Application of Artificial Intelligence in Clean Cooking Energy Technologies for Enhancing Access to Carbon Credits in Tanzania

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ABSTRACT

This study explores how Artificial Intelligence (AI) can be used to improve clean cooking energy technologies in Tanzania, particularly in enhancing system performance and supporting access to carbon credit markets. The research is based on a critical review and comparison of existing studies and real-world applications of AI in technologies such as improved biomass stoves, biogas systems, and electric cooking devices. It focuses on key AI functions, including real-time monitoring, predictive maintenance, user behavior analysis, and digital systems for measurement, reporting, and verification (MRV). The results show that AI can make a practical difference in how these technologies operate. For example, real-time monitoring helps improve fuel efficiency and reduce emissions by optimizing how stoves are used. Predictive maintenance reduces breakdowns and extends the lifespan of equipment, while analysis of user behavior provides insights that can help reduce the common practice of using multiple fuels (fuel stacking). In addition, AI-based MRV systems improve the accuracy and transparency of carbon credit verification by automating data collection and identifying irregularities. Overall, the study finds that AI is not only a promising concept but a practical tool that can improve efficiency, reduce emissions, and strengthen carbon accounting systems. However, challenges such as limited digital infrastructure, high costs, and lack of technical expertise may slow down its large-scale adoption in Tanzania. This paper contributes by bringing together existing knowledge and presenting a clear, Tanzania-focused perspective on how AI can support the growth of clean cooking technologies and access to climate finance.

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1.0 Introduction

While clean cooking technologies such as improved biomass stoves, biogas systems, LPG, and electric cooking solutions are increasingly promoted in Tanzania, their adoption and sustained use remain limited. This limitation is not simply a lack of available technologies; it rather reflects deeper challenges related to affordability, user behaviour, weak monitoring systems, and inadequate performance tracking (Ashagri *et al.,* 2024; Katutsi *et al.,* 2023; Rosenthal *et al.,* 2018). In practice, many households continue to rely on multiple fuels simultaneously, a phenomenon known as 'fuel stacking', which significantly reduces the expected health and environmental benefits of clean cooking interventions (Palit & Bhattacharyya, 2014; D. Shen *et al.,* 2015). In addition, the absence of reliable and continuous data on stove usage, fuel consumption, and emissions makes it difficult to evaluate real-world performance and limits the ability to access carbon finance through robust Measurement, Reporting, and Verification (MRV) systems (Kreibich & Hermwille, 2021; Trencher *et al.,* 2024).

In this context, Artificial Intelligence (AI) offers a critical opportunity that is particularly relevant for developing countries. Rather than depending on already high adoption levels, AI can directly address the underlying barriers that constrain the effectiveness and scalability of clean cooking technologies. AI-enabled systems, supported by Internet of Things (IoT) sensors and machine learning algorithms, can provide real-time monitoring of stove usage, detect inefficiencies, and generate actionable insights into user behaviour and system performance (C. Pandit *et al.,* 2025; Pantelic *et al.,* 2023). Furthermore, predictive analytics can improve system reliability by anticipating maintenance needs, while AI-driven MRV frameworks can automate data collection and enhance the accuracy and transparency of carbon credit verification (Ecklu & Thomas, 2025; Khan & Li, 2024). These capabilities are particularly valuable in Tanzania and similar contexts, where traditional monitoring approaches are often costly, fragmented, or absent. By improving performance, accountability, and financial viability, AI has the potential to accelerate the adoption and long-term sustainability of clean cooking solutions rather than merely optimise already mature systems, as commonly observed in developed countries.

Despite the growing body of research on clean cooking technologies and the emerging role of Artificial Intelligence (AI) in energy systems, important gaps remain in the current literature. First, most existing studies examine AI applications in isolation, focusing either on technical optimisation or data analytics without clearly linking these capabilities to real-world clean cooking challenges in low-income settings (Jiao *et al.,* 2025; Tabaku *et al.,* 2025). Second, while carbon credit mechanisms are widely discussed, there is limited evidence on how AI can practically strengthen Measurement, Reporting, and Verification (MRV) systems for decentralised and household-level energy technologies such as cookstoves and biogas systems (Ecklu & Thomas, 2025; Mercer & Burke, 2023). Third, hardly any studies provide a context-specific analysis for Tanzania, where constraints such as limited digital infrastructure, fuel-stacking behaviour, and affordability significantly influence technology adoption and performance (Katutsi *et al.,* 2023; Kuika Watat & Jonathan, 2020b; Rosenthal *et al.,* 2018). As a result, there is a lack of an integrated framework that connects AI applications, clean cooking performance, and carbon finance in a way that reflects local realities.

To address these gaps, this study provides a structured and context-specific analysis of AI integration in clean cooking energy systems in Tanzania. Specifically, the study:

a) evaluates how AI-based tools such as real-time monitoring, predictive maintenance, and user behaviour analytics improve the performance and reliability of improved biomass stoves, biogas systems, and electric cooking technologies;
b) examines the role of AI in strengthening MRV systems for accurate and transparent carbon credit verification; and
c) analyses the key technical, economic, and institutional barriers affecting the large-scale deployment of AI-enabled

clean cooking solutions in Tanzania. Based on these findings, the study proposes a practical framework linking AI applications with clean cooking performance and carbon finance mechanisms to support policy design and investment decisions.

The integration of AI technology in clean cooking is also pivotal for facilitating carbon credit mechanisms that incentivise emissions reductions. Carbon financing, through mechanisms such as the Clean Development Mechanism (CDM) and voluntary carbon markets, requires robust measurement, reporting, and verification (MRV) frameworks to quantify emission reductions accurately (Group, 2022; Impact, 2024). AI methodologies enhance MRV by enabling automated data capture, anomaly detection, and predictive modelling, thereby improving the reliability and transparency of carbon accounting processes (Carbon, 2024). This capability is particularly important in Tanzania, where access to carbon markets can provide vital financial resources to scale up clean cooking technologies and support broader climate change mitigation efforts (Aamaas & Grimsby, 2024; Okoko *et al.,* 2018).

Beyond technical considerations, the socio-economic impacts of AI-enabled clean cooking energy solutions bear significant implications for sustainable development. By improving cooking efficiency and reducing fuel expenditure, AI-optimised technologies contribute to enhanced household welfare, time savings, and gender equality, as women and children are often most affected by traditional cooking practices (Akter & Pratap, 2022; Tsekane *et al.,* 2024). Furthermore, environmental benefits are realised through decreased deforestation and lower GHG emissions, aligning with Tanzania's nationally determined contributions (NDCs) under the Paris Agreement (Aamaas & Grimsby, 2024).

This paper examines the potential of integrating Artificial Intelligence into clean cooking energy technologies within the Tanzanian context. It discusses how AI can optimise the performance, monitoring, and management of various clean cooking solutions while facilitating accurate carbon credit tracking. The socio-economic and environmental dimensions of this integration are analysed, and policy recommendations are proposed to promote widespread adoption and sustainable development outcomes.

2.0 Literature Review

Tanzania's household energy landscape is overwhelmingly reliant on traditional biomass fuels, mainly firewood and charcoal, which supply over 85%–90% of cooking energy needs in rural and peri-urban areas (Mwampamba *et al.,* 2013; Rosenthal *et al.,* 2018), as Tables 1 and 2 indicate. Transitioning to clean cooking solutions is essential for reducing household air pollution, alleviating pressure on forest resources, and contributing to greenhouse gas mitigation targets, consistent with Tanzania's commitments under the Paris Agreement (Rosenthal *et al.,* 2018). The country's clean cooking technologies fall into four principal categories: improved biomass cookstoves, household biogas digesters, liquefied petroleum gas (LPG) systems, and electric cooking appliances (Cannon & Chu, 2021; Johnstone *et al.,* 2013). While each offers distinct socio-economic and environmental advantages, adoption remains constrained by affordability limitations, accessibility gaps, and infrastructural shortcomings (Lange *et al.,* 2021; Lee *et al.,* 2019).

2.1 Improved Biomass Cookstoves

Improved cook stoves (ICS) are engineered to burn biomass fuels such as firewood, charcoal, and crop residues more efficiently, thereby lowering smoke emissions and reducing fuel consumption compared to traditional three-stone fires. Evidence from studies in Sub-Saharan Africa indicates that ICS can reduce household fuel use by approximately 30–50% and decrease fine particulate matter emissions by up to 70% (Bruce *et al.,* 2018). In Tanzania, widely used ICS designs include clay-liner stoves and portable metal stoves. Although these options are generally more affordable than other clean cooking technologies, adoption remains constrained by low consumer awareness, the limited durability of locally manufactured models, and persistent "fuel stacking" practices, in which households use ICS alongside traditional stoves, thereby undermining potential health and environmental benefits (Energy, 2014).

2.2 Biogas Digesters

Biogas technology converts organic waste (animal manure, crop residues, and food waste) into methane-rich gases for cooking while producing bioslurry that can be used as organic fertiliser. In Tanzania, domestic fixed-dome and tubular plastic digesters are promoted in rural areas with livestock availability.

The environmental benefits are significant: zero net CO_2 emissions from combustion, reduced methane emissions from decomposing manure, and lowered pressure on forests for fuelwood (Vasileiadou, 2024). However, adoption remains low, under 5%, in potential rural households due to high initial investment costs, water scarcity in some areas, maintenance challenges, and the need for a consistent feedstock supply (Ghimire, 2013; Kulugomba *et al.,* 2024).

2.3 Liquefied Petroleum Gas (LPG) Systems

LPG offers a cooking option with near-zero particulate emissions and is widely recognised for its convenience, high heat efficiency, and compatibility with urban lifestyles (Rosenthal *et al.,* 2018). In Tanzania, LPG use is growing, particularly in urban centres such as Dar es Salaam, Arusha, and Mwanza, where supply chains are stronger.

However, LPG adoption is constrained by high recurring fuel costs, limited rural distribution networks, and safety concerns over gas handling. Price volatility linked to global oil markets can lead to fuel switching back to biomass during price surges (Organisation, 2014).

2.4 Electric Cooking Solutions

Electric cooking technologies include induction cookers, hotplates, rice cookers, and electric pressure cookers. With Tanzania's expanding electricity grid and rural electrification programmes, electric cooking is becoming more feasible, especially in peri-urban areas. When powered by renewable electricity, these systems can provide a virtually zero-emission cooking pathway (Opoku *et al.,* 2022).

Challenges include unstable electricity supply in rural areas, high appliance costs, and limited user familiarity with electric cooking. Additionally, tariffs for electricity can influence affordability, and grid reliability remains a barrier to widespread adoption.

Table 1
Summary of Clean Cooking Energy Technologies in Tanzania

Technology	Description	Key Advantages	Main Challenges	Key Journal Sources
Traditional Biomass Fuels (Firewood & Charcoal)	Burning unprocessed wood or charcoal on three-stone fires or simple metal stoves	Low upfront cost; widespread availability	Very high PM emissions; significant health risks (HAP); major driver of deforestation; low efficiency (10-15%)	(Masera *et al.,* 2015; Mwampamba *et al.*, 2013)
Improved Biomass Cookstoves (ICS)	Efficiently burn biomass (firewood, charcoal, crop residues) with better combustion chamber design	30-50% less fuel use; up to 70% lower PM emissions; affordable compared to other clean options	Low durability of local models; limited awareness; fuel stacking reduces benefits	(Bruce *et al.*, 2018; Energy, 2014; Nakyeyune Doctor, 2022)
Biogas Digesters	Convert organic waste into methane-rich gas for cooking; produce nutrient-rich bio-slurry as fertilizer	Net-zero CO_2 combustion; reduced methane emissions; reduced fuelwood demand	High upfront costs; water scarcity; maintenance issues; need for steady feedstock supply	(Ghimire, 2013; Kulugomba *et al.,* 2024; Okuthe, 2024)
Liquefied Petroleum Gas (LPG)	Pressurized gas for cooking with high thermal efficiency and controllability	Near-zero PM emissions; fast cooking; urban compatibility	High recurring fuel costs; limited rural supply; safety concerns; price volatility	(Bruce *et al.*, 2018; Rosenthal *et al.*, 2018)
Electric Cooking	Includes induction cookers, hotplates, rice cookers, and electric pressure cookers	Potential zero emissions with renewable power; efficient; no direct household air pollution	Appliance cost; unreliable rural electricity; limited user familiarity	(Batchelor *et al.*, 2018)

Table 2
Cooking Energy Sources in Tanzania

Cooking Energy Source	Approximate Share (%)	Key Notes	Key Journal Sources
Firewood	60-65%	Predominantly rural; major cause of deforestation and indoor air pollution.	(Masera *et al.,* 2015; Mwampamba et al., 2013)
Charcoal	25-30%	Widely used in urban/peri-urban areas due to convenience and market accessibility.	(Mwampamba et al., 2013; Rosenthal *et al.,* 2018)
Agricultural Residues & Other Biomass	2-3%	Used seasonally, especially in rural households with limited access to wood.	(Bruce *et al.,* 2018; Nakyeyune Doctor, 2022)
Liquefied Petroleum Gas (LPG)	5-7%	Increasing in cities (Dar es Salaam, Arusha, Mwanza) but constrained by cost and supply chains.	(Bruce *et al.,* 2018; Rosenthal *et al.,* 2018)
Electricity (e-cooking)	1-2%	Limited to grid-connected households; emerging with renewable electricity expansion.	(Batchelor *et al.,* 2018; Opoku *et al.,* 2022)
Biogas	<1%	Low adoption due to high upfront costs, feedstock, and water requirements.	(Ghimire, 2013; Kulugomba *et al.,* 2024)
Kerosene/Other Fuels	<1%	Declining use because of high costs and WHO restrictions on kerosene for household use.	(Dutta & Olopade, 2024; Supply & Programme, 2014)

3.0 Role of AI in Clean Cooking Technologies

The incorporation of AI into clean cooking systems opens multiple transformative avenues to improve technical performance, user experience, and transparent participation in the carbon market. AI techniques such as machine learning, computer vision, and predictive analytics, when linked with IoT infrastructure, provide round-the-clock, data-driven insights that enable the optimal design, operation, and sustainability outcome of systems. This point is strongly underlined in the Tanzania scenario, where infrastructure gaps, weak technical capacity, and the absence of strong measurement frameworks hinder the much-needed large-scale clean cooking solution uptake, as Table 3 indicated.

3.1 Performance Monitoring

AI-enabled Internet of Things (IoT) devices, incorporating embedded temperature, pressure, and flow sensors, can capture high-frequency, real-time operational data from cookstoves, biogas digesters, LPG burners, and electric cooking appliances. Such systems track key performance metrics, including cooking duration, fuel consumption, combustion efficiency, and pollutant emissions such as $PM_{2.5}$ and CO. Machine learning algorithms can analyse these datasets to estimate thermal efficiency, detect suboptimal operating conditions, and autonomously adjust operational parameters, for example, modulating airflow in biomass stoves to enhance combustion performance. In the Tanzanian rural context, where stove misuse or inadequate maintenance often leads to efficiency losses, AI-driven feedback delivered through SMS or mobile applications can guide users toward optimal cooking practices, thereby improving fuel savings and reducing exposure to harmful household air pollution (S. Pandit *et al.,* 2025; Pantelic *et al.,* 2023; Tagle *et al.,* 2019).

3.2 Predictive Maintenance

AI models trained on historical performance data can be employed to forecast component wear, mechanical failures, or sensor degradation before these issues arise. Using supervised learning algorithms such as Random Forest and Gradient Boost, patterns in stove temperature profiles, gas pressure variations, or anomalies in energy consumption can be analysed to predict potential breakdowns. This predictive maintenance approach offers several operational benefits, including reduced downtime, an extended equipment lifespan, lower repair costs, and minimal user inconvenience. In the context of Tanzania's distributed clean cooking initiatives, such as pay-as-you-go LPG supply chains or rural biogas programmes, predictive maintenance enables service providers to prioritise technical interventions for households most at risk of equipment failure, thereby reducing the frequency of on-site technician visits and optimising resource allocation (Bello *et al.,* 2024; Patel & Reynolds, 2024; Suci *et al.,* 2025).

3.3 User Behaviour Analysis

AI algorithms can be applied to time-series usage data to detect patterns in cooking frequency, meal preparation types, and stove switching behaviour, commonly referred to as "fuel stacking". By uncovering these behavioural trends, AI can support the design of culturally adapted stoves that align with local cooking practices; the targeting of specific user groups with customised awareness campaigns or microfinance options; and the quantification of adoption barriers, such as seasonal variations in fuel availability or shifts in household affordability. In the Tanzanian context, where many households continue to use charcoal and firewood alongside cleaner cooking technologies, AI-based behaviour analysis can provide policymakers and programme implementers with actionable insights to develop incentives and interventions aimed at reducing fuel stacking and accelerating the transition to modern cooking energy (Palit & Bhattacharyya, 2014; Rosenthal *et al.,* 2018; and G. Shen *et al.,* 2015).

3.4 Carbon Credit Verification

Robust measurement, reporting, and verification (MRV) frameworks are essential for securing carbon financing through internationally recognised mechanisms, such as the Gold Standard and the Clean Development Mechanism (CDM). Artificial Intelligence can significantly strengthen MRV processes by automating data acquisition through IoT-enabled sensors that continuously log actual stove usage, employing anomaly detection algorithms to identify inconsistent or potentially fraudulent data, and using predictive models to estimate avoided CO_2-equivalent emissions based on verified reductions in fuel consumption. Furthermore, AI systems can generate secure, verifiable digital records for auditors and carbon registries, thereby reducing MRV transaction costs, improving transparency, and expediting the issuance of carbon credit. In Tanzania, integrating AI-driven MRV into carbon-financed clean cooking projects could help ensure that emission reduction claims remain credible, fully verifiable, and compliant with stringent international standards (Chen *et al.,* 2023; Manikandan *et al.,* 2025; Priya *et al.,* 2023).

4.0 Case Studies and Technological Applications

A wave of pilots across Africa has demonstrated that data-driven and AI-augmented clean cooking systems can lift operational performance while presenting credible and auditable data for carbon market participation. Three application areas stand out: smart-metered LPG, sensor-equipped biomass stoves, and IoT-monitored biogas systems, as indicated on Tabs 3 and 4.

AI-ready, smart-metered LPG (PAYG) in Kenya. In Nairobi's informal settlements, Pay-As-You-Go (PAYG) LPG paired with smart meters has demonstrated strong potential to sustain clean fuel use under real-world stress (e.g., during the 2020 COVID-19 lockdown). High-frequency meter telemetry captured usage patterns and payments, enabling analytics on cooking continuity and affordability; such data streams are precisely the substrate on which ML models can forecast demand, flag anomalies, or tailor tariff designs to reduce reversion to polluting fuels. Subsequent analyses of PAYG users' "fuel stacking" behaviours in Nairobi highlight how usage telemetry can guide targeted interventions—an avenue where AI classification and segmentation can further sharpen programme design (Chaney *et al.,* 2025).

Sensor-instrumented improved biomass stoves. A decade of work has validated low-cost, wireless temperature and current sensors for determining cooking duration, fuel consumption, and stove-use intensity first in controlled tests and then in African households. Wireless Cookstove Sensing System (WiCS) trials showed that temperature-based algorithms can infer cooking events and estimate fuel use, with data transmitted via cellular networks to cloud databases; modern ML pipelines can now build on these foundations to automate event detection and efficiency tracking at scale. Ghana field studies combining Stove Use Monitors (SUMs) with surveys quantified real-world adoption and stacking, while subsequent "CookED" work released labelled minute-resolution datasets and event-classification methods – precisely the kind of supervised-learning tasks (e.g., HMMs, gradient methods) that underpin reliable, automated usage inference for MRV. Comparative signal-analysis research has also refined how raw sensor traces are converted into robust usage metrics, strengthening the evidentiary chain from sensors to carbon accounting (Graham *et al.,* 2014; Kanta *et al.,* 2016).

Smart biogas digesters with cloud monitoring (Uganda & Kenya). Recent pilots have equipped household and community biodigesters with IoT sensors (e.g., gas flow/pressure and temperature) streaming to cloud platforms, then applied machine-learning models to improve system uptime and quantify delivered clean energy. These studies report that ML adds value by forecasting gas production, detecting sensor faults or underperformance, and converting usage histories into credible, time-stamped evidence of fossil fuel displacement – directly supporting verification needs for carbon finance (Coffey *et al.,* 2021).

From pilots to carbon markets via digital MRV. Together, these deployments illustrate a maturing "sensors → analytics/AI → verified outcomes" pipeline. By automating data capture, event detection, and emissions estimation—and by producing tamper-evident digital audit trails, AI-assisted, sensor-rich systems can lower MRV costs and bolster the integrity of issued credits for clean cooking projects in the voluntary and compliance markets. Emerging peer-reviewed work on digital MRV underscores how such technologies (including anomaly detection and predictive modelling) can catalyse higher-quality credits and faster issuance benefits that clean cooking programmes can leverage as they scale (Ecklu & Thomas, 2025).

The African pilots show that when smart meters and IoT sensors are paired with modern data analytics and machine learning, clean cooking programmes gain two compounding advantages:

a) Tighter operational control (higher uptime, lower costs, better user experience) and
b) Stronger, more transparent evidence for carbon accounting, unlocking finance to expand access and impact (Graham *et al.,* 2014).

Table 3
Critical Analysis of AI-Enabled Clean Cooking Case Studies and Their Relevance to Tanzania

Aspect	Observed in Case Studies (Kenya, Uganda, Ghana)	Key Insights (Analysis)	Implications for Tanzania
Technology Application	Smart-metered LPG (Kenya), sensor-based biomass stoves (Ghana), IoT-monitored biogas systems (Uganda)	AI integration enables real-time monitoring, performance tracking, and data-driven decision-making	Tanzania can adopt similar technologies but must ensure they are adapted to local infrastructure conditions
Success Factor 1: Real-Time Monitoring	Use of IoT sensors to track stove usage, fuel consumption, and emissions	Improves efficiency, transparency, and system performance	Low-cost, robust sensors suitable for rural environments are needed
Success Factor 2: Data Analytics & AI Models	Machine learning used for predictive maintenance, anomaly detection, and usage analysis	Enhances reliability, reduces downtime, and improves user experience	Requires investment in local data systems and technical skills
Success Factor 3: Financing Models	Pay-as-you-go (PAYG) LPG and carbon finance support	Improves affordability and sustained adoption	Tanzania needs strong financing mechanisms and stable energy supply chains
Success Factor 4: Institutional Support	Strong involvement of private sector and development partners	Ensures scalability and sustainability of projects	Public–private partnerships (PPPs) are critical for scaling
Limitation 1: High Initial Cost	Cost of sensors, smart meters, and AI systems remains high	Limits adoption among low-income households	Subsidies, microfinance, and local manufacturing should be promoted
Limitation 2: Connectivity & Infrastructure	Dependence on stable internet and electricity	Data gaps and system interruptions occur in rural areas	Systems must be designed for low-connectivity environments (offline capability)
Limitation 3: Fuel Stacking Behavior	Users continue using traditional fuels alongside clean technologies	Reduces environmental and health benefits	Behavioral interventions and user-centered design are essential
Limitation 4:	Many pilots rely on donor	Raises sustainability concerns	Build local capacity and reduce

Aspect	Observed in Case Studies (Kenya, Uganda, Ghana)	Key Insights (Analysis)	Implications for Tanzania
Dependence on External Support	funding and foreign expertise	after project completion	reliance on external funding
Transferability Challenge	Success varies depending on local policies and market conditions	One-size-fits-all solutions are ineffective	Tanzania must adapt solutions to its socio-economic and policy context
Opportunity: Carbon Finance (MRV Systems)	AI improves measurement, reporting, and verification of emissions	Enhances credibility and reduces transaction costs	Strong opportunity for Tanzania to scale projects through carbon markets
Overall Scaling Requirement	Integration of technology, finance, and institutional support	Multi-dimensional approach needed for success	Tanzania must align policy, infrastructure, and investment strategies

Table 4
Role of AI in Clean Cooking Technologies

Role of AI Function	Description	Benefits/Outcomes
Performance Monitoring	AI-enabled sensors and IoT devices track stove usage, fuel efficiency, and emissions in real time.	• Provides real-time data on stove use and efficiency • Identifies inefficient or unsafe usage • Supports user feedback and targeted interventions
Predictive Maintenance	Machine learning models analyze data to anticipate system failures and optimize maintenance schedules.	• Reduces downtime and repair costs • Enables proactive repairs • Extends lifespan of stoves and related systems
User Behavior Analysis	AI algorithms analyze cooking patterns, fuel preferences, and usage frequency to understand user habits.	• Designs user-centric clean cooking technologies • Informs awareness campaigns and personalized feedback • Encourages sustained adoption
Carbon Credit Verification	AI systems automate data collection, anomaly detection, and emissions estimation for carbon credits.	• Ensures transparent, accurate, and verifiable emissions reductions • Enhances trust in carbon markets • Reduces transaction and verification costs

5.0 Carbon Credits and Climate Finance

Carbon credits reward verified emission reductions in both compliance schemes (e.g., CDM) and voluntary carbon markets, channelling climate finance into clean energy. In developing-country contexts, such signal prices have historically supported the diffusion of low-carbon technologies by supplementing domestic policy and mitigating capital constraints; evidence from the CDM shows carbon finance can act as a catalyst for technology transfer and deployment when technology transfer and deployment programmes are credibly measured and certified. (Dechezleprêtre *et al.,* 2011; Michaelowa & Jotzo, 2005) Accurate, transparent measurement–reporting–verification (MRV) is therefore the linchpin: without robust baselines, additionality tests, and ongoing monitoring, credits risk being over- or under-counted, eroding environmental integrity and investor confidence. Recent analyses of the VCM underscore that inconsistent data and weak verification have allowed low-quality credits to proliferate exactly the kind of failure that stringent MRV must prevent (Kreibich & Hermwille, 2021; Trencher *et al.,* 2024).

Artificial intelligence (AI) strengthens MRV across the full project lifecycle. First, AI-enabled digital MRV systems combine IoT sensors with machine learning pipelines to capture high-frequency usage and emission data, automate quality control, and standardise reporting—improving reproducibility and auditability compared to manual surveys. (Ecklu & Thomas, 2025) Second, anomaly-detection and predictive models flag suspicious patterns (e.g., implausible device uptime and outlier fuel savings) and estimate avoided CO_2e with quantified uncertainty, providing auditors with explainable evidence trails. (Li *et al.,* 2024) Second, anomaly-detection and predictive models flag suspicious patterns (e.g., implausible device uptime and outlier fuel savings) and estimate avoided CO_2e with quantified uncertainty, providing auditors with explainable evidence trails. (Li *et al.,* 2024) Third, when paired with tamper-evident data infrastructures (e.g., permissioned distributed ledgers used in energy systems), AI pipelines can write hashed telemetry and model outputs to immutable logs, tightening the chain of custody for MRV datasets and further deterring data manipulation (Andoni *et al.,* 2019).

By digitising evidence collection and verification, AI can also shrink the historically high transaction costs that have limited participation, especially for small, distributed projects typical of clean cooking, thus unlocking more projects to access carbon finance. Classical work on the CDM documented how validation, verification, and documentation costs disproportionately burden smaller activities; newer digital/MRV-automation approaches are explicitly designed to streamline these steps while preserving credibility. In combination, these advances lower per-credit costs; accelerate issuances; and, most importantly, raise trust among buyers and regulators that claimed reductions are real, additional, and durable, helping carbon markets function as a reliable incentive for scaling clean cooking and other decentralised energy solutions (Trencher *et al.,* 2024).

6.0 Challenges and Barriers

Despite its transformative potential, the deployment of AI in clean cooking technologies in low- and middle-income countries such as Tanzania faces multiple interrelated barriers.

Limited digital infrastructure in rural areas. Reliable mobile network coverage, stable electricity supply, and affordable internet access are prerequisites for AI-enabled Internet of Things (IoT) monitoring systems. In many rural Tanzanian settings, intermittent connectivity and frequent power outages disrupt continuous data transmission, limiting the effectiveness of real-time monitoring and predictive analytics (Kuika Watat & Jonathan, 2020a; Msoffe & Lwoga, 2019). These infrastructural gaps increase reliance on offline data storage and periodic uploads, which can delay detection of performance issues and compromise Measurement, Reporting, and Verification (MRV) timelines.

High cost of AI-enabled devices. AI-integrated clean cooking solutions such as smart meters for LPG, stove use monitors, and IoT-equipped biogas digesters entail higher upfront costs than conventional devices. While prices are gradually declining, affordability remains a major adoption barrier, especially for rural and low-income households without access to microfinance or subsidy programmes (Dutta & Olopade, 2024; Energy, 2014). Limited economies of scale in the African clean cooking market exacerbate this challenge.

Data privacy and security concerns. AI systems require continuous collection of energy usage data at the household level, which raises concerns over user consent, data ownership, and potential misuse. Studies highlight that weak data governance frameworks in many sub-Saharan African countries increase the risk of privacy breaches and erode trust in digital energy solutions (Arunthavanathan *et al.,* 2024; Shao *et al.,* 2025). Ensuring compliance with ethical AI principles, anonymising data, and using secure transmission protocols is therefore critical for sustainable deployment.

Limited technical expertise and institutional capacity. Effective integration of AI in clean cooking programmes requires skilled personnel to manage sensor hardware, develop and train algorithms, interpret analytics, and maintain cloud-based infrastructure. In Tanzania, shortages of data scientists, AI engineers, and clean energy technicians slow technology adoption and reduce the likelihood of sustained operation after pilot projects end (Qureshi *et al.,* 2024). Institutional challenges such as fragmented policy frameworks and limited coordination between energy, ICT, and climate sectors further hinder scaling efforts.

7.0 Conclusion

This study shows that Artificial Intelligence (AI) can play a meaningful role in improving clean cooking technologies in Tanzania. Using tools such as real-time monitoring, predictive maintenance, and user behaviour analysis, AI can make these technologies more efficient, reliable, and easier to manage. It also improves how emissions are tracked and reported, making carbon credit systems more accurate and trustworthy. This creates new opportunities for accessing climate finance and supporting the expansion of clean cooking solutions.

At the same time, the study recognises that implementing AI in Tanzania is not without challenges. Issues such as limited digital infrastructure, high costs of technology, data privacy concerns, and a shortage of technical skills may slow down large-scale adoption. Overcoming these barriers will require strong collaboration between governments, the private sector, and development partners, along with investments in infrastructure and capacity building.

This study primarily contributes three key insights. First, it brings together existing research and clearly shows how AI can be connected to real challenges in clean cooking, rather than treating it as a separate technical concept. Second, it provides a Tanzania-focused perspective, showing how local conditions such as fuel stacking, affordability, and infrastructure gaps affect the use of both clean cooking technologies and AI. Third, it offers practical insights on how AI can support better monitoring systems and improve access to carbon credits, which can help scale up these technologies. Overall, this study demonstrates practical applications of AI in supporting clean cooking in developing countries. It provides a useful foundation for future research, policy decisions, and investment aimed at expanding clean cooking solutions in Tanzania and similar contexts.

8.0 Recommendations

8.1 Supportive Regulatory Frameworks and Incentives

a) Establish clear and consistent government regulations to support AI adoption in clean cooking.
b) Implement financial incentives such as subsidies, tax exemptions, and reduced import duties to encourage uptake of AI-enabled clean cooking devices.
c) Enforce quality assurance and standards to build user confidence and facilitate scalable supply chains.
d) Develop regulatory clarity for cookstove-related carbon credits to unlock domestic and international climate finance.

8.2 Invest in Digital Infrastructure and Capacity Building

a) Improve rural digital infrastructure, including reliable electricity, internet connectivity, and cloud computing resources.
b) Invest in AI literacy training and governance frameworks to foster local capacity for managing AI-enabled systems.
c) Encourage open-source AI solutions and data repositories tailored to local contexts.

8.3 Promote Public-Private Partnerships (PPPs)

a) Leverage PPPs to share financing risks and technical expertise and accelerate last-mile deployment of clean cooking technologies.
b) Support technology pilots, local manufacturing, and integration of AI for monitoring, predictive maintenance, and impact evaluation.
c) Draw lessons from regional initiatives such as Kenya's KOKO Networks that blend innovation, carbon finance, and private investment.

8.4 Facilitate Access to Climate Finance and Carbon Markets

a) Utilise blended finance models combining grants, concessional loans, guarantees, and carbon credit revenues to bridge funding gaps.

d) Employ AI-based Measurement, Reporting, and Verification (MRV) systems to provide transparent and credible emissions-reduction data.
e) Lower transactional barriers for small and distributed clean cooking projects to access carbon finance.
f) Enhance data integrity and auditability of carbon credits through tamper-evident AI systems and decentralised ledgers.

8.5 Address Barriers and Enable Sustainable Scale-Up

a) Address infrastructural challenges such as intermittent rural connectivity and power outages to ensure continuous AI monitoring.
b) Develop affordable AI-enabled cooking devices and explore microfinance or subsidy schemes to improve affordability.
c) Enhance data privacy and security frameworks to protect user data, fostering trust in digital solutions.
d) Build institutional expertise in AI, data science, and clean energy technologies to support ongoing system management and scaling.
e) Harmonise policy sectors, including energy, ICT, and climate, to enable coherent and coordinated clean cooking programmes.

These recommendations aim to unlock the transformative potential of AI to improve clean cooking technology performance, increase adoption, and enhance access to climate finance, ultimately supporting health, environmental sustainability, and socioeconomic development goals in Tanzania.

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11.0 Declaration of Conflicting Interests

The authors declare no conflict of interest.

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