion plan for electric vehicle charging station (EVCS) to reach the increase demand for EV charging in the district. Parthasarathy *et al.,* [36] performed an extensive analysis for identifying the most appropriate lithium-ion batteries for EV sector. Tarafdar *et al.,* [37] propose a technically durable, uncertainty aware EV assessment methodology in response to market demands. Zhou and Yang [38] adopted a GIS based approach for EV supply equipment allocation in urban area. Subash and Narmadhai [39] proposed a systematic framework for identifying appropriate locations for EV charging hubs. Sathya *et al.,* [40] introduce a hybrid approach for ranking the EV charging stations. Bouraima *et al.,* [41] proposed a decision support framework to assess the challenges and solutions related to EV adoption in sub-Saharan Africa (SSA) region. The applications of MCDM approaches to electric mobility studies are indicated in Table 2.

Table 2
MCDM applications to electric mobility studies

Authors	Objective	Methodology
Pala [31]	Assessing competitive edge of electric and integrated powertrain architecture	Entropy, AHP, SAW
Roy *et al.,* [32]	Developing an optimized model for durable EVCS placement	CRITIC, Entropy, Multi-swarm particle swarm optimization algorithm
Şimşek *et al.,* [33]	Electric vehicle selection	ML; CRITIC, LOPCOW
Parmar *et al.,* [34]	Assessing the barriers and solutions for shared mobility adoption	BWM, CoCoSo
Bi *et al.,* [35]	EV site selection	GIS, FAHP; MABAC
Parthasarathy *et al.,* [36]	Lithium-ion battery selection for increasing the EV's efficiency	CIVq-ROFS; CRITIC; CRADIS
Tarafdar *et al.,* [37]	EV assessment in response to EV market demands	T-SF; MARCOS; MOORA
Zhou and Yang [38]	Optimization of EV supply equipment allocation	GIS-MCDA
Subash and Narmadhai [39]	Assessment of optimal location of EV charging station	COPRAS
Sathya *et al.,* [40]	Ranking of EV charging infrastructure	ExPHS-TOPSIS
Bouraima *et al.,* [41]	Prioritization of EV transition policies	RANCOM; CODAS; SWOT

Note: BWM- Best-Worst Method; CIVq-ROFS- Complex Interval q-Rung Orthopair Fuzzy Set; CRADIS- Compromise Ranking of Alternatives from Distance to Ideal Solution; CRITIC- CRiteria Importance Through Intercriteria Correlation; CoCoSo- Combined Compromise Solution; CODAS- COmbinative Distance-based Assessment; COPRAS- Complex Proportional Assessment; ExPHS- Extended Plithogenic Hypersoft Set; FAHP- Fuzzy Analytic Hierarchy Process; GIS- Geographic Information System; LOPCOW- Logarithmic Percentage Change-driven Objective Weighting; MABAC- Multi-Attribute Border Approximation Area Comparison; MCDA-Multi-Criteria-Decision Analysis; ML-Machine Learning; RANCOM- RANking COMparison; SWOT- Strengths, Weaknesses, Opportunities, and Threats; TOPSIS- Technique for Order of Preference by Similarity to Ideal Solution.

3. Problem definition

To identify the policy mechanisms evaluated in this study, a two-stage procedure was adopted. First, a comprehensive review of the existing literature on electric mobility policies in Africa and other developing regions was conducted to identify the most frequently recommended policy interventions. Second, the preliminary list of mechanisms was reviewed by domain experts with extensive experience in electric mobility, sustainable transportation, and transport policy in Africa. The experts validated the relevance of the mechanisms to the African context, refined their descriptions where necessary, and proposed additional mechanisms that are currently underrepresented in the literature but considered critical for accelerating electric vehicle adoption. Only those mechanisms that were supported by the literature or validated through expert consensus were retained for further analysis. Table 3 outlines the policy mechanisms that have been recommended to fill the electric mobility policy gaps in Africa based on the experts' opinions and previous studies [17, 42-45].

Table 3
Policy mechanisms related to electric mobility

Policy mechanisms	Description	References
Implement innovative fiscal incentives (S1)	African governments should prioritize context-specific fiscal incentives like tax exemptions and direct purchase subsidies.	[42]
Encourage non-fiscal incentives (S2)	Preferential EV policies are crucial for Africa's transition to electric mobility.	[43]
Improve energy availability (S3)	African policymakers should use renewables to tackle electricity and charging gaps.	Expert opinion

Table 3
Continued

Policy mechanisms	Description	References
Enhance emission standards and limit the importation of used ICE vehicles (S4)	African governments should enforce regulations limiting old, polluting vehicles to foster an EV market.	Expert opinion
Increase public awareness and EV policy communication (S5)	Public awareness campaigns are key to promoting EV adoption and changing negative perceptions	[44]
Establish workforce training programmes (S6)	A sustainable EV ecosystem needs a skilled local workforce.	[17]
Public transport and paratransit electrification (S7)	Transport authorities and partners must develop innovative schemes to electrify public and paratransit transport.	[45]

4. Methodology

The obtention of exact values can be done through expert assessment or data; however, there is uncertainty in real-world decision-making, frequently depending on incomplete, vague, and non-numeric input of experts. In this context, deterministic techniques fail, requiring more adaptable frameworks. Zadeh [46] proposed a fuzzy set (FS) approach for handling this issue through the incorporation of linguistic variables that apprehend the complexity of subjective assessments. However, the FS theory fails to successfully overcome the feasible challenges of skepticism and reluctance. Later, Atanassov [47] introduced the intuitionistic fuzzy sets (IFSs) concept by including a non-membership level, thus extending the FSs concept. However, the adequate definitions for membership and non-memberships does not effectively apprehend the ambiguity and hesitation exits in real-life situations. Our study applied a Fermatean fuzzy (FF) approach that express the uncertainty representation by allowing independent resolution of indeterminacy. Greater adaptability is provided for a given membership and non-membership elements in Fermatean fuzzy sets (FFSs), making correct mathematical expression of linguistic variables (LVs) [48]. FFSs are useful in difficult situations related to decision-making. They manage incomplete data, inexactitude, and uncertainty [49, 50]. Therefore, the FF- Stepwise Weight Assessment Ratio Analysis (SWARA) methodology is applied for ranking the policy mechanisms related to electric mobility, with following steps.

Step 1. Experts have used the LVs from Table 4 to provide their opinions.

Table 4
Linguistic terms to evaluate the criteria

Linguistic Term	μ	v
Very High Importance-VHI	0.975	0.10
High Importance-HI	0.85	0.20
Medium High Importance-MHI	0.70	0.35
Fair Importance-FI	0.55	0.50
Medium Low Importance-MLI	0.35	0.70
Low Importance-LI	0.20	0.85
Very Low Importance-VLI	0.10	0.975

Step 2. These LVs are transformed to Fermatean fuzzy numbers (FFNs) and Fermatean fuzzy weighted geometric operator (FFWG) operator for aggregating the opinions of experts.

Step 3. There is a computation of scores valued related to aggregated experts' opinions.

Step 4. There is a criteria ranking from most important to less one according to their respective scores.

Step 5. There is a computation of associated significance (c_j) of each criterion through the determination of differences between the scores of criteria (j) and the positive score of the criterion ranked just above it.

Step 6. Computation of comparative coefficient (p_j) of the criteria using Eq (1).

$$p_j = \begin{cases} 1, & j = 1 \\ c_j + 1, & j > 1 \end{cases} \tag{1}$$

Step 7. Determination of recomputed weights (q_j) through Eq (2).

$$q_j = \begin{cases} 1, & j = 1 \\ \frac{q_{(j-1)}}{p_j}, & j > 1 \end{cases} \tag{2}$$

Step 8. Obtention of final subjective weights of criteria using Eq (3).

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{3}$$

5. Application

The FF-SWARA method is applied to evaluate and rank the EV policy mechanisms in Africa. To ensure a reliable assessment, we conducted interviews with four experts selected based on their background indicated in Table 5. Using Table 4, the experts provided their evaluations, which were subsequently used to assess the strategies in Table 3.

Table 5
Participant's backgrounds

Experts	Gender	Profession	Sector/Role	Experience (Years)
E-1	Male	Energy and environment consultant	Consulting/Policy Advisor	5-10 years
E-2	Male	Energy planner	Industry/Utility	0-5 years
E-3	Female	Entrepreneur in EV conversions	Private sector/Entrepreneurship	0-5 years
E-4	Male	Entrepreneur in EV manufacturing	Private sector/ Manufacturing	5-10 ears

5.1 Prioritizing strategies

Step 1. The strategies are evaluated by the experts according to their knowledge and experience. Table 6 presented the compiled evaluations.

Table 6
Strategies evaluations by each expert

Main strategies	E1	E2	E3	E4
S1	V	V	E	V
S2	M	S	M	M
S3	E	V	E	E
S4	V	I	V	I
S5	S	M	N	N
S6	N	V	U	N
S7	I	M	I	M

Step 2. The FFNs are obtained through the conversion of LVs into numerical values. The assessment of the experts have been consolidated, as shown in Table 7. In our study, equal weight is provided for each expert assessment. The following example of step 2 computation for strategy S1 is shown:

=$(0.85)^{0.25}$×$(0.85)^{0.25}$×$(0.975)^{0.25} \times (0.85)^{0.25}$

=0.886

$= (1-(((1-(0.2^{3}))^{0.25}) \times ((1-(0.2^{0.3}))^{0.25}) \times ((1-(0.1^{0.3}))^{0.25}) \times ((1-(0.2^{0.3}))^{0.25})))^{1/3}$
$=0.184$

Table 7
Aggregated strategies evaluations

Main criteria	μ	$\boldsymbol{v}$
S1	0.886	0.184
S2	0.592	0.570
S3	0.936	0.140
S4	0.806	0.295
S5	0.465	0.771
S6	0.324	0.915
S7	0.687	0.439

Steps 3-8. The determination of strategy scores is made through the aggregation assessments offered in Table 8. These scores were then employed to rank the strategies. The weights for each strategy are employed and provided in Table 8, obtained from the next steps of our methodology.

The example of steps 3-8 calculation for strategy S1 is as follows.
$=1+(0.885^{3}) -(0.184^{3})$
$=1.688$
$=1.834-1.688$
$=0.146$
$=0.146+1$
$=1.146$
$=1/1.146$
$=0.872$
$=0.872/ (1+0.872+0.733+0.582+0.478+0.347+0.252)$
$=0.205$

Table 8
Results of the FF-SWARA application

Main criteria	Scores	c_j	k_j	q_j	Weights
S3	1.834		1	1	0.234
S1	1.688	0.146	1.146	0.872	0.205
S4	1.498	0.190	1.189	0.733	0.172
S7	1.239	0.218	1.258	0.582	0.137
S2	1.022	0.380	1.217	0.478	0.112
S5	0.642	0.373	1.379	0.347	0.081
S6	0.268	0.508	1.373	0.252	0.059

In Table 8, it was revealed that the top three appropriate policy mechanisms for electric mobility in Africa are improving energy availability (S3), implementing innovative fiscal incentives (S1), and enhancing emission standards and limiting the importation of used ICE vehicles (S4). Figure 1 indicated the final weights of all the strategies.

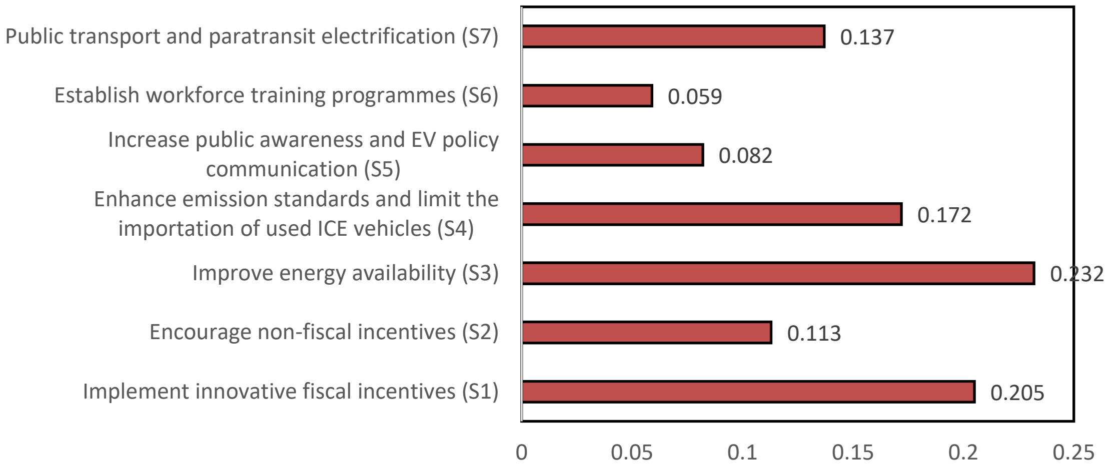

Fig. 1. Final weights of strategies

5.2 Findings and Discussion

In previous research, while the policy mechanisms for an effective electric mobility in Africa are provided, their ranking based on their significance importance is missing. Our present study fills this gap by adopting a framework under Fermatean fuzzy approach. Three most appropriate policy mechanisms are found as follows. Improving energy availability (S3) is the most appropriate policy mechanism. This confirms the study of Oginga [51], who highlighted that incorporating renewable energy sources (RES) into national energy mix, together with strengthening electricity grids, should be a top priority for policymakers across Africa in order to tackle the inaccessibility of electricity and the restricted presence of charging infrastructure. Simple charging alternatives should also be promoted by utilities and private investors. These solutions have already been successful in other developing areas and can be adopted more largely across the transportation sector in the continent. Especially, the achievements of private attempts, such as the battery swapping networks established by East African e-mobility startups Ampersand Spiro reveal a scalable, market-validated model able of functioning successfully despite the restrictions related to grid.

Implementing innovative fiscal incentives (S1) is the second most important policy mechanism. As indicated by Lieven [52], context-specific and new fiscal incentives adapted to the economic realities should be a top priority for governments. While China and Norway have adopted tax exemptions and direct purchase subsidies to effectively reduce EV costs, such measures may be complicate to maintain in Africa because of restricted fiscal ability. Instead, targeted options should be designed by the ministries of trade and finance to diminish upfront costs while backing the industry at local level. Kenya's policy of exempting locally assembled electric motorcycles from import duties and taxes is a practical example, which helps make EVs more accessible for the paratransit and simultaneously improve domestic assembly activities.

Enhancing emission standards and limiting the importation of used ICE vehicles (S4) is the third most appropriate policy mechanism. Nnene *et al.,* [17] stated that governments through their environment and trade ministries and backed by national standard agencies should strengthen rules that impede the entry and use of aging, high-emission vehicles. While a completed prohibition of ICE vehicle imports show a bold pathway in Ethiopia, such initiative may not be appropriate each national context. A more appropriate way is the step by step system in Egypt that restricts ICE imports based on the emission performance and vehicle age, which progressively diminishes polluting vehicles on the market and promotes the uptake of cleaner transport solutions.

5.3 Sensitivity Analysis

This section extends the calculations in the FF-SWARA methodology under two categories of sensitivity analysis. The first category is related to expert judgment modeled by the Monte Carlo simulation. Each expert judgment (μ, ν) for every criterion and expert is randomly perturbed with Gaussian noise of standard deviation sigma (0.05 or 0.10). After perturbation, values are clipped to [0,1]; if the Fermatean Fuzzy constraint $(\mu^3, \nu^3$ <= 1) is violated, the pair (μ, ν) is rescaled to lie exactly on the boundary of the feasible region (preserving the μ *and* ν ratio). For each of 3000 simulation the full FF-SWARA procedure is recomputed (aggregation, score, ranking, k/q coefficients, normalized weights). Figure 2 presents the obtained results. Furthermore, based on the obtained simulation outcomes, the distribution (mean/std/percentiles) of each criterion's weight, and the probability of each criterion occupying each rank position is presented, as shown in Figure 3.

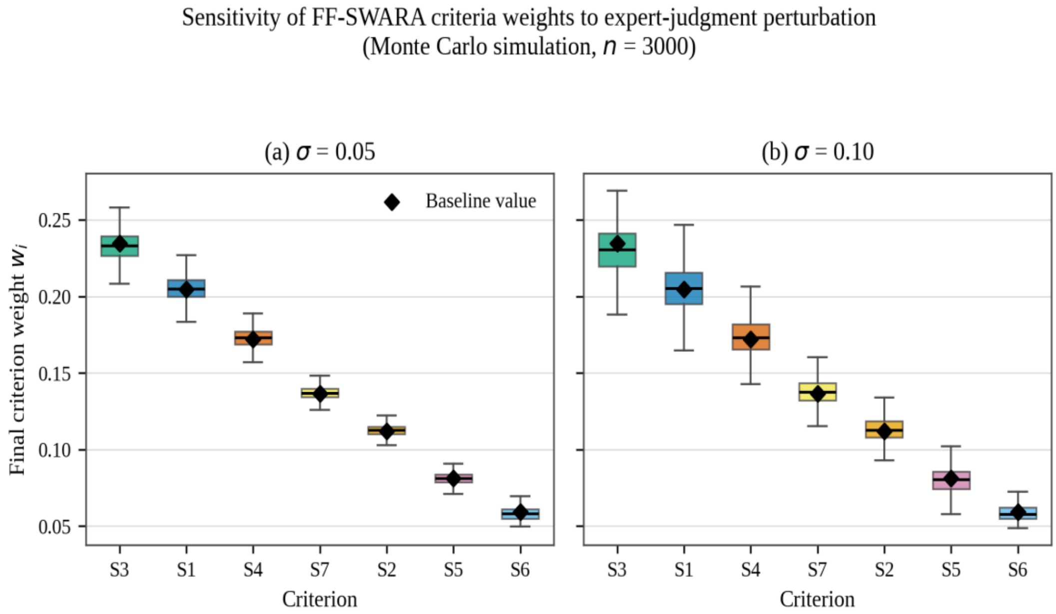

Fig. 2. Sensitivity analysis of criteria weights with respect to expert judgment perturbation

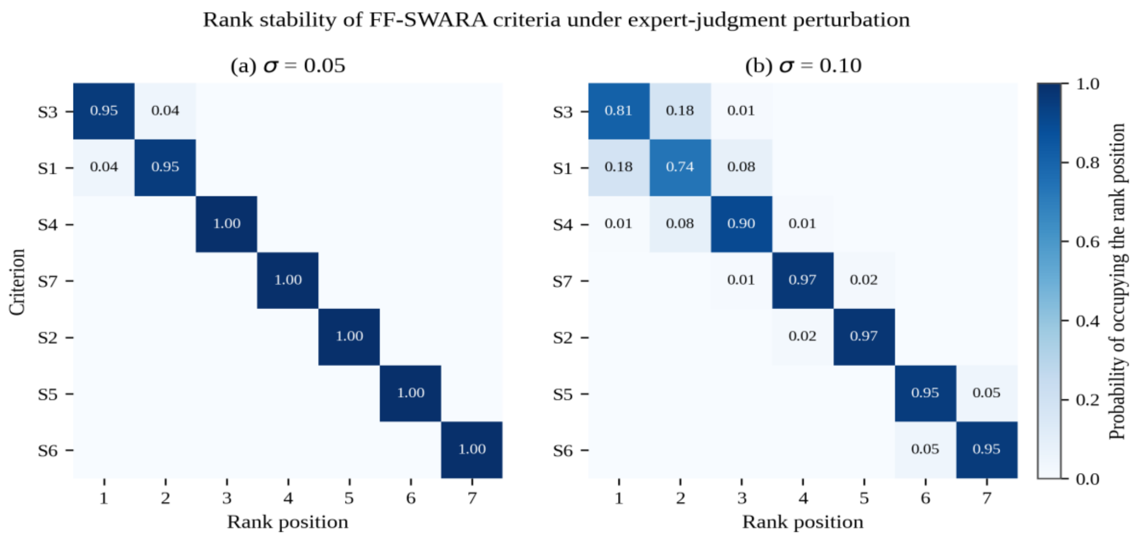

Fig. 3. Ranking stability of FF-SWARA criteria under expert-judgment perturbation

The second category is related to experts' weights modeled as scenario analysis. The expert weights (baseline: equal, 0.25/0.25/0.25/0.25) are replaced with 8 alternative sets in Figure 4: each of the 4 experts made “dominant” in turn (weight 0.55, the remaining three at 0.15) and each expert 'excluded' in turn (weight 0, the remaining three at 1/3). The expert judgments (μ, ν) are left unchanged, only the aggregation weights vary. In Figure 5, it can be observed how the weights change during each scenario.

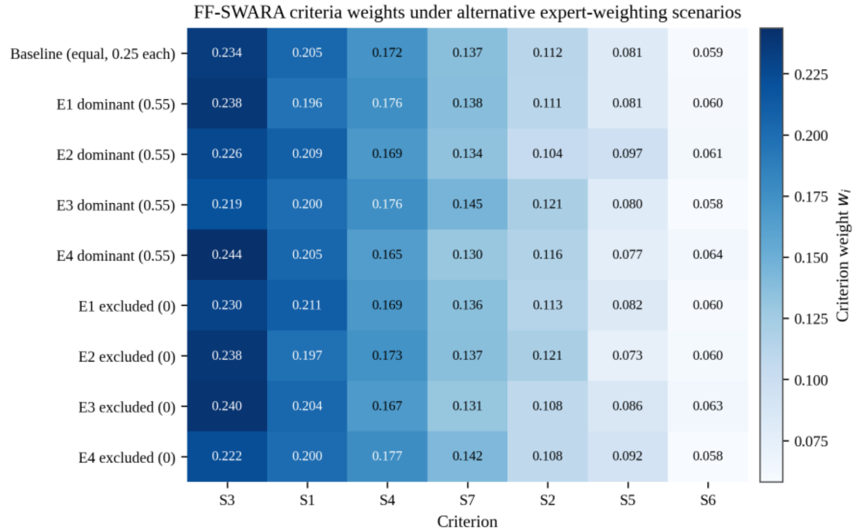

Fig. 4. FF-SWARA criteria weights under alternative-weighting scenarios

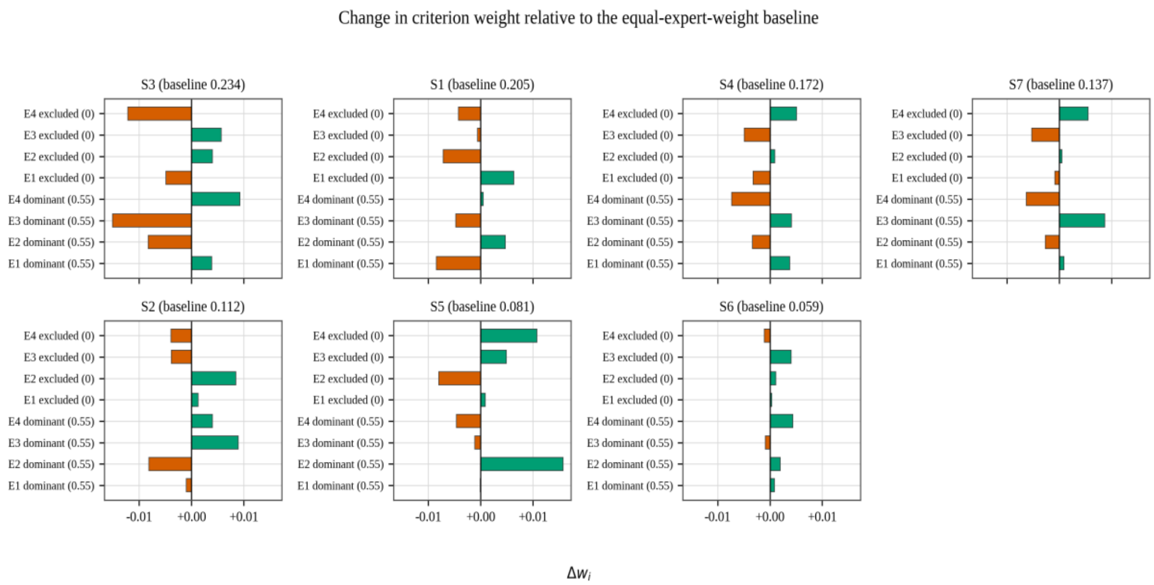

Fig. 5. Change in criterion weight relative to the equal-expert-weight baseline

6. Managerial implications

Some managerial guidance for the promotion of e-mobility in Africa are provided in this study. At first, adequate energy supply should be guaranteed by policymakers through the integration of renewable energy into national grids and expansion of electricity infrastructure, while solar-powered battery swapping options should be supported. Secondly, targeted and fiscally durable incentives should be provided by the governments to reduce the costs related to EV purchases. Meanwhile, local assembly and industry development should be promoted, instead of depending on expensive direct subsidies. At third, emission standards should be gradually tightened by the regulators, while the importation of old, polluting ICE vehicles should be limited via phased initiatives according to emission performance and vehicle age. Together, a feasible and scalable pathway is offered through these coordinated initiatives to extend clean mobility, enhance local industries, and diminish environmental effects in Africa.

7. Conclusions

In this study, a Fermatean fuzzy SWARA methodology is used to evaluate the policy mechanisms for promoting the e-mobility in Africa. For that, seven policy mechanisms are identified based on experts' opinions and literature review. To collect the data, four experts are involved. The results indicated that improving energy availability, implementing innovative fiscal incentives, and enhancing emission standards and limiting the importation of used ICE vehicles are the topmost appropriate mechanisms. While the study has made some contributions, it has some limitations. First, a small number of experts participated. Second, since Africa is comprised of 54 countries, the findings cannot be generalized because every country may have specific characteristics. Future studies should consider increasing the number of experts, conducting the study at national or regional levels. In addition, new methodology can be adopted using an integration of data envelopment analysis (DEA) and fuzzy logic [53]. Moreover, we should consider the clustering approach as a future research direction given the number of African countries with various characteristics. In addition, the methodology proposed in this paper can be further extended using frameworks such as Neutrosophic sets, Pythagorean fuzzy sets, spherical fuzzy sets [54], circular complex picture fuzzy sets [55], and pentagonal intuitionistic fuzzy sets [56].

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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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