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CRITICAL ASSESSMENT OF THE HIDDEN CARBON FOOTPRINT OF SMART HOME DEVICES IN NIGERIA

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Abstract

Smart home devices represent the flagship of modern residential living. They integrate Internet of Things (IoT) technologies, artificial intelligence (AI), and sophisticated automation plexuses to facilitate efficiency, security, and comfort. While these advancements are eulogised for their eco-conscious potential, their hidden carbon footprints remain underexamined, especially in developing contexts like Nigeria. This study thoroughly examines the hidden environmental costs of smart home devices in Nigeria, with emphasis on their operational energy demands, embedded carbon during production, and the ecological burden of cloud infrastructures that support AI-enabled functionalities. Nigeria presents a unique context for this inquiry due to its fast-paced growth, tech adoption, epileptic power supply, and overarching dependence on carbon-intensive options such as fossil-fuelled power generators. A mixed-methods research design was adopted, merging systematic literature review, real-time energy tracking, life-cycle assessment (LCA) data, and semi-structured discussion sessions with occupants and energy experts across selected urban and peri-urban Nigerian locales. Findings reveal a sustainability paradox: while intelligent high-ends can lower household energy consumption by up to 30% through enhanced usage, this gain is often eroded by spiking energy consumption statistics of cloud-based data hubs and AI processing. The dearth of localized LCA structures and regulatory oversight in Nigeria worsens the problem of clinically quantifying the net carbon impact of these technologies. This study proffers key strategies to lower the hidden carbon footprint of smart home devices in Nigeria, including localized eco-designs, integration of renewable energy plexuses, sustainable procurement of electronic components, and encouragement of responsible digital usage. Moreso, it pushes for policy structures and industry standards customized for the Nigerian context towards aligning smart technology implementation with national and global carbon reduction objectives. This way, concerned stakeholders will be offered viable insight into balancing digital innovation with ecological responsibility in a rapidly changing African market.

Keywords: artificial intelligence, carbon footprint, internet of things, life cycle assessments, sustainability paradox

1.0 INTRODUCTION

Smart homes are mutating into advanced ecosystems that incorporate Internet of Things (IoT) high-ends, artificial intelligence (AI), and virtual plexuses to improve energy efficiency, safety, and occupant wellness (Murdan, 2023). These interlinked technologies support remote control and digitization of household functions, learning user preferences to enhance operations, and reducing energy usage. Raza (2023) opined that the seamless incorporation of AI and IoT devices creates avenues for predictive maintenance and individualized experiences, marking a paradigm shift towards more responsive and smart living locales. While intelligent homes are often celebrated for their energy efficiency and environmental gains, they also present latent ecological quagmires. This scenario plays out in the production of smart high-ends which involves the extraction of base resources and manufacturing techniques that lead to environmental degradation (Abid, Mohd, Ravi, Rajiv, & Mohd, 2023). Furthermore, the repeated operation of these high-end devices, particularly those in standby mode, can exacerbate energy consumption, potentially derailing anticipated energy savings (Aníbal, et al., 2010). Moreover, the dependence on cloud facilities for data containment and processing adds to the carbon footprint, as data hubs gulp substantial energy. Frimpong (2025) identified the sustainability paradox of intelligent homes, particularly their dual effect on the environment. While crafted to improve energy efficiency, the extensive deployment of IoT high-ends and AI plexuses can lead to spiking energy usage due to the continuous utilization of devices and the significant energy demands of data hubs that support cloud services (Aya, Yassine, Faycal, & Abbes, 2022). This raises concerns about the actual environmental benefits of smart enclaves in the country. In the Nigerian context, this study thoroughly evaluates the hidden carbon footprint of smart home devices as driven by the adoption of increasing smart technologies, epileptic power supply, dependence on fossil-fuel generators, and lack of regulatory frameworks guiding sustainable energy consumption in digitally connected households. A thorough evaluation of smart homes' environmental impact is important to fully comprehend their sustainability. While these advancements are targeted to enhance energy efficiency, their overall ecological footprint is hinged upon various indices, including the energy expended during production, the operational energy use of devices, and the energy requirements of running and maintaining data hubs (Nikolaos & Dimitris, 2023). Directing comprehensive life cycle assessments (LCAs) is vital to evaluate the gains and possible issues of smart home technologies in Nigeria. Such evaluations should take into consideration user attitudes, as they significantly affect energy utilization patterns (S, C, & J, 2013). By incorporating these indices, stakeholders can proffer informed judgments to enhance the sustainability of smart homes.

1.1 Problem Statement: In agreement with Sunday Olayinka Oyedepo (2022), the adoption of smart home technologies in Nigeria is skyrocketing. Such rapid advancement with their concomitant hidden carbon footprint, is exacerbated by unreliable power supply, dependence on fossil fuels, and inadequate sustainability assessments. This presents a major obstacle to aligning digital advancement with the nation’s carbon reduction objectives.

1.2 Aim and objectives: This study is targeted to critically examine the hidden carbon footprint of smart home devices in Nigeria, prioritizing their full environmental impact within the context of Nigeria’s energy-insecure and carbon-intensive environment using a mixed-methods research approach. The objectives include:

i. Evaluate the life-cycle carbon emissions of smart home devices in Nigeria by integrating data from real-time energy tracking, literature review, and life-cycle assessment (LCA) records.

ii. Evaluate the specific energy efficiency gains of smart home gadgets in selected Nigerian living units and ascertain the extent to which cloud computing and AI infrastructure erode such gains.
iii. Recommend localised approaches to guide stakeholders and professionals in reducing the hidden carbon impact of smart technologies in Nigerian residential enclaves.

2.0 LITERATURE REVIEW

Smart home devices are increasingly integrated into residential environments to improve energy efficiency through automation, artificial intelligence (AI)-powered controls, and smart metering systems (Sneha & Shweta, 2022). Studies in advanced economies suggest these technologies can yield energy savings of up to 30%. However, within the Nigerian context which is characterized by energy insecurity and a fossil-fuel-dependent infrastructure, there is growing concern that the full environmental cost of such devices is not adequately accounted for (Ahmad & Odetokun, 2023). This literature review explores three key dimensions critical to understanding the hidden carbon footprint of smart home devices in Nigeria: life-cycle carbon emissions, net energy efficiency gains, and context-specific sustainability interventions.

While smart devices promise operational energy savings, their broader life-cycle carbon emissions—from raw material extraction to manufacturing, operation, data processing, and end-of-life disposal—remain underexamined in Nigeria. Studies show that the carbon footprint of smart technology can be significant during upstream phases such as production and transportation (Novatia, 2024) . However, in Nigeria, where local data on embedded emissions is scarce, life-cycle assessment (LCA) frameworks are either rudimentary or absent. This limitation constrains the ability of policymakers and researchers to quantify the total carbon cost of widespread smart device adoption (Mohammed, Ayedu, & Kazuyo, 2025). The integration of real-time energy tracking systems and region-specific LCA models is essential to accurately evaluate these hidden emissions and align with Nigeria's carbon reduction goals.

Although smart gadgets are deployed to enhance energy use efficiency in residential spaces, these gains may be eroded by the intensive energy requirements of AI and cloud-computing infrastructure that support their functionality. In Nigeria, smart devices often rely on off-grid, fossil-fuel-powered backup systems due to unreliable electricity supply, which offsets their operational benefits (Folasade, et al., 2022). Furthermore, Dhanabalan, et al. (2025) highlight that data centers, which are integral to smart AI operations, demand continuous, high-power inputs, often supplied by non-renewable sources. The result is an energy paradox: while homes may use less electricity at the point of consumption, the backend systems that process and analyse this data increase overall emissions. Without factoring in the carbon footprint of these digital infrastructures, efficiency claims remain incomplete.

Given Nigeria's unique socio-energy context, scholars argue for contextualized sustainability strategies to mitigate the hidden carbon impact of smart technologies. Jiayu (2024) recommends a multi-pronged approach: developing eco-friendly and modular device architectures that allow for reuse and easier upgrades; promoting low-carbon AI systems; and transitioning to renewable energy sources for both residential use and digital infrastructure. Additional proposals include establishing circular economy policies to reduce e-waste, creating local e-waste recycling hubs, and encouraging stakeholder investment in closed-loop supply chains. Applying whole-life carbon metrics and energy return on investment (EROI) calculations can also help contextualize the net benefits of smart technologies and inform smarter policy choices.

Despite their energy-saving promise, smart home devices in Nigeria pose a complex sustainability challenge when viewed through the lens of full life-cycle emissions and infrastructural dependencies. Existing research has primarily focused on immediate operational efficiencies, largely neglecting upstream and downstream environmental costs. This gap underscores the need for a mixed-methods approach that combines real-time energy tracking with localized LCA frameworks. Furthermore, it calls for a rethinking of energy policy and design practices to ensure that smart technologies deliver genuine, long-term environmental benefits within Nigeria's carbon-intensive and energy-insecure landscape.

2.1 Conceptual Framework

i. Eco-Dilemma in Smart Living Spaces

The sustainability paradox in smart enclaves, as shown in Figure 1, stems from the dispute between energy efficiency benefits and the shrouded environmental costs of digital infrastructure (Patricia & Peter, 2017). While smart plexuses enhance energy usage, the manufacture, maintenance, and distribution of IoT high-ends, along with the carbon footprint of cloud facilities, contribute immensely to environmental deterioration. Balancing innovation with eco-conscious design is necessary for true sustainability in smart home plexuses.

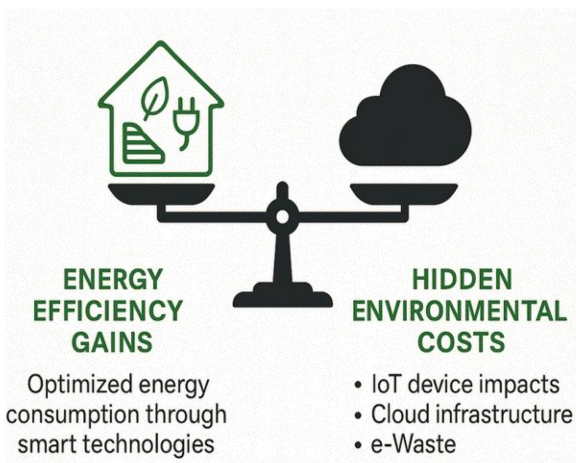

Figure 1. Sustainability Paradox in smart homes. Authors' workstation.
Source: Authors' Workstation (2022)

ii. Impact of IoT and AI on Energy Demands

The incorporation of IoT and AI in smart enclaves improves automation and energy conservation, but also increases energy needs (Benedict & Christian, 2024). As shown in Figure 2, IoT high-ends demand steady connectivity and data transfer, while AI plexuses constantly process information to enhance performance. This escalates electricity usage, particularly when cloud facilities and data hubs are involved. A thorough approach is required to ensure equilibrium between innovation and energy sustainability.

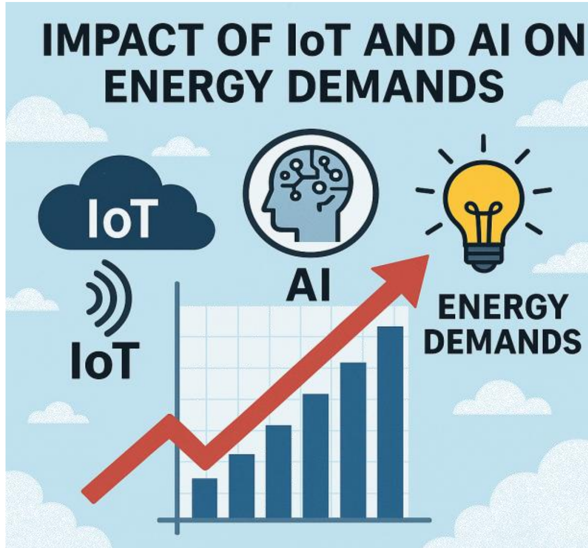

Figure 2. Impact of Internet of Things and AI on Energy Demands. Authors' workstation. Source: *Authors' Workstation (2022*

iii. *Life-Cycle Assessment as a Missing Tool*

Life-Cycle Assessment is vital for comprehending the full environmental significance of smart homes, yet it is often neglected. Ongoing assessments focus particularly on energy-efficient gains, neglecting the carbon footprint of the production, utilization, and distribution of IoT devices (Abderahman, Zailani, Karim, Stefan, & Horst, 2022). Integrating a complete LCA, as shown in Figure 3, would offer a thorough view, facilitating better judgment towards reducing the hidden environmental costs of smart home infrastructure.

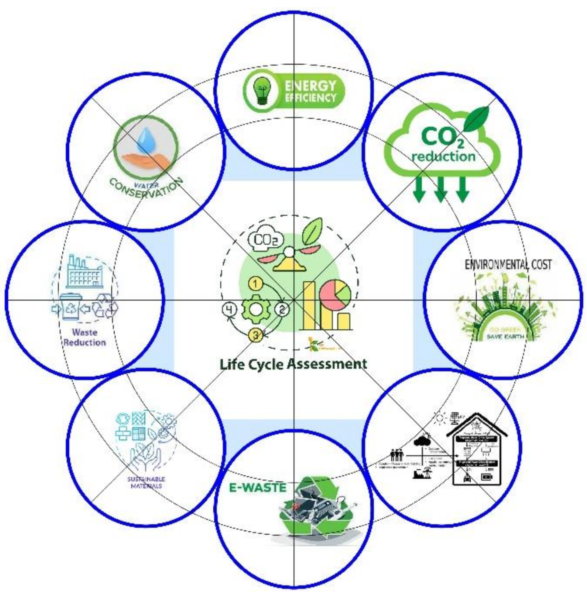

Figure 3. Life-Cycle Assessment as a Missing Tool. Authors' workstation.
Source: Authors' Workstation (2023)

3.0 METHODOLOGY

This study employs a mixed-methods approach to critically assess the hidden carbon footprint of digitalization in smart homes in Nigeria.

3.1 Primary Data: Primary data is obtained through real-time energy monitoring of smart home devices, capturing electricity consumption patterns, standby power usage, and fluctuations in energy demand under different operating conditions. Through purposive sampling, sixty residential units, ten from each geopolitical zone of the country, were selected for the study. Distribution of these units includes Port Harcourt - 10 units, Abuja - 10 units, Kaduna -10 units, Jalingo - 10 units, Lagos - 10 units, and Owerri - 10 units.

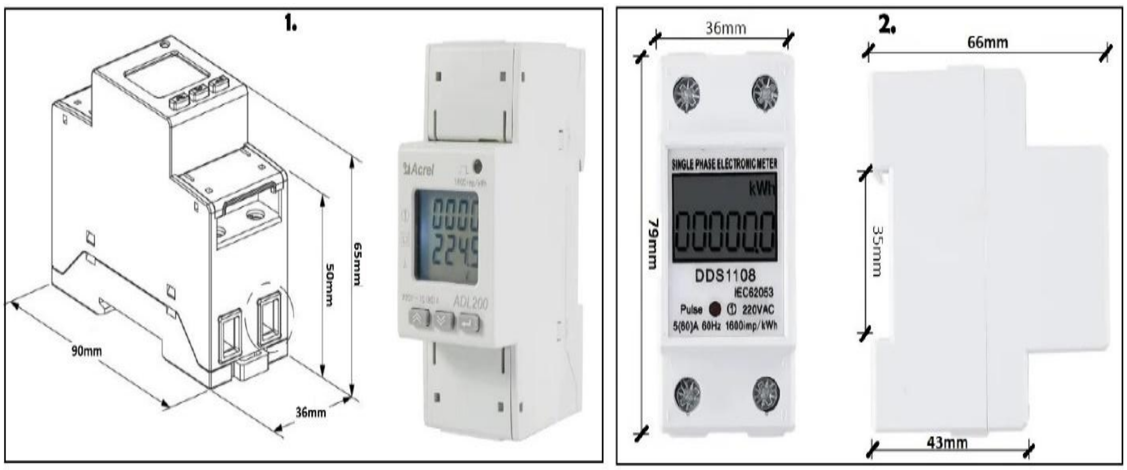

Figure 4. Measuring devices - (1): The ADL200 Single Phase DIN Rail Energy Meter and (2) - DDS1108 Smart Meter with 220-240V Operating Voltage. All devices were temporarily installed at homeowners' permission by specialist energy personnels.

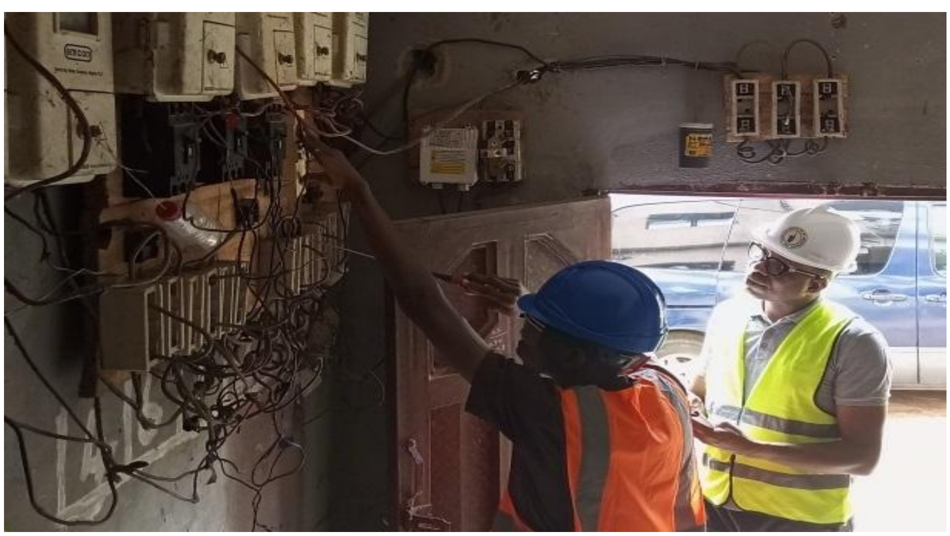

Figure 5. An installation session of one of the ADL200 Single Phase DIN Rail Energy Meters by a specialist energy personnel at one of the residential units. This was supervised to ensure optimal performance and accurate energy monitoring. The technician meticulously checked all connections and calibrated the meter to guarantee precise

For each residential unit, measurements of operation time (hrs/day), energy consumption (kWh/day), standby power (kWh/day), energy demand variations (kWh), and peak consumption period (hrs/day) of five gadgets were taken. These gadgets include smart thermostats, smart lighting, smart televisions, smart refrigerators, and smart speakers. Operation time (hrs/day), energy consumption (kWh/day), and standby power (kWh/day) were measured with a digital electric single-phase DIN rail electric energy meter. Energy demand fluctuations (kWh) and peak consumption periods (hrs/day) were measured with a single-phase, DDS1108, smart electric meter with 220- 240v operating voltage.

3.2 Secondary data: Secondary data encompasses life-cycle assessment (LCA) records, producer specifications, and carbon footprint repositories, which help approximate the integrated carbon discharges associated with smart device manufacture, operation, and decommissioning. The LCA records, producer specifications, and carbon footprint repositories approximate the integrated carbon discharges (kg CO_{2e}) for five (5) commonly used smart home devices mentioned in 4.1 across a 10-year usage period. The 10-year usage period ran from March 2015 to March 2025, during which various operational and environmental factors were examined. This timeframe gave room for an exhaustive evaluation of energy consumption patterns and their concomitant emissions, offering valuable insights into the sustainability of each gadget.

3.3 Semi-structured Interviews: Flexible interviews with industry specialists and participant polls on smart home usage patterns offer qualitative insights into the environmental significance of digitalization. The interview sessions engaged smart device engineers (6), IoT product designers (6), sustainability consultants (6), policy analysts (6), household members (60), and independent users (60).

Table 1: Summary Table of Respondents by City

City	Household Members	Independent Users	Smart Device Engineers	IoT Product Designers	Sustainability Consultants	Policy Analysts
Port Harcourt	10	10	1	1	1	1
Abuja	10	10	1	1	1	2
Kaduna	10	10	1	1	1	1
Jalingo	10	10	1	0	1	0
Lagos	10	10	2	2	1	1
Owerri	10	10	0	1	1	1
Total	**60**	**60**	**6**	**6**	**6**	**6**

Note: This table shows the composition of respondents in relation to the cities under study.

Source: Authors' Compilation (2023)

The heterogeneous pool of participants ensures triangulation of data by incorporating expert, regulatory, and user-level insights. It provides a balanced qualitative dataset from technical stakeholders and end-users. The sample size of these users ensures a statistically robust base for trend identification and behavioural analysis.

3.4 Energy Assessments: Energy assessments involve direct measurements of electricity consumption for various smart home devices, analysing both operational energy use and standby power demand. Comparative analysis with conventional home systems helps determine energy savings versus hidden environmental costs. The study also applies carbon footprint estimation models, incorporating grid energy sources, renewable energy adoption, and embodied carbon in digital infrastructure.

4.0 RESULTS AND ANALYSIS

4.1 *Primary Data: Results and Analysis*

Table 2: Smart Home Device Energy Usage and Operational Requirements in Sixty Selected Residential Units (Averages per Unit)

Device	Avg. Operation Time (hrs/day)	Avg. Energy Consumption (kWh/day)	Avg. Standby Power (kWh/day)	Avg. Energy Demand Fluctuations (kWh)	Avg. Peak Consumption Period (hrs/day)
Smart TV	5.5 hrs	0.55 kWh	0.16 kWh	±0.18 kWh	6 PM – 12 PM (6 hrs)
Smart Refrigerator	12 hrs	1.20 kWh	0.18 kWh	±0.25 kWh	1 PM – 6 PM (5 hrs)
Smart Thermostat	8 hrs	0.15 kWh	0.05 kWh	±0.21 kWh	5 AM – 9 AM (4 hrs)
Smart Lighting	6 hrs	0.35 kWh	0.22 kWh	±0.22 kWh	7 PM – 3 AM (8 hrs)
Smart Speaker	4 hrs	0.3 kWh	0.08 kWh	±0.11 kWh	4 PM – 11 PM (7 hrs)

Note. Data is extracted from devices mounted in meter areas with full permission from the occupiers of such units. See Figure 5 for mounting sessions.

Source: Data compiled by authors, February 2023.

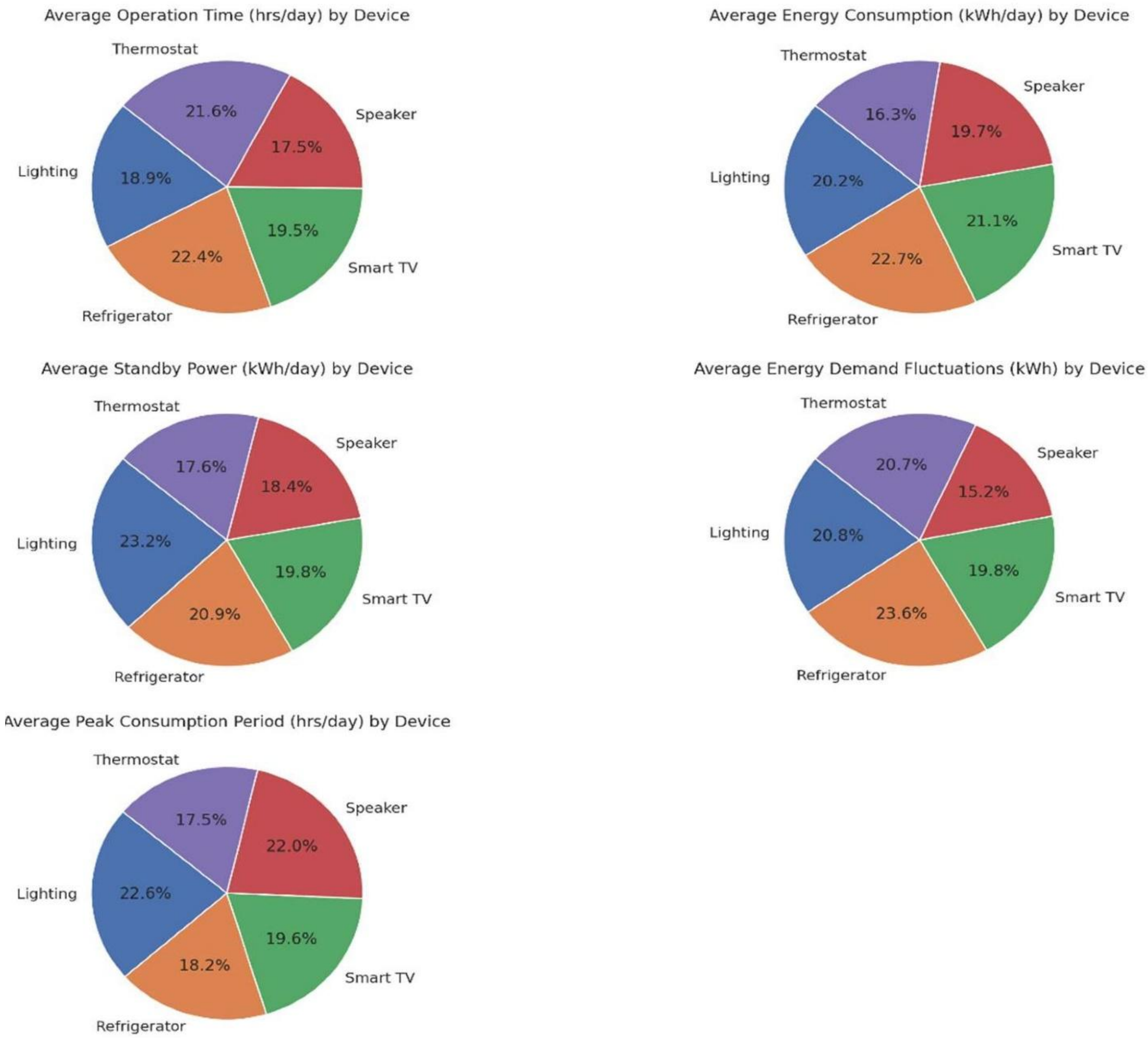

Figure 6. Pie chart visualizations provide insights into how each device contributes to overall energy metrics.

Source: Data compiled by authors, April 2023.

4.1.1 *Primary Data: Key Observations*

i. The operation duration differs significantly across devices, with smart refrigerators typically having the maximum operational hours.

ii. Smart refrigerators and smart televisions tend to use more energy compared to other devices.

iii. Idle power shows that even when not in use, gadgets like smart refrigerators and smart lighting still draw a remarkable amount of power.

iv. Energy demand fluctuations show instability in energy usage. This could be crucial for handling maximum demand, especially in smart refrigerators.

v. Peak consumption periods highlight the hours during which energy consumption is highest. This can inform energy management strategies in smart lighting fixtures.

4.2 *Secondary Data: Results and Analysis*

Table 3: Extracting the Life-Cycle Carbon Footprint of Smart Devices between March 2015 and February 2025.

Smart Device	Manufacturing Emissions (kg CO_2e/unit)	Operational Emissions (kg CO_2e/year)	Decommissioning Emissions (kg CO_2e/unit)	Total Life-Cycle Emissions (10-year span) (kg CO_2e)
Smart Thermostat	45	12	6	171
Smart Lighting (LED)	35	10	5	140
Smart TV	300	100	25	1,325
Smart Refrigerator	400	140	40	1,840
Smart Speaker	50	15	8	208

Note. Data from (Cordella, Alfieri, & Sanfelix, 2025), (Statista, 2025), (European Commission, 202), (Simon, Matthias, & Frank, 2021) (Newsroom, 2015), (Scope3, 2025), (Samuel, et al., 2023), (ecoinvent, 2025), (Masatsugu, Takashi, & Machiko, 2025), (Ruediger, David, & Terry, 2024)

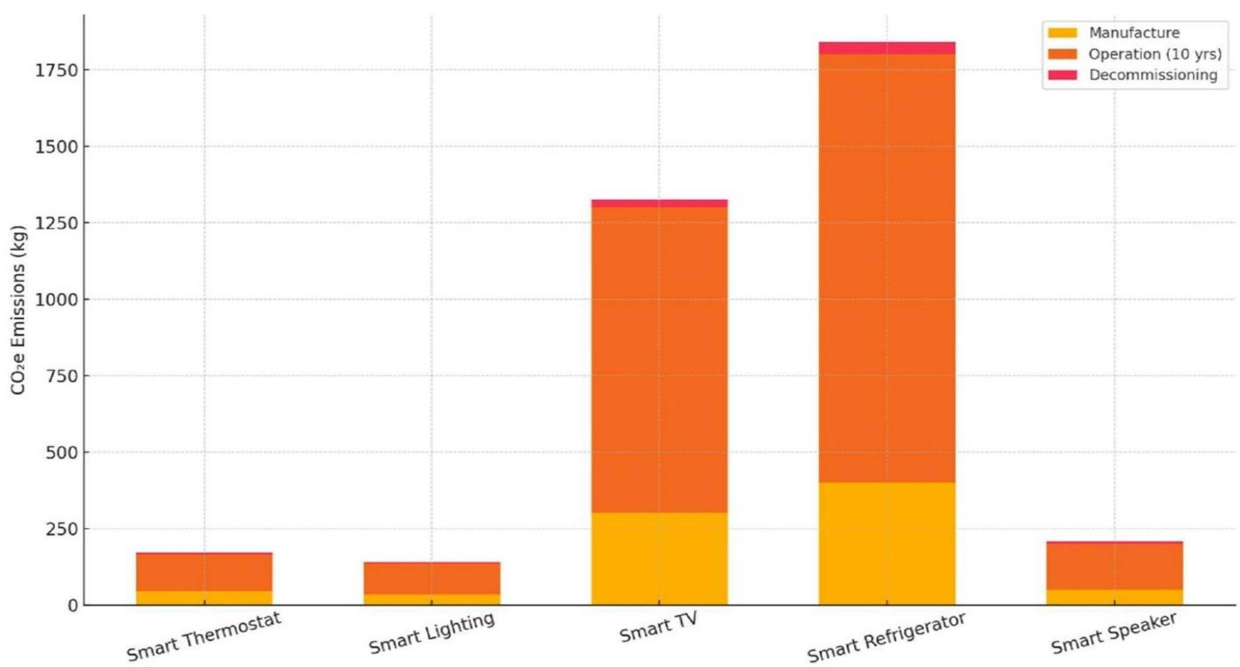

Figure 7. Life-Cycle Carbon Footprint of Smart Devices (kg CO2e over 10 years).

Source: Data compiled by authors, August 2023.

4.2.1 *Secondary Data: Key Observations*

i. Operation accounts for 20–40% of the total life-cycle carbon footprint, especially for continuously running devices like smart refrigerators.
ii. Smart lighting has a lower per-unit footprint, but often exists in higher quantities per home, amplifying cumulative emissions.
iii. End-of-life (EoL) emissions remain poorly documented by manufacturers and are likely underestimated in the subsisting literature.
iv. Smart refrigerators and smart television sets have the highest overall carbon emissions.
v. Operational emissions become a major share for long-use devices.
vi. Smart speakers and smart thermostats seemingly have a low-impact carbon footprint. However, they accumulate a notable footprint over time.

4.3 *Semi-structured Interviews: Results and Analysis*

Table 4: Flexible Interview Sessions with Industry Specialists.

Role	Number Interviewed	Key Themes Identified	Sample Insights / Quotes
Smart Device Engineers	3	Energy efficiency design gaps; limited attention to standby loads	*"Devices are optimized for peak use, but standby loads are mostly ignored."*
IoT Product Designers	2	Trade-off between user features and environmental footprint	*"User demand drives complexity, which increases energy and material requirements."*
Sustainability Consultants	4	Lifecycle carbon cost often not disclosed; embodied carbon underestimated	*"There's still a data vacuum when it comes to full lifecycle emissions of most smart devices."*
Policy Analysts	3	Need for regulatory frameworks to track and label digital carbon emissions	*"There's very little oversight or eco-labelling for digital systems. That has to change."*

Source: Authors' Compilation (2024).

Table 5: Participant Polls for Smart Home Users

Households Surveyed	Devices Used	Common Usage Patterns Identified	Key Observations
10	Smart lighting, Smart thermostats, Smart TVs, Smart refrigerators, Smart speakers	Automation often overrides energy-saving intent; devices left on due to default settings	68% of users reported not adjusting automation schedules, leading to longer device runtime
75 Users (Adults, Mixed Ages)	Multiple smart home platforms (Alexa, Google Nest, etc.)	Limited awareness of energy consumption during standby or idle modes	81% were unaware that their “off” devices still consume energy
		Perceived energy efficiency not backed by actual usage behaviour	Users assumed smart meant sustainable, with few checking actual energy stats

Source: Authors’ Compilation (2024).

4.3.1 *Semi-structured Interviews: Key Qualitative Insights*

i. Conversations with engineers and sustainability specialists showed that standby power is often ignored in product design. Despite being in "off" or idle status, many smart devices continue to use immense amounts of electricity. Surveys support this, with over 80% of participants oblivious to the fact that their devices consume power even when not actively in operation.

ii. While computerization is designated as energy-saving, user response indicates otherwise. In 68% of residential units, smart lighting and smart thermostats were left in active mode due to default or misconfigured automation settings, leading to superfluous energy use.

iii. Sustainability personnel highlighted the absence of accessible life-cycle assessment (LCA) statistics for most smart devices. Many producers do not publish embodied carbon or emissions from manufacture and disposal, shrouding the exact environmental cost of these advancements.

iv. Most users equate “smart” with “green.” Yet, polling showed that fewer than 25% of participants had checked their devices’ energy stats, and many were surprised at their actual consumption levels. This misperception promotes unsustainable behaviours.

v. Interviews with policy analysts indicated a critical gap in digital carbon regulation. Unlike traditional appliances, smart devices and their supporting infrastructure (e.g., cloud data centres) are largely unregulated in terms of emissions reporting.

4.4 *Energy Assessments: Results and Analysis*

Table 6: Energy Consumption Dataset for Smart Devices extracted from 60 Residential Units (kWh/day)

Device	Average Energy Consumption (kWh/day)	Standby Power (kWh/day)
Smart Television	1.8	0.2
Smart Refrigerator	3.2	0.5
Smart Thermostat	0.7	0.05
Smart Lighting	1.1	0.15
Smart Speaker	0.3	0.08

Note. Data extracted using TP-Link Kasa Smart Plugs with Energy Monitoring. These are average daily values per device, aggregated across 60 homes for an 18-month monitoring period.

Source: Authors' Compilation (2024).

Table 7: Comparative Data Framework: Smart Consumption Vs. Conventional Consumption

Device	Smart Avg. Consumption (kWh/day)	Conventional Avg. (kWh/day)	Difference	Notes
Smart Thermostat	~1.63	~2.0	↓ 0.37	Smart thermostats optimize heating/cooling cycles
Smart Lighting	~0.64	~1.5	↓ 0.86	LEDs and motion sensors reduce unnecessary use
Smart TV	~1.28	~1.5	↓ 0.22	Smart TVs may auto-power down or go into deep standby
Smart Refrigerator	~3.54	~4.5	↓ 0.96	Newer smart models use inverter tech for efficiency
Smart Speaker	~0.13	~0.2	↓ 0.07	Slight savings, but adds standby power load

Note. Total Daily Consumption (Smart Home) ≈ 7.2 kWh; Total Daily Consumption (Conventional Home) ≈ 9.7 kWh; Estimated Daily Savings ≈ 2.5 kWh; Annual Savings per Home ≈ 912.5 kWh/year. This translates to reduced electricity bills and fewer CO_2 emissions (average grid CO_2 = 0.4–0.7 kg CO_2/kWh, depending on region).

Source: Authors' Compilation (2024).

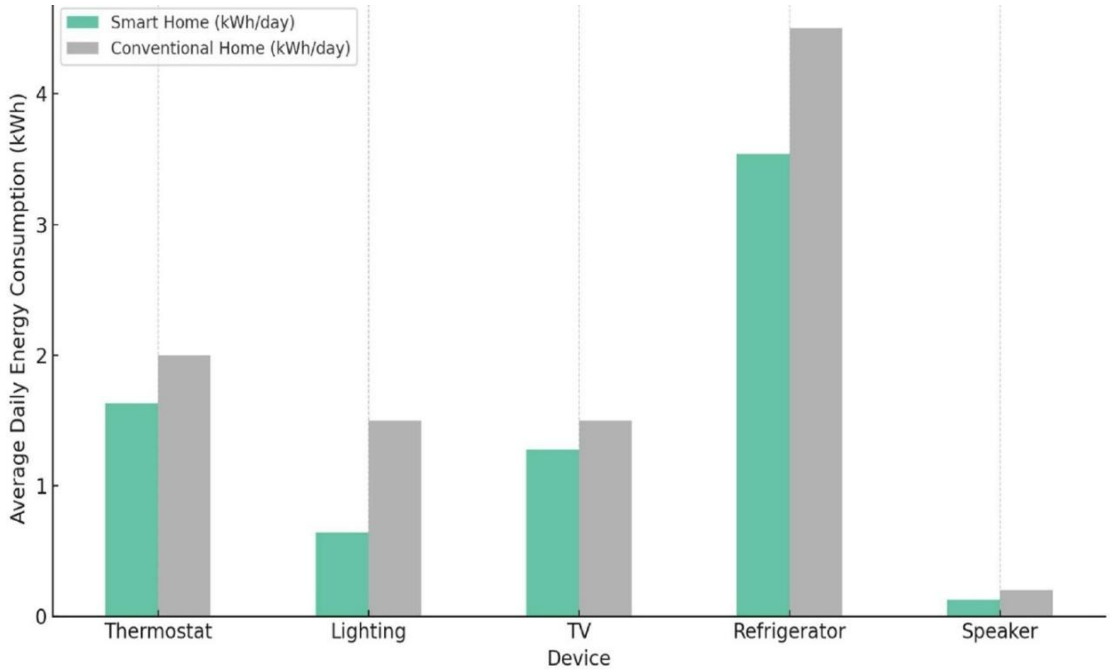

Figure 8. Comparative Bar Chart showing the daily energy consumption of Smart Vs. Conventional Home Systems for common devices

Source: Authors' Compilation (2024).

4.4.1 *Energy Assessments: Key Observations*

Table 6:

i. Smart refrigerators consistently use the most energy daily, with standby power demand exceeding 0.50 kWh/day.
ii. Smart television sets are the second-largest consumers, with relatively high standby consumption, indicating constant background processes (updates, network listening).
iii. Smart thermostats and smart speakers, while low in operational use, exhibit persistent standby energy use that accumulates significantly over time.
iv. Variations across homes can be attributed to device age, firmware settings, usage patterns, and power management habits.

Figure 8:

i. Smart lighting offers the most significant energy savings, cutting consumption by over 50%.
ii. Smart refrigerators and smart thermostats also show meaningful reductions in daily usage.
iii. Smart television sets and smart speakers provide moderate savings but still contribute to overall efficiency.
iv. Across the board, smart devices consume less energy daily than conventional ones.

4.5 *Carbon Footprint Estimation Models: Results and Analysis*

Table 8: Operational Carbon Footprint (Electricity Usage)

Energy Source	Carbon Intensity (kg CO_2/kWh)
Coal-based grid	0.8 – 1.0
Natural gas grid	0.4 – 0.6
Renewable mix	0.05 – 0.2

Note. Carbon Intensity Reference Values for diverse energy sources showing electricity usage of smart devices.

Source: (IPCC, 2025), (EPA, 2025), (GHG, 2025), and (Anders & Tomas, 2015).

Table 9: Embodied Carbon Comparison: Smart vs. Non-smart Devices

Device Category	Smart Device	Embodied Carbon (kg CO_2e/unit)	Non-Smart Equivalent	Embodied Carbon (kg CO_2e/unit)
Thermostat	Smart Thermostat	40	Thermostat	12
Lighting	Smart Lighting (LED)	18	LED Lighting	12
Television	Smart TV	320	Standard TV	260
Refrigerator	Smart Refrigerator	410	Standard Refrigerator	360
Speaker	Smart Speaker	35	Passive Speaker	10

Note. Smart home devices have higher upfront carbon costs due to microchips, sensors, batteries (high-energy manufacturing) and software dependencies (cloud servers, data centres).

Sources: (UKGBC, 2025), (Ellen MacArthur Foundation, 2021), (Matthew, Victoria, Stephen, James, & Cristina, 2019), (Bri-Mathias, et al., 2020), *and* (European Commission, 2025).

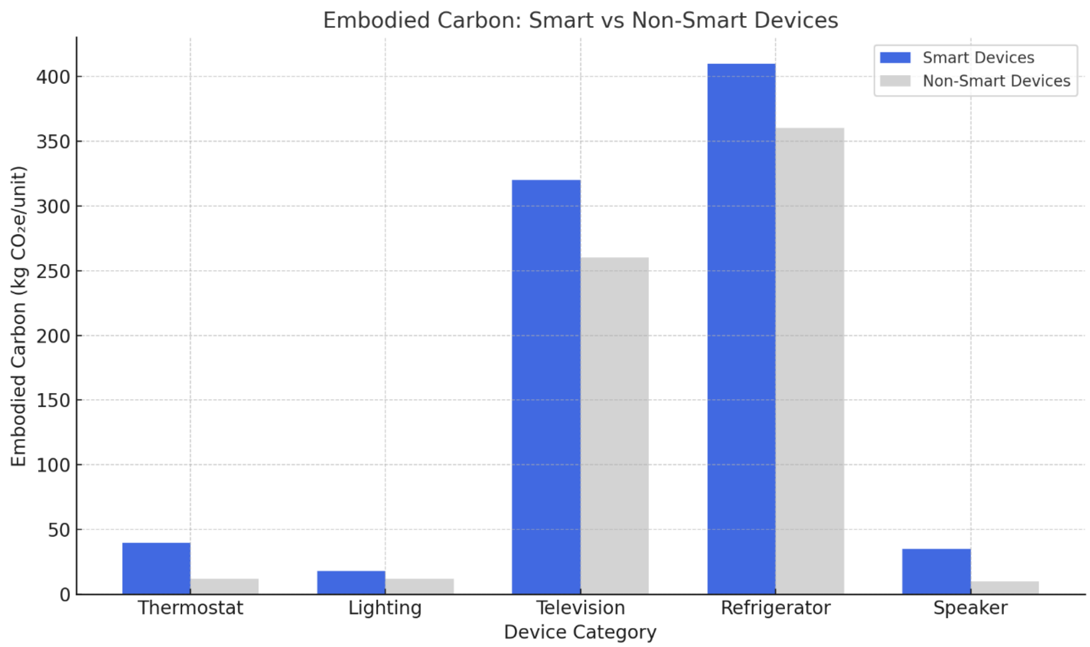

Figure 9. Embodied Carbon Footprint: Smart vs. Non-smart devices.

Note. Smart versions generally have higher embodied carbon due to additional electronic components and manufacturing complexity.

Source: Authors' Compilation (2024).

4.5.1 *Carbon Footprint Estimation Models: Key Observations*

Table 8:

i. A coal-powered grid, a smart home (2,628 kWh/year) emits ~2,100 kg CO_2/year, while a conventional home (3,540 kWh/year) emits ~2,800 kg CO_2/year (Sivaraman, Carriveau, & Ting, 2013).

Figure 9:

ii. Smart refrigerators and smart television sets have higher embodied carbon emissions.
iii. Smart lighting and smart speakers provide significant energy savings and lower lifetime emissions.
iv. Smart homes emit more annually as the manufacturing footprint of smart devices is higher due to embedded electronics.

5.0 RECOMMENDATIONS

Based on the results and analysis, these suggestions are proposed to enhance the sustainability and efficiency of smart home devices:

i. Manufacturers Association of Nigeria (MAN) should, as a matter of urgency, mandate its members to implement features that limit power draw when smart devices are inactive. This includes integrating auto-sleep or hibernation modes, using low-power processors and firmware to reduce standby energy use.

ii. Awareness campaigns must be launched to assert the fact that “smart” does not automatically mean “energy-efficient.” Clear tagging of device energy use, standby consumption, and lifecycle emissions should become best practice to help users make knowledge-based decisions.

iii. Regulatory bodies should require producers to disclose standardized LCA reports for smart devices, covering embodied carbon, operational energy use, and end-of-life environmental impact to foster openness and sustainable innovation.

iv. Architects must be urged to prioritize the use of materials that are recycled, low-carbon, and locally sourced in smart home construction. This lowers embodied energy and supports closed-loop economy principles.

v. To tackle the carbon footprint of digital infrastructure, smart home systems should utilize energy-efficient gadgets, local edge computing, regenerative energy technologies, and perform lifecycle assessments for each component adopted.

vi. In a bid towards migrating to green architecture, smart homes should be retrofitted with renewable energy sources like photovoltaic panels, small-scale wind turbines, and energy-harvesting plexuses. These are capable of offsetting carbon emissions from device usage while improving long-term energy resilience.

6.0. CONCLUSION

This study has critically examined the hidden ecological costs of smart home devices in Nigeria, with a particular focus on operational energy use and the environmental footprint of supporting cloud facilities. Primary data disclosed that despite comprehensive energy savings compared to conventional systems, smart refrigerators and smart televisions remain energy-intensive devices, with significant standby power usage even when inactive. Secondary data analysis emphasized that operational emissions make up a notable share of overall life-cycle carbon footprints, while end-of-life emissions are inadequately recorded and likely underestimated. Guided interviews further exposed lacunae in user awareness, device design practices, and regulatory systems, reinforcing the sustainability paradox where "smart" is often misconstrued as "green." Energy assessments showed that while smart home devices achieve meaningful reductions in energy consumption, saving approximately 912.5 kWh annually per unit, these gains are eroded through persistent idle loads. Overall, the results highlight that tackling the carbon footprint of smart enclaves demands a multi-pronged strategy: evolving energy-efficient designs, enhancing user education, implementing clear life-cycle assessments, and controlling digital carbon emissions. Without these initiatives, the promise of sustainability in smart living may remain impaired by disregarded environmental costs ingrained deep within our progressively digital way of life.

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