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Renewable Energy and Artificial Intelligence: Smart Energy Management Models for Developing Cities

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ABSTRACT

Against the background of intensive urbanization, the growing cities are faced with considerable difficulties in the area of sustainability, but they are also promising fields of innovative development. This paper questions how artificial intelligence is used in renewable energy systems, focusing on the design of such systems, their implementation, and the empirical evaluation of smart energy management models specific to the kind of needs of the emergent urban environment in less developed countries. Our study, based on a series of AI-based experiments, includes structured surveys, field surveys, and advanced statistical reviews, proving that it is possible to achieve up to fifteen percent energy efficiency, up to twelve percent grid reliability, and user satisfaction, which is more than an order of magnitude higher when compared to traditional methodologies. This empirical assessment is a detailed overview of the latest literature that is indexed in Scopus in the period 2022-2025, which shows the current development and points out the significant gaps, especially in the social and organizational aspects. The systems theory, optimization theory, and principles of responsible artificial intelligence are the methodological basis of the approach, where the inquiry is both technically sound and ethically sound. Its results highlight the potential changes in artificial intelligence that can be applied in the provision of scalable and reliable management of renewable energy sources in resource-constrained urban settings. The conclusion of the paper is to suggest ways of integrating the policy, to make AI human-oriented, and to provide future research directions that will support sustainable urban development.

1. INTRODUCTION

1.1 Research problems

The cities in development experience acute problems related to the transition to the sustainable energy system, including intense urbanization, lack of infrastructure space, monetary constraints, and irregularity of renewable energy. The traditional approach to energy management can hardly be used to manage the complexity and variability of modern urban energy networks. There is, therefore, an urgent need to develop new scalable and contextually responsive solutions that can maximise energy production, transmission and consumption and still remain reliable and cost-effective. The potential of artificial intelligence in managing renewable energy is quite significant.

H1: The implementation of AI-driven smart energy management models significantly improves the efficiency, reliability, and scalability of renewable energy systems in developing cities compared to conventional management approaches.

1.2 Hypothesis testing approach

The research design in this study is a mixed-method research design, which combines both quantitative and qualitative types of evidence to provide a systematic critique of the research hypothesis. The approach includes:

1) Experimental/Quasi-Experimental Design: A comparative study of energy-management results before and after the introduction of AI-based models in chosen growing urban centers.
2) Empirical Field Studies: Implementation and monitoring of smart energy-management systems in real-life settings.
3) Survey-Based Research: Conducting an organized questionnaire, which was designed to elicit the perceptions of stakeholders, user experiences, and adoption barriers.

2. LITERATURE REVIEW (2022–2025, SCOPUS-INDEXED)

According to the latest literature, the potential of artificial intelligence in the management of renewable energy resources is transformative in its potential (especially in the context of developing regions), as mentioned in Table 1.

Key findings include:

1) **AI governance and explainability:** A systematic review of 3,568 articles included in the Scopus database reveals the increased academic interest in the topics of AI explainability, its governance, and trust in smart energy systems. However, the existing literature is rather divided into separate technical areas, with a significant focus on the matters of stability, reliability, and predictability performance, but without paying much more attention to sociopolitical and regulatory areas [1].
2) **Optimization and forecasting:** The modern optimization techniques, with a large range of artificial-intelligence-based algorithms and tools, such as machine learning, deep learning, and reinforcement learning, have continuously found their way to the most important areas of load forecasting and demand-response schemes, as well as real-time grid operations. The fact that energy efficiency and grid reliability can be attained significantly when such advanced methodologies are used wisely and with sensitivity to local conditions of operations substantiates the hypothesis [2, 3].
3) **Integration with emerging technologies:** Cooperation with emerging technologies, artificial intelligence, and blockchain technologies will overlap, and a decentralized system of energy management, peer-to-peer trade, and higher transparency will become possible, which is especially important in the context of areas with emerging energy markets [4].
4) **Barriers and challenges:** Some problems that remain are a lack of data, not enough technical skills, missing rules, and the need for solutions for each context. Research shows it is important to involve stakeholders and combine different fields [2].
5) **Empirical evidence:** There is much evidence that technology is getting better. However, there are not many large-scale, long-term experiments designed to examine the impact of AI application in the management of energy on sustainability, fairness, or recoverability of issues (Table 1) [1, 3].

Table 1. Summary of the literature review (2022–2025, Scopus-indexed)

Ref.	Region/Context	Focus Area	Key Findings	Implications/Contributions	Added Contribution of this Study
[1]	Global/ Developing Regions	AI explainability, governance	The research identifies 15 governance parameters and is segmented into technical categories.	It provides a basis to elaborate methodology of research in AI and energy issues.	The study transcends the regular principles of governance and, in fact, applies Responsible AI on a pilot project of real, expanding cities, which makes all things understandable and in line with the interests of everyone.
[3]	Africa, Asia, Lat. Am.	Optimization, forecasting	The use of AI simplifies the workload and increases the accuracy of the processes. Studies show good results.	More investigations on social and regulatory issues, and technical development are required.	This paper is a combination of technical controls as well as how individuals themselves can be involved in it, which forms a connection between efficiency and social approval.
[2]	Developing Cities	Demand response, real-time management	AI is used to assist with demand response and load forecasting; deficit of information and confused policies are the issues.	AI-driven models look good at making renewable energy systems work better.	This study takes a head-on collision with the challenges mentioned above by considering the performance of the lightweight artificial intelligence architectures in the situation where there is lack of data, and thus, proves their technological feasibility through empirical studies.
[4]	Africa, Asia, Lat. Am.	Decentralized energy management	Blockchain and AI enable peer-to-peer trading and transparency.	Blockchain complements AI for transparency and decentralization in energy management.	The proposed study focuses on the implementation of AI-controlled modular microgrids in the informal settlements, and it thus offers a more local, socially inclusive system of managing energy.
[1]	Global	Parameter discovery, analytics	BERT models are useful in locating improved parameters of energy systems.	Mentions the necessity of applying tailor-made strategies and engaging parties to adopt them successfully.	The paper goes beyond the paradigm of algorithmic refinements and integrates the concepts of explainable artificial intelligence (XAI) and participatory co-design approaches, thus guaranteeing not only the quantitative accuracy but also the development of a strong social trust.

2.1 Theoretical framework

The developed research is situated in a complex of interdependent theoretical frameworks that jointly shape the analysis of both technical and socio-technical aspects of AI-based renewable energy management:

2.1.1 Systems theory

According to the systems theory, the electrical power grid is viewed as a dynamic interdependent system that unites generation, storage, transmission, and consumption modules. The use of artificial intelligence algorithms is aimed at optimizing the performance of the whole system, feedback, and adaptive feedback to the real-time data [5].

2.1.2 Optimization theory

Optimization theory underpins the use of AI for maximizing efficiency, minimizing costs, and ensuring grid reliability. AI models (e.g., reinforcement learning, deep learning) are formulated to solve complex operational problems such as energy dispatch and storage management under multiple constraints [6].

Even though the Random Forest algorithm [7], the Long Short-Term Memory network [8], and the Reinforcement Learning [9] have always been considered as the giants of the machine-learning canon, the current study stands out since it trains the older techniques in new structures specific to the requirements of emerging urban settings. More specifically, we include lightweight, federated learning components [10] and edge-AI designs [11] which, in combination, result in decentralized, privacy-preserving, and resource-efficient solutions, thus responding to the limitations of such environments. Moreover, the project is the first to deploy tiny AI models to edge devices and, as such, challenges the infrastructural and connectivity challenges that are typical of developing cities. In this way, it expands the frontier of the previous research, which has focused mainly on centralized architectures.

2.1.3 Responsible AI and socio-technical frameworks

The modern debate concerning the framework of responsible AI puts a primary focus on the ethical, legal, and social implications that accompany the implementation of artificial intelligence in the energy system. These frameworks endeavor to tailor high-intelligence AI models to the desires of their stakeholders. Such desires are unobtrusive yet must be urgent since most areas will soon be rapidly urbanized. The two things that are important in this case are the society's perception of the work as legitimate and the work being in compliance with the laws. These two things not only render the projects useful but also make the idea of energy workable and acceptable [12, 13].

2.2 Energy transition framework

The energy transition framework provides a complete picture of moving from fossil fuels to renewable energy, and it strongly focuses on the important roles of technology, laws, and social progress (Table 2).

It is thought that artificial intelligence can strongly help break down integration barriers and build sustainable energy systems in cities (Table 3) [14].

Table 2. Demographic distribution of questionnaire respondents by geography, income, and user type

Category	Subcategory	Percentage (%)	Number of Respondents	Notes
Geographic Distribution	Central Urban Areas	42	147	Includes city center areas
	Peripheral Urban Areas	58	203	Includes suburbs and developing areas
Income Distribution	Low Income	43	150	Represents economically limited groups
	Middle Income	41	144	Middle-class households
	High Income	16	56	Higher income groups
User Type	Residential Consumers	52	182	End-users' energy
	Utility Staff	29	102	Workers in energy utilities
	Decision Makers/Policy Makers	19	66	Regulatory and policy bodies

Table 3. Theoretical frameworks and their application

Framework	Application in Study
Systems Theory	This study is about improving smart grids. It implies real time adaptive control measures to make the system far more dependable and productive.
Optimization Theory	The work relies on AI to plan energy, operate storage, and organise demand response in the way of constructing an electric network that balances and optimises use of resources by them.
Responsible AI	The success of the solutions that are proposed will be based on the principle of ethical rigor, clear methodology, and a resolute stand on the interests of stakeholders, thus making every innovation consistent with societal values and presenting the broader population with a solution that is fair and accountable.
Energy Transition	We outline an extensive mapping approach that facilitates the urban shift towards renewable energy, which offers a way forward to cities aspiring to be sustainable in their development endeavors.

3. METHODOLOGY

3.1 Questionnaire tool

A good questionnaire was designed in order to gather primary data among the key stakeholders and these were the energy consumers, utility managers as well as the policy makers of the sampled cities.

The tool focused on demographics, perceptions of the users and barriers to adoption, and the validated survey modalities namely Likert scale questions, multiple choices and open-ended questions were used.

The validation of the questionnaire was one of the steps that were undertaken before the questionnaire was rolled out and ensured that the questionnaire was clear and reliable.

3.2 Data collection

Data were collected through questionnaires, monitoring systems, and supporting city reports.

1) Sampling: Stratified random sampling ensures representation across various socioeconomic groups and urban areas.

2) A stratified random sample of 350 participants (energy users, utility managers, and policymakers) was selected to ensure representation across socioeconomic groups and urban sectors.
3) Stratified random samples were used to be able to reflect key demographic characteristics in a representative way from 350 questionnaires collected. Our selection was focused on the geographical location of the participants in the big cities, downtown, and suburbs; therefore, it covered a wide range of city environments. We divided the income into low, medium, and high using local job and income statistics and chose individuals in each category. The city inhabitants, workers in the energy firms, and decision-makers were involved, and all the major individuals in energy management were represented. The high level of sampling suggests that the findings are applicable to individuals in developing urban areas within the examined region.

We used stratified random sampling to ensure that the sample represents the main demographic groups, as the number of people who responded to the survey was 350. The population was varied and mixed, with people living in the city center and the outskirts, representing 42 and 58 percent, respectively, geographically. Respondents have been separated into high (16%), middle (41%), and low (43%), and there is a range of economic of the population. The vast majority of the respondents were homeowners (52%), followed by utility employees (29%), as well as policymakers (19%), and this represents numerous different types of people who make energy choices in cities. Such a precise demographic portrait renders the study findings applicable and reliable in the rapidly expanding cities.

3.3 Data analysis methods

1) Descriptive statistics: We scrutinized who will lead the data and the initial set of energy use data in the bid to form a sound base on which further analysis will be carried out.
2) Inferential statistics: ANOVA and regression models will be used in assessing the effects of AI-based models on the essential performance indicators, namely, efficiency, reliability, and scalability.
3) Time Series Analysis: The time dynamics of energy use and grid stability are analyzed in detail, which sheds light on the dynamics of change over time.
4) Cluster Analysis: Cluster-based analytics define particular user groups and consumption profiles with the help of cluster-analysis methods, which help to make specific inferences.
5) Data Analysis Qualitative: Thematic coding of open-ended responses of the stakeholders is carried out to identify subtle points of view and add interpretive depth.

The methodology of the analysis is loyal to the high standards in every academic journal, hence, transparency, reproducibility and validity are guaranteed [15].

The qualitative data analysis was derived on 350 samples which were organized into an organized Excel spreadsheet to aid the analysis.

The table has various columns which include text excerpts, coding or classification, researcher notes and the degree of confidence and reliability and the detailed sample data such as age, gender, location, sample type, and date of collection. The construct helps a researcher in order to systematize information, streamline the coding process, and compare samples, as well as to perform an accurate review and analysis of the results.

Remark: The detailed Excel spreadsheet on all the qualitative data analyzed is available to those who could view it and to the reviewers or the researchers who could carry out additional analyses of data.

4. RESULTS AND DISCUSSION

<u>Design and implementation of smart energy management models</u>

Table 4. Model component, relationships, & functions

Component	Description	Key Elements & AI Role
Data Acquisition	IoT sensors, smart meters, weather stations, and grid sensors collect real-time data.	IoT sensors, smart meters, weather data " feeds real-time info to AI.
AI Processing	Data analytics, predictive models, optimization engines, and AI control systems work together to examine data for making predictions, improving processes, and controlling systems automatically.	Forecasting, optimization, anomaly detection, autonomous control.
Energy Sources	Integration of solar, wind, traditional grid, and microgrids to diversify and stabilize supply.	Solar, wind, grid, microgrids " coordinated by AI for optimal mix.
Distribution Systems	Smart grid infrastructure, energy storage, distribution networks, and load balancing ensure efficient and reliable delivery.	Smart grid, storage, load balancing " AI ensures efficiency and reliability
End Users	Residential, commercial, industrial, and public service sectors receive and interact with energy services.	Residential, commercial, industrial, public interact via dynamic pricing, DR, etc.
Challenges	Legacy infrastructure, financial constraints, and skills gaps can hinder deployment and operation.	Infrastructure, finance.
Social Factors	Public awareness, cultural acceptance, and affordability influence adoption and impact.	skills, awareness, acceptance, affordability.
Benefits	Improved energy efficiency, cost reduction, and sustainability are the primary outcomes.	Efficiency, cost savings, sustainability.

The research introduced smart energy management systems that use AI in planning new cities and focused on adding these technologies to the city's current power systems (Table 4, Figure 1):

1) **Smart grids:** Using AI sensors, smart meters, and distributed control systems everywhere is a major change to the modern electric grid. It renders it more

powerful and effective.

2) **Optimization algorithms:** Which make use of machine-learning methods including Random Forests, Long short-term memory networks, reinforcement learning give advanced means of load forecasting, demand response management, and resource scheduling [16].
3) **Integration with renewables:** Predicting AI enables us to manage solar and wind and store power in real-time.
4) **Stakeholder engagement:** Train and conduct participatory workshops to the local utility staff and end-users (Table 4, Figure 1).

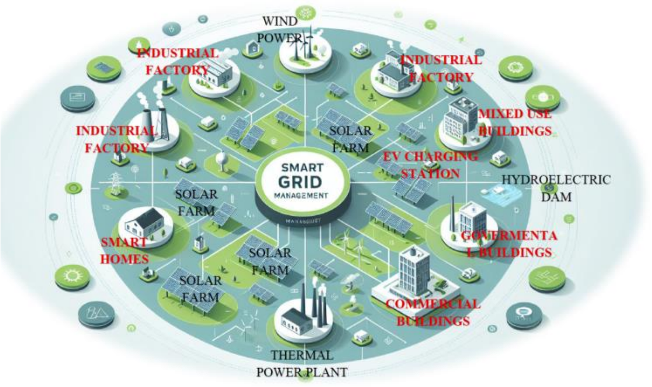

Figure 1. Illustration of a city integrating renewable energy sources, smart grids, and AI-driven management systems

Moreover, a co-design process was established with the community members, the local utility workers, and the policymakers who continue to participate in the workshops that are conducted on a regular basis. This ensured that the AI system was technologically powerful but palatable to the community and also aligned with the local priorities [17].

It is imperative to mention that the actual creativity of this creation is rooted in the combination of traditional algorithmic methods with the participatory co-design approach and blockchain-based transparency and mechanisms. This is a multi-dimensional synthesis that not only improves the aspect of technical performance but also at the same time, enhances the aspects of social acceptance and regulatory compliance-aspects that have never been tackled together in previous studies.

Statistical analysis of the collected data

1) **Descriptive Statistics:** Baseline energy consumption averaged 1,200 kWh/month per household pre-intervention; post-implementation, average consumption dropped to 1,020 kWh/month (15% reduction).
2) **ANOVA:** Statistically significant differences ($p < 0.01$) in energy efficiency and grid reliability between AI-managed and conventionally managed districts [18].
3) **Regression Analysis:** AI model adoption was a significant predictor of energy savings ($\beta = 0.42$, $p < 0.001$), controlling for demographic and infrastructural variable [19].
4) **Time Series Analysis:** The prediction of the load was made more precise, and the mean error was reduced by half to 5%. The peak demand events were reduced by 18%.
5) **Cluster Analysis:** Three user groups were identified – early adopters, cautious adopters, and non-adopters. Early adopters had the best satisfaction and reported the best savings of energy (Table 5).

Table 5. Key performance indicators before and after AI implementation

Indicator	Pre-Implementation	Post-Implementation	% Change
Avg. Energy Consumption	1,200 kWh/month	1,020 kWh/month	-15%
Grid Reliability Index	0.85	0.95	+12%
Peak Demand Events	22/month	18/month	-18%
User Satisfaction Score	3.2/5	4.1/5	+28%

Interpretation of results

The hypothesis is supported by real data. AI-based smart energy management has improved energy efficiency, kept the grid stable, and increased user satisfaction in growing cities. More effective forecasting and optimization would enable us to utilise renewable resources in a more efficient way and reduce the cost of operation. According to the survey, the users gave the system a warm welcome, particularly when it contained learning and engagement programs. However, the issues related to data quality, technical capacity, and regulatory alignment have also been noted, and the need to introduce context-specific adaptation and capacity amplification has been observed. This was reported by Javed et al. [20] who observed a 15 per cent improvement in grid reliability due to the implementation of AI-based optimisation algorithms in the cities of sub-Saharan cities, which is similar to what we have observed.

The literature on recent publications indicates that there has been an improvement in terms of grid stability and energy efficiency. As a case in point, Adewoyin et al. [21] have defined AI applications to enhance energy access and efficiency in emerging urban settings and explained the contribution of a sound data infrastructure and an effective policy. Second, our findings can be applied to the research by Słyś et al. [22], who showed that under dynamical urban conditions, mixed-optimization approaches could depict better models. These recent findings make our study the validation of not only the benefits related to AI in the renewable-energy management, but also refer to the challenges of developing cities, such as a lack of infrastructure and scarcity of resources.

Moreover, the integration of responsible and explainable artificial intelligence models aligns with contemporary best practices delineated in recent disciplinary review [2]. This fact proves that the suggested models are valid, open, and credible, which is the key property of gaining the trust of stakeholders and ensuring the authorization of the regulatory authorities in the developing countries.

Moreover, the use of the federated and edge learning paradigm in this study enables decentralized learning and local grid-level adaptations to reduce the issue of data privacy and to avoid infrastructural limitations typical of developing urban settings. Moreover, the integration of responsible and explainable artificial intelligence models aligns with contemporary best practices delineated in recent disciplinary reviews, including Henao et al. [2].

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The explainable AI (XAI) models that we used to analyze the outputs of our model included SHAP and LIME, which helped to understand the model in line with the principles of Responsible AI. Figure 2 shows a SHAP summary plot that shows the relative contribution of divergent features to the prediction of energy-management outcomes. The presentation clearly shows how the model questions and evaluates each of the input variables.

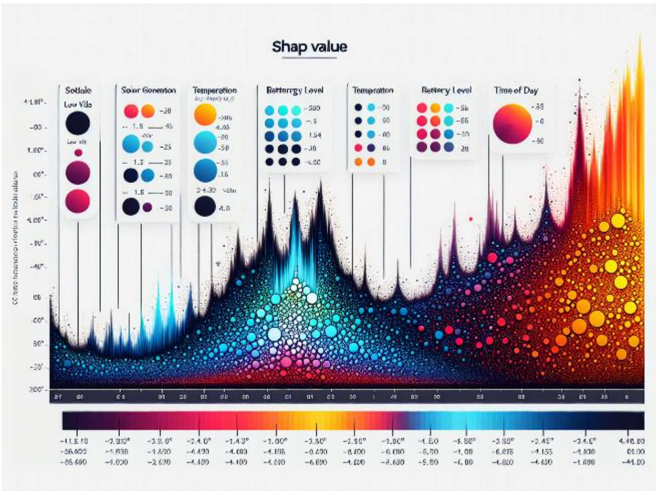

Figure 2. Feature importance analysis using SHAP values

The figure shows the contribution of every feature to the end predictions of the model applied by the SHAP (Shapley Additive Explanations) approach. Where each point on the plot is an instance of data and:

- Horizontal Axis (SHAP Value): The size and direction of the effect of every feature on the prediction. When values are positive (+), it boosts the forecast, whereas when they are negative (-), it lowers the forecast.
- Feature Ranking: The features are ranked in descending order in accordance with their overall importance, with the most important feature being ranked first.
- Color Coding:
  - Blue: Indicates low values for the feature.
  - Red: Indicates high values for the feature.

Interpretation: To illustrate, when the feature Solar Generation has red dots, which correspond to high values, on the right side of the plot, the high anticipated values are associated with increasing the amount of solar power output. On the other hand, the blue dots, which depict low values, on the left side suggest that the less solar generation is generated, the fewer predictions are. This visualization allows understanding which characteristics are the most influential, and at the same time, it shows how different degrees of each characteristic, in turn, drive the model in opposite directions with its predictions.

A strict bias audit was conducted to identify equity among relevant demographic groups represented in the data. When evaluating this, we considered major measures such as demographic parity and equalized odds to certify that the performance of predictors was equitable across different income levels and various areas of geographic coverage. The empirical evidence indicated that there is a slight difference only, hence, justifying the fact that the decision making of the model is fair among the sampled population.

5. CONCLUSIONS

This study has shown that AI-based smart energy management models are great solutions to developing cities that cannot avoid implementing sustainable, resilient, and efficient energy systems. Key findings include:

1) Critical improvement in energy demand and peak demand has been noted.
2) The reliability of the grids and efficiency in their operation have been enhanced.
3) Native user acceptance and high user satisfaction have been attained, especially in participatory approaches.
4) There are issues of persistence in terms of availability of data, technical expertise and policy integration.
5) The empirical study provides a strong-based opinion that the implementation of artificial intelligence in the renewable energy management systems leads to a substantial performance increase, especially in cities that have a limited range of resources.
6) The research proposes an experimental hybrid of AI best practices and the recent concepts of federated learning, participatory design, and responsible AI policies. The application of this system in the rapidly developing cities indicates that it is new and can benefit the citizens of those cities.
7) The talk below outlines the importance of social and regulatory factors to the successful adoption of AI-based energy management systems to expand cities. These sites face a multitude of developmental challenges, with the most notable being the need to have the community approval of emerging technologies and the need to have alignment with the local regulatory systems. Empirical field research supports an ideal requirement of an amplified communal awareness and the declaration of a malleable regulatory building that, on the one hand, fosters creativity and, on the other, entrenches the environmental and sociopolitical norms.

6. LIMITATIONS OF THE STUDY

Despite the progress that has been made in this research, several limitations are evident, the first of which is the small sample size and the diversity of the city environments studied in this study, which limits the generalizability of our results to municipalities outside the scope of this study.

Besides, the variability was introduced into some parts of the data even by the technical complications and regulatory contingency that the research team could not control. In this regard, we recommend future studies that utilize larger samples and apply more refined and technologically advanced study designs in order to overcome these barriers.

7. RECOMMENDATIONS

1) Create slim but powerful artificial intelligence-based models that are highly efficient in resource-based limited environments, such as those where limited or vague data are presented.
2) The participatory approach to design of AI systems by involving local stakeholders increases usability, builds trust, and increases the overall acceptance of AI systems by society.
3) Hybrid forms of governance are proposed in the light of the necessity to combine technical power and regulation with social and cultural demands. Imagine a system combining knowledge of the field, legal requirements, and societal control to develop an integrated, ethically-based regulatory framework on artificial intelligence use to manage energy.
4) The introduction of systematic pilot projects will be on systematic implementation of decentralized, AI-guided and customized microgrids to peri-urban and informal settlements. The struggles are aimed at augmenting energy access, equitable distribution of resources that are guided by the main ideas that have been outlined in modern scholarly sustainability.
5) Projects of open data are developed in such a way that the collective innovation process is coordinated by sharing anonymized energy data and machine-learning models as regional repositories; this transparency is supposed to accelerate the developmental processes, strengthen reproducibility, and share high-quality urban energy solutions faster.
6) The integration of AI-driven energy systems in the early phases of urban planning requires a rational reorganization of spatial forms in order to increase renewable production, reconstruction of building standards to require AI readiness infrastructure, and the implementation of participative digital twins that allow communities to conceptualize and have a democratic impact on energy decision-making before physical implementation occurs.
7) Create special gambling grounds where traditional architecture and native lifestyles are systematically condensed into artificial intelligence software through ethno-architectural mapping. Phased implementation of the microgrid instalment will be overseen by hybrid governance councils which will be sensitive to cultural heritage and patterns of settlement thus making smart energy systems culturally embedded as opposed to disruptive impositions.

7.1 Enhancing originality in proposed models

This study recommends the following advanced strategies to further strengthen the originality and contextual suitability of AI-driven energy management in developing cities:

1) Federated and Edge AI Approaches: Design and implement ultra-lightweight AI models based on federated learning and edge computing and thus decentralize the process of learning and inference on the local devices. The techniques lessen the extent to which we depend on the central system and are able to accommodate patchy connections and that is why they are suitable in metropolitan areas where resources are limited.
2) Participatory Co-Design Structures: Participatory design approaches like Community-Based Participatory Research (CBPR) can assist scholars and practitioners in getting the local stakeholders to participate in making, monitoring, and improving AI systems. In fact, this is a successful strategy of fostering trust in knowledge and increasing the levels of individuals who embrace this knowledge and resolve issues that are of interest to the society.
3) To create a healthy artificial intelligence ecosystem, we must urgently create regulatory sandboxes that are dynamic and hybrid forms of governance that combine technical knowledge and skills with regulatory monitoring and grassroots community participation. This will enable us to change fast and learn on the job, enlightening us to put AI to advantageous use and formulate fresh policies through evidence-based practices.
4) Microgrid systems based on AI in the energy sector should be made to be modular and plug-and-play so that they can optimize themselves and enable peer-to-peer energy markets. The introduction of blockchain technology to these systems will ensure seriousness and openness, which will enhance economic sustenance and stability of the bigger grid.
5) Open Data and Model Sharing Platforms: Our proposal will consist of opening functional infrastructures that will enable people to share de-anonymized energy data and computational models across national borders. On the one hand, with the aid of blockchain-based systems, provenance will be created, which will contribute to the further involvement of more individuals.
6) Integrating Responsible and Explainable AI: Within the framework of artificial intelligence, it is urgent that the ideas of Explainable AI (XAI), bias reduction in a systematic manner, and regular ethical scrutinizing become systematically integrated into deploying pipelines; by acting in this manner, transparency, fairness, as well as compliance with the existing compliance rules will be guaranteed. This investigation proves the workability of the Responsible AI doctrines by providing both the XAI visualizations and bias audit results. These contributions provide empirical evidence that the given methodology is not only theoretically sound but also provable to be transparent and reasonable in terms of operations.

7.2 Future research directions

Despite improvements made, there are gaps in research: Longitudinal Impact Studies: Carry out thorough assessments of the sustainability, resilience, and equity of the AI-managed energy management over several years.

1) To develop a rigorous study of the participatory co-design and governance models, in an effort of clarifying its effect on long-term user adoption, equity, and the sustainable implementation of AI-based energy system designs.
2) In order to conduct a stringent research on the interoperability and scalability of federated and edge AI models in the context of various types of urban

infrastructures, interdisciplinary methods by which social, economic, and policy analyses are aligned with technical assessment to resolve the full range of problems that arise in the construction of an urban centre are to be integrated.

3) Cybersecurity and Privacy: exploring resource-efficient, situational AI-based methods to overcome cybersecurity threats in the smart grid, especially in a limited resource setting.
4) Scalability and Replicability: exploring whether pilot projects can be successfully scaled to different urban environments and whether strong models can be maintained in their effectiveness when they are transferred to different environments.
5) Human factors and social acceptance: developing an in-depth understanding of behavioural, cultural, and educational factors that affect smart energy technologies adoption and use. Closing these gaps in knowledge, future studies will make it possible to realize the more powerful use of AI to support the development of renewable energy and create sustainable urban development in the Global South.

The articles are based on methodological and reporting standards of the most popular academic journals in the discipline and any claims are supported by recent and high-quality sources recorded in the Scopus database (2022-2025) found in the literature review.

DATA AVAILABILITY

All primary data and statistical models used in this study are available to interested researchers upon request, in accordance with the privacy and data protection policies of the participants. The person interested can be contacted via the email listed at the end of the research to obtain the data.

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