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RESEARCH

# Understanding adoption of smart energy technology and sustainability outcomes in Nigerian cities: a partial least squares structural equation modelling approach

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## Abstract

Nigeria has experienced rapid urbanisation, exacerbating existing energy problems such as unreliable power supply, energy inefficiency, and rising environmental impacts. Although the Adoption of Smart Energy Technologies (e.g., smart grids, advanced metering infrastructure, distributed renewable systems, and energy management platforms) have been widely adopted in developed contexts, their potential to address the socio-technical and infrastructural constraints of Nigerian cities has not been sufficiently explored. Most existing studies focus on technical potential or policy discourse, with limited empirical evidence on real-world performance within Nigerian urban environments. This study aims to assess the role of the Adoption of Smart Energy Technologies in addressing urban energy challenges in Nigeria. Specifically, it seeks to examine the current state of urban energy challenges in Nigerian cities; evaluate the level of Adoption of Smart Energy Technologies; assess the effectiveness of these technologies in improving energy efficiency, reliability, and sustainability; identify key barriers to their adoption and implementation; and propose policy and strategic recommendations to enhance their integration into Nigerian urban energy systems. The research uses a quantitative approach that integrates survey data from key stakeholders with statistical modelling to assess adoption levels, perceived benefits, and implementation challenges of smart energy technologies. The study contributes to the literature by providing context-specific insights into the socio-technical dynamics of smart energy deployment in developing urban environments. It further offers policy and strategic recommendations for scaling smart energy solutions, emphasising the necessity of regulatory systems that provide support, capacity building, and investment in technological infrastructure to achieve sustainable and resilient urban energy systems in Nigeria.

**Keywords** Adoption of smart energy technologies · Urban energy system · Urban energy challenges · Sustainable urban environment · Resilient urban energy systems · Nigeria

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## Introduction

Empirical studies on the Adoption of Smart Energy Technologies (AST) have demonstrated their significant contributions to improving energy efficiency, reliability, and sustainability, particularly in developed countries (Wang et al. 2026; Shafiei et al. 2025; Abid et al. 2024). Applications such as smart grids, advanced metering infrastructure, and distributed renewable energy systems have been widely implemented across regions in Europe, North America, and parts of Asia. These technologies enable real-time energy monitoring, demand-side management, and integration of renewable energy sources, leading to reduced energy losses and enhanced grid resilience (Shafiei et al. 2025; Pena-Bello et al. 2021; Morelli et al. 2022). For instance, smart grid deployments in countries such as the United States and Germany have improved load balancing and facilitated the transition toward low-carbon energy systems (International Energy Agency, 2021). Similarly, smart meters have been effective in influencing consumer behaviour and promoting energy conservation through dynamic pricing and feedback mechanisms.

Rapid urbanisation in Nigeria has significantly intensified energy demand, placing considerable pressure on already strained energy infrastructure. Major cities such as Lagos, Abuja, and Port Harcourt continue to experience persistent electricity shortages, unreliable supply, and heavy dependence on alternative energy sources such as diesel and petrol generators, which contribute to environmental degradation and increased greenhouse gas emissions (Adenikinju 2005; Oyedepo 2012; Huber et al. 2021). These urban energy challenges not only hinder economic productivity but also affect the quality of life and overall sustainability of cities. The importance of reliable, efficient, and sustainable energy systems in urban areas cannot be overstated. Access to a stable energy supply is essential for supporting industrial activities, improving living standards, and achieving broader sustainable development goals, particularly in rapidly growing urban environments (International Energy Agency, 2023). Efficient energy systems help reduce wastage, lower operational costs, and minimise environmental impacts, while sustainable energy solutions, including renewable energy integration, contribute to long-term resilience and climate change mitigation (Agboola et al. 2023; Citaristi 2022).

Globally, the emergence of AST has transformed how energy is generated, distributed, and consumed. Innovations such as smart grids, advanced metering infrastructure, distributed renewable energy systems, and digital energy management platforms enable real-time monitoring, improved efficiency, and better demand-side management (Shafiei et al. 2025; Baby et al. 2026). These technologies have been widely adopted in developed countries, demonstrating their potential to enhance energy reliability and support sustainable urban development. Despite these advancements, the applicability and performance of AST in developing countries remain underexplored. Existing studies in these contexts often focus on theoretical potential, policy discussions, or pilot projects, with limited large-scale empirical validation. In countries like Nigeria, challenges such as inadequate infrastructure, high implementation costs, weak regulatory frameworks, and low technical capacity significantly constrain adoption and scalability (Oyedepo 2012; Onuh et al. 2024). Furthermore, socio-economic factors, including limited user awareness and affordability issues, affect the accep-

tance and effective utilisation of these technologies. Therefore, a critical research gap exists in providing context-specific, empirical evidence on the effectiveness of AST in addressing urban energy challenges in developing countries, particularly Nigeria.

This study addresses this gap by adopting a quantitative approach to evaluate both the technical performance and socio-technical dynamics influencing the adoption and impact of AST in Nigerian urban environments. However, existing studies on AST have largely focused on their technical capabilities and applications in developed contexts, with limited empirical evidence on their effectiveness within the socio-economic, infrastructural, and regulatory realities of Nigerian cities. There is a notable gap in context-specific research examining the opportunities and constraints associated with AST to address urban energy challenges in Nigeria. This study aims to assess the role of AST in addressing urban energy challenges in Nigeria. Specifically, the objectives are to:

i. Evaluate the level of adoption and application of Adoption of Smart Energy Technologies (AST).
ii. Assess the perceived benefits of these AST in improving energy efficiency, reliability, and sustainability.
iii. Identify key barriers to the Adoption of Smart Energy Technologies (AST).
iv. Examine the relationships between the Adoption of Smart Energy Technologies (AST) and Sustainability Outcomes (SO).
v. Propose policy and strategic recommendations to enhance the Adoption of Smart Energy Technologies (AST) in Nigerian urban energy systems.

This study is significant as it contributes to the growing discourse on urban energy sustainability by providing context-specific insights into the role of AST in Nigerian cities. From a policy perspective, the findings offer evidence-based guidance for urban energy planning, supporting the development of policies that integrate digital energy systems into national and municipal infrastructure strategies. This is particularly important for mid-sized and rapidly growing cities where energy demand is increasing faster than infrastructure capacity. In terms of digital transformation, the study highlights how technologies such as smart grids, smart meters, and EMS can support the shift toward data-driven, efficient, and low-carbon urban systems.

From a sustainable planning perspective, the study contributes to understanding how energy efficiency, renewable integration, and demand-side management can be embedded into urban development frameworks. It also demonstrates how sustainability goals can be operationalised within the realities of developing urban contexts such as Nigeria. Practically, the study is highly relevant for urban planners, policymakers, and technology developers. Urban planners can use the findings to design more resilient, energy-responsive cities, while policymakers can leverage the evidence to strengthen regulatory frameworks, incentivise adoption, and address infrastructural gaps. Technology developers can also benefit by better understanding local constraints such as affordability, infrastructure limitations, and user acceptance, enabling them to design more context-appropriate and scalable solutions.

The structure of the paper is organised as follows. The second section presents a comprehensive review of relevant literature on AST, urban energy challenges, and

sustainability transitions, identifying key gaps in existing research. The third section outlines the research methodology, including the study design, data collection methods, sampling strategy, and analytical techniques employed in the study. The fourth section presents the results of the empirical analysis, focusing on the performance, adoption, and effectiveness of AST in Nigerian urban contexts. The fifth section provides a detailed discussion of the findings in relation to existing literature and theoretical frameworks, highlighting implications for policy and practice. Finally, the sixth section concludes the study by summarising key findings, outlining policy recommendations, and suggesting areas for future research.

## Literature review

### Urban energy challenges in Nigeria

Nigeria has persistent infrastructure, access and reliability issues with urban energy systems. Although Nigeria is one of the largest economies in Africa and is considered one of the regional manufacturing hubs (Onuh et al. 2024; International Energy Agency, 2021), it still faces wide-ranging electricity supply shortages, with available grid supply far below total demand. Most urban houses and businesses use diesel and gas generators for self-generation due to recurrent electricity disruption and poor grid performance (Adenikinju 2005; Oyedepo 2012). This reliance reflects systemic issues such as ageing infrastructure, insufficient generation capacity, transmission bottlenecks, and high technical and non-technical losses across the power sector.

Energy access also remains uneven, particularly in rapidly expanding urban areas where population growth outpaces infrastructure development. Informal settlements and peri-urban communities often experience limited or no access to reliable electricity, further exacerbating urban inequality (Huber et al. 2021; Xiao et al. 2022). Additionally, inefficiencies in distribution networks and weak regulatory frameworks contribute to poor service delivery and reduced investor confidence in the sector (Ololube 2025; Pena-Bello et al. 2021). The environmental implications of these energy challenges are significant. The widespread use of fossil fuel-based generators contributes to increased greenhouse gas emissions, air pollution, and urban heat effects, undermining efforts toward climate change mitigation (Agboola and Baby 2026). These environmental impacts are particularly severe in densely populated cities, where emissions from generators and inefficient energy use contribute to declining air quality and public health risks.

From a socio-economic perspective, unreliable energy supply imposes substantial costs on households and businesses. Firms often incur high operational expenses due to reliance on backup power systems, which reduces productivity and competitiveness (Adenikinju 2005; Saeed et al. 2020). For households, energy insecurity affects quality of life, limiting access to essential services such as healthcare, education, and digital connectivity. Moreover, energy poverty in urban areas reinforces social inequalities and constrains sustainable urban development (Citaristi 2022). Overall, urban energy challenges in Nigeria are deeply interconnected, involving technical, environmental, and socio-economic dimensions. Addressing these issues requires

integrated and innovative approaches that not only improve infrastructure and reliability but also promote sustainability and inclusivity in urban energy systems.

### Adoption of Smart energy Technologies and associated barriers

AST have emerged as critical enablers of efficient, reliable, and sustainable energy systems, particularly in urban environments. Central to these innovations are smart grids, which integrate advanced communication and information technologies into traditional electricity networks to enable real-time monitoring, two-way communication, and improved demand–supply balancing (International Energy Agency, 2021; Shafiei et al. 2025; Obuseh et al. 2025). Smart grids enhance grid resilience, reduce transmission losses, and facilitate the integration of renewable energy sources, making them essential for modern energy transitions. Complementing smart grids are smart meters, which provide detailed, real-time data on energy consumption, allowing both consumers and utility providers to make informed decisions regarding energy use (Fayiah and Kallon 2025; Marinakis et al. 2020; Zhou et al. 2016). These devices promote energy efficiency by enabling demand-side management, dynamic pricing, and improved billing accuracy. In developing urban contexts, smart meters can also reduce energy theft and enhance revenue collection.

Another key component of smart energy systems is the deployment of distributed renewable energy systems and digital energy monitoring systems. These decentralised systems reduce reliance on centralised power generation and improve energy access, particularly in areas with unreliable grid infrastructure (Xiao et al. 2022; Zhou et al. 2016; Saeed et al. 2020). Distributed energy resources also contribute to reducing carbon emissions and enhancing environmental sustainability. In addition, Energy Management Systems (EMS) and digital platforms play a vital role in optimising energy consumption across residential, commercial, and industrial sectors. These systems use data analytics to monitor, control, and optimise energy usage in real time, thereby improving operational efficiency and reducing energy waste (Ali et al. 2024; Mocanu et al. 2025). Digital platforms further support integration across energy systems by enabling predictive maintenance, load forecasting, and enhanced user engagement. Overall, ASTs represent a transformative approach to addressing contemporary energy challenges. By combining advanced infrastructure, digital tools, and renewable energy integration, these technologies support the transition toward more resilient, efficient, and sustainable urban energy systems.

The AST in African cities is increasingly recognised as a critical pathway toward achieving sustainable, efficient, and resilient urban energy systems (International Energy Agency, 2021; Xiao et al. 2022). However, their implementation remains uneven due to a range of interconnected challenges. High capital investment requirements, infrastructural constraints, and limited technical capacity continue to hinder large-scale deployment (Pena-Bello et al. 2021; Edomah 2021). These barriers extend beyond technical issues to include institutional, financial, and socio-cultural dimensions, reflecting the complexities of developing urban contexts. In particular, gaps in skilled human resources, inadequate digital and data infrastructure, weak governance frameworks, and low public awareness further constrain effective adop-

tion and utilisation. Table 1 summarises the key barriers, outlining their underlying issues and implications for smart energy transitions in Africa.

**Table 1** Key barriers to the adoption of smart energy technologies in African cities

| Barrier Category | Descriptions | Key Issues | Implications for Adoption | References |
|---|---|---|---|---|
| 1.Limited Technical Expertise | Limited availability of skilled professionals to design, implement, and maintain smart energy systems such as smart grids, EMS, and IoT-based platforms | - Shortage of trained engineers and data analysts<br>- Limited expertise in AI, data analytics, and system integration<br>- Inadequate training programs and knowledge transfer mechanisms | Poor system design, operational inefficiencies, and reliance on foreign expertise, increasing costs and reducing long-term sustainability | Pena-Bello et al. (2021); International Energy Agency (2021); Obuseh, et al. (2025). |
| 2.Inadequate Infrastructure | Weak infrastructure is required to support real-time data collection, processing, and communication across energy systems | - Limited broadband and communication networks<br>- Poor data management systems<br>- Lack of interoperability between platforms<br>- Cybersecurity vulnerabilities | Restricts real-time monitoring and optimisation, reduces system reliability, and limits the effectiveness of smart technologies such as smart meters and EMS | Shafiei et al. (2025); Pena-Bello et al. (2021); Edomah (2021). |
| 3.High Implementation Cost | High upfront costs and limited access to funding for smart energy infrastructure deployment and maintenance | - High capital investment for smart grids and renewable systems<br>- Limited government funding and private sector investment<br>- Dependence on international financing<br>- Uncertain return on investment (ROI) | Slows down implementation, limits scalability, and creates uneven adoption across regions, particularly in low-income urban areas | World Bank (2022); International Energy Agency (2021). Morelli et al. (2022). |
| 4.Weak Policy and Regulatory Framework | Weak policy frameworks and a lack of supportive policies for smart energy integration | - Inconsistent or unclear regulations<br>- Lack of incentives for renewable adoption<br>- Bureaucratic delays in project approvals. | Reduces investor confidence and delays the implementation of smart energy projects | International Energy Agency (2021); World Bank (2022); Giwah et al. (2020) |
| 5.Institutional Fragmentation | Limited public awareness and acceptance of AST. | - Resistance to smart meters due to trust issues<br>- Low awareness of energy-saving benefits<br>- Cultural and behavioural resistance to new technologies | Hinders user adoption and reduces the effectiveness of demand-side management strategies | Saeed et al. (2020), World Bank (2022); Morelli et al. (2022). |

## Adoption of smart energy technologies (AST) in African urban contexts

AST have become central to advancing efficient, reliable, and sustainable energy systems, particularly within rapidly urbanising regions. Across African cities, the adoption of these technologies reflects both the opportunities and constraints associated with transitioning from traditional energy systems to more resilient and low-carbon alternatives. Core components of smart energy systems, including smart grids, smart meters, distributed renewable energy systems, and energy management platforms, are increasingly being implemented to address persistent challenges such as energy inefficiency, unreliable supply, and limited access (International Energy Agency, 2021; Xiao et al. 2022; Morelli et al. 2022).

Smart grids represent a foundational element of this transition by integrating advanced communication and information technologies into conventional electricity networks. These systems enable real-time monitoring, bidirectional communication, and improved demand–supply balancing, thereby enhancing grid resilience and reducing transmission losses (Shafiei et al. 2025; International Energy Agency, 2021). In countries such as South Africa and Egypt, smart grid initiatives have been deployed to modernise ageing infrastructure and facilitate the integration of renewable energy sources. However, despite these advancements, challenges remain, including high capital costs, policy inconsistencies, and unequal access to upgraded infrastructure, which often exacerbate existing socio-economic disparities (International Energy Agency, 2021; Pena-Bello et al. 2021).

Complementing smart grids, smart metering technologies have been widely introduced in countries such as Nigeria and Ghana to improve energy management and billing efficiency. Smart meters provide detailed, real-time data on electricity consumption, enabling demand-side management and supporting dynamic pricing mechanisms (Osunmuyiwa et al. 2018; Morelli et al. 2022). In many African urban contexts, these technologies also play a critical role in reducing non-technical losses, including electricity theft, and improving revenue collection for utility providers (Saeed et al. 2020). Nevertheless, their implementation has not been without controversy. Issues such as consumer resistance, perceived billing inaccuracies, and limited public awareness have hindered widespread acceptance and trust in these systems.

Distributed renewable energy systems, particularly smart meters and other digital energy monitoring systems, have gained significant traction in countries like Kenya, Rwanda, and Tanzania. These decentralised solutions are especially valuable in urban and peri-urban areas where grid infrastructure is either unreliable or insufficient. By reducing dependence on centralised power generation, distributed energy resources contribute to improved energy access, enhanced system resilience, and reduced greenhouse gas emissions (Huber et al. 2021; Xiao et al. 2022; Saeed et al. 2020). Morocco's large-scale investment in digital monitoring of energy systems further illustrates the potential of renewable integration within national energy strategies. However, the intermittent nature of renewable energy sources, combined with limited storage capacity and grid integration challenges, continues to constrain their effectiveness (Xiao et al. 2022; Pena-Bello et al. 2021).

In addition to physical infrastructure, digital technologies such as EMS and integrated platforms are playing an increasingly important role in optimising energy con-

sumption. These systems utilise data analytics, automation, and artificial intelligence to monitor and control energy usage across residential, commercial, and industrial sectors (Pena-Bello et al. 2021). In countries such as Ghana and Senegal, EMS applications have demonstrated potential in improving operational efficiency, enabling predictive maintenance, and supporting load forecasting. Overall, the implementation of AST across African cities reflects a dynamic but uneven transition toward sustainable urban energy systems. While these technologies offer substantial benefits in terms of efficiency, resilience, and environmental performance, their effectiveness is shaped by contextual factors such as governance structures, economic capacity, regulatory frameworks, and social acceptance (International Energy Agency, 2021; Xiao et al. 2022). In conclusion, ASTs present a transformative pathway for addressing urban energy challenges in Africa. However, their successful deployment requires not only technological advancement but also institutional strengthening, inclusive policy design, and context-sensitive implementation strategies to ensure equitable and sustainable outcomes (International Energy Agency, 2021; Pena-Bello et al. 2021).

Table 2 synthesises key smart energy concepts, including smart grids, smart meters, distributed renewable energy systems, EMS, and digital platforms, within the context of African urban environments. These technologies collectively represent the foundation of modern energy transitions aimed at improving efficiency, reliability, and sustainability in rapidly urbanising cities. However, their implementation across African contexts remains uneven due to a range of persistent constraints. The identified criticisms reflect common challenges in developing cities, particularly high capital costs, inadequate infrastructure, limited technical capacity, weak governance structures, and low levels of public awareness. Together, these barriers highlight the gap between technological potential and real-world application, underscoring the need for integrated policy, institutional strengthening, and capacity development to support effective adoption.

## Theoretical framework and variable measurement

### Theoretical framework

This study is grounded in Socio-Technical Systems (STS) Theory and Technology Adoption and Diffusion Theory, which together provide an integrated framework for understanding the complex relationship between AST and the socio-institutional contexts in which they are implemented in Nigerian urban environments (Fig. 1). Socio-Technical Systems (STS) theory offers a holistic perspective that explains how technological systems are deeply interconnected with social, institutional, and infrastructural structures (Geels 2002, 2004; Mariscal et al. 2026). It argues that technological innovations cannot be effectively understood in isolation from the social systems in which they operate, as both evolve simultaneously and influence one another (Pena-Bello et al. 2021). In the context of urban energy systems, technologies such as smart grids, smart meters, and EMS are shaped not only by technical capabilities but also by governance structures, user behaviour, regulatory frameworks,

**Table 2** Comparative study of adoption of smart energy technologies (AST) across African cities

| Region / Country | Main Characteristics / Objectives | Criticisms / Weaknesses | References |
|---|---|---|---|
| Nigeria | Deployment of smart meters and grid modernisation to improve billing accuracy, reduce energy theft, and enhance demand-side management | High implementation costs, limited infrastructure, and resistance from consumers due to billing concerns | International Renewable Energy Agency (IRENA) (2022); Saeed et al. (2020). |
| South Africa | Advanced smart grid initiatives integrating renewable energy and improving grid reliability | Inequality in access, high cost of infrastructure upgrades, and policy inconsistencies | Shafiei et al. (2025); World Bank (2022) |
| Kenya | Adoption of distributed renewable energy (mini-grids) to improve energy access in urban and peri-urban areas | Intermittency of renewable sources and limited grid integration capacity | World Bank (2022) |
| Ghana | Integration of smart meters and EMS to enhance energy efficiency and monitoring | Data management challenges and limited technical capacity | Pena-Bello et al. (2021). Saeed et al. (2020) |
| Egypt | Large-scale smart grid development and renewable energy integration for urban sustainability | Centralised system dominance and slow adaptation to decentralised models | International Renewable Energy Agency (IRENA) (2022) |
| Rwanda | Use of digital platforms and off-grid renewable systems to expand energy access and improve efficiency | Limited financial resources and dependence on external funding | World Bank (2022) |
| Morocco | Strong focus on renewable energy integration supported by smart grid technologies | High initial investment costs and technological dependency | International Renewable Energy Agency (IRENA) (2022); Shafiei et al. (2025) |
| Tanzania | Expansion of distributed energy systems and smart metering in urban areas | Weak regulatory frameworks and infrastructure limitations | World Bank (2022) |
| Ethiopia | Development of hydropower-integrated smart systems and emerging digital energy platforms | Limited technological advancement and grid instability issues | International Renewable Energy Agency (IRENA) (2022) |
| Senegal | Implementation of smart energy solutions to improve urban energy efficiency and reduce losses | Technical skill gaps and limited scalability | Pena-Bello et al. (2021) |

and infrastructural readiness. In Nigeria, the application of STS theory is particularly relevant due to persistent mismatches between technological advancement and institutional capacity. Challenges such as inadequate infrastructure, limited technical expertise, weak policy enforcement, and socio-economic constraints demonstrate that technological efficiency alone is insufficient without corresponding social and institutional alignment. Therefore, STS theory is used in this study to explain how effective deployment of AST requires the integration of technological innovation with stakeholder engagement, institutional strengthening, and supportive governance systems (Geels 2004; Zhou et al. 2016; Mariscal et al. 2026).

Complementing this, Technology Adoption and Diffusion Theory, particularly Rogers' Diffusion of Innovations framework, provides insight into how AST are

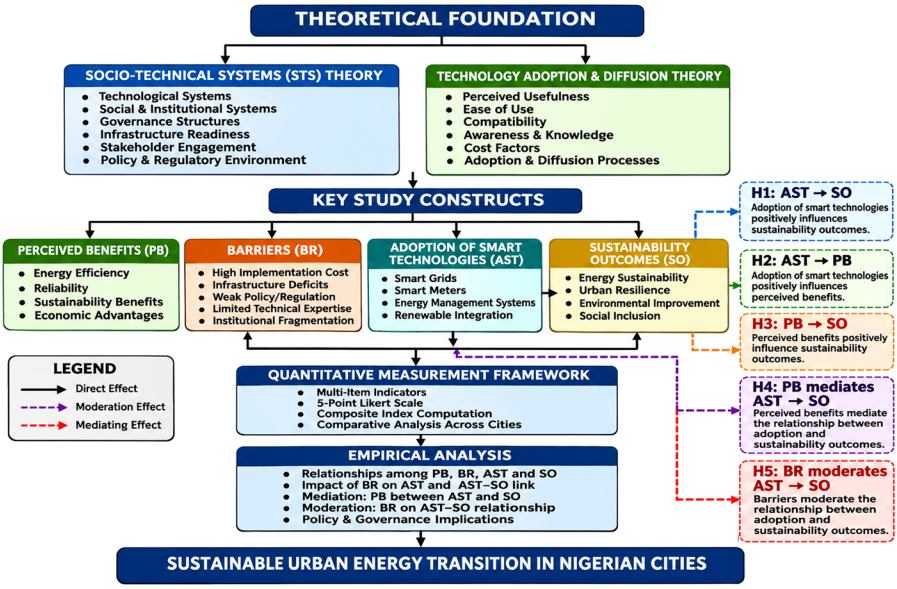


**Fig. 1** Study's theoretical framework

introduced, accepted, and scaled within urban systems (Rogers 2003; Barrane et al. 2018; Zhou et al. 2016). According to the hypothesis, elements including perceived utility, usability, compliance with current systems, cost, and awareness all have an impact on adoption (Agorsor et al. 2026). In the Nigerian context, while AST offer significant benefits such as improved energy efficiency, reliability, and sustainability, their adoption is constrained by high implementation costs, limited awareness, infrastructural deficits, and regulatory challenges. The theory also highlights the influence of key stakeholders, including government agencies, private sector actors, and end-users, in shaping adoption patterns and diffusion rates across different urban areas. As such, it provides a useful lens for explaining variations in adoption levels and identifying strategies such as policy incentives, capacity building, and awareness campaigns that can enhance uptake (Barrane et al. 2018; Rogers 2003; Nyström and Gavuzzi Roos 2024).

Together, these theoretical frameworks provide a comprehensive foundation for this study. While STS theory captures the broader interaction between technological and socio-institutional systems, Diffusion of Innovations theory explains the behavioural and adoption dynamics influencing smart energy technology uptake. Their integration enables a more complete understanding of both structural and behavioural factors shaping smart energy adoption in Nigerian cities, thereby offering valuable insights into pathways for achieving sustainable urban energy transitions.

## Variable measurements for SmartPLS

This study operationalises its key constructs, Perceived Benefits (PB), Barriers (BR), Adoption of Smart Technology (AST), and Sustainability Outcomes (SO), using a

structured quantitative measurement framework. Drawing on the comparative patterns presented in Supplementary Table S1, each variable was measured through multiple indicators and standardised using a five-point Likert scale to ensure consistency, reliability, and comparability across the selected case study cities. All perceptual variables were measured on a 5-point Likert scale ranging from 1 = Very Low / Strongly Disagree to 5 = Very High / Strongly Agree. This method is frequently used in sustainability studies and technological acceptance to quantify subjective assessments (Barrane et al. 2018; Nyström and Gavuzzi Roos 2024). Composite scores for each construct were computed by averaging the responses across its respective indicators. All constructs were operationalised using multi-item indicators adapted from established literature in technology adoption, innovation diffusion, and smart city research. The use of a standardised 5-point Likert scale ensures consistency and comparability across variables. Composite indices were computed by averaging the indicator scores for each construct, enabling subsequent statistical analysis of relationships between perceived benefits, barriers, adoption levels, and sustainability outcomes.

To facilitate systematic comparison across the five case-study cities, Infrastructure Readiness (IR), Policy Support (PS), Adoption Level (AL), and Relative Performance (RP) were operationalised using the quantitative survey as presented in Supplementary Table S2. These dimensions were selected because they represent key enabling conditions, implementation characteristics, and comparative outcomes of smart energy technology adoption. The indicators were derived from the corresponding survey measures relating to infrastructure availability and reliability, regulatory and institutional support, deployment of AST, and observed sustainability-related performance.

A standardised five-point coding scale was applied to the quantitative results to enable consistent comparison across Lagos, Abuja, Port Harcourt, Kano, and Ibadan. Scores were coded as 1 = Low, 2 = Low–moderate, 3 = Moderate, 4 = High, and 5 = Very high/Highest. Infrastructure Readiness captured the extent to which cities possess the physical and digital infrastructure required to support AST, including grid reliability, digital connectivity, and technological infrastructure. Policy Support represented the strength of regulatory frameworks, institutional support, incentives, policy implementation, and inter-organisational coordination. Adoption Level reflected the extent of deployment and utilisation of AST, including smart metering, renewable-energy systems, digital monitoring, and related intelligent energy systems.

Relative Performance (RP) was used as a comparative synthesis indicator rather than as an independently measured qualitative variable. It reflects the relative pattern of sustainability-related outcomes associated with the combined levels of infrastructure readiness, policy support, and technology adoption. The resulting city-level classifications were therefore generated from the quantitative evidence and subsequently coded into the five-point comparative scale. The comparative synthesis was undertaken to identify patterns and differences in smart-energy readiness and adoption across the selected urban contexts. Importantly, the resulting classifications are not to be seen as new empirical measurements. Rather, they provide a transparent summary of patterns emerging from the quantitative dataset. This approach was adopted to ensure methodological consistency.

## Methodology

This study adopts a quantitative research approach to provide a comprehensive assessment of the role of AST in addressing urban energy challenges in Nigeria. A quantitative method is appropriate as the validity of findings supports a more holistic understanding of complex socio-technical systems (Creswell and Plano Clark 2018). It is particularly suitable for energy-related studies where both technical performance and human, institutional, and behavioural factors interact in shaping outcomes. The quantitative component of the study focuses on gathering structured data from relevant stakeholders in the Nigerian urban energy sector, including energy professionals, policymakers, utility operators, and end-users. This approach allows for the measurement of adoption levels, perceived effectiveness, and barriers associated with AST (Oyewunmi and Ehanmo 2021; Zhou et al. 2016; Alabdali et al. 2023). Statistical techniques are used to analyse relationships between variables such as technology adoption, energy efficiency, reliability, and sustainability outcomes, providing empirical evidence on the performance of smart energy systems. The research uses a cross-sectional stakeholder survey; modelled paths are interpreted as associations rather than causal effects.

### Study area and justifications

The research focuses on selected Nigerian urban centres, specifically Lagos, Abuja, Port Harcourt, Ibadan and Kano (Fig. 2), which represent some of the most dynamic and rapidly urbanising cities in West Africa. These cities were selected due to their high population density, accelerating economic activities, and increasing pressure on




**Fig. 2** Map of the study cities in Nigeria.Source: Gayawan et al. (2014).

existing energy infrastructure. Collectively, they provide a representative picture of Nigeria's urban energy landscape, particularly in relation to energy demand growth, infrastructure deficits, and emerging interest in AST (Oyedepo 2012; Chukwuemeka et al. 2023). Lagos, the commercial hub of Nigeria and one of the largest cities in Africa, is characterised by intense industrial, commercial, and residential energy consumption. Lagos city experiences persistent electricity supply shortages, leading to widespread reliance on private generators and off-grid energy solutions. This dependence increases carbon emissions, raises energy costs, and highlights inefficiencies in the national grid system (Oyedepo 2012; Pena-Bello et al. 2021). Lagos, therefore, presents a critical case for examining how AST such as smart meters, distributed generation systems, and demand-side management tools can improve energy reliability and efficiency.

Abuja, the capital city, provides a contrasting but equally important context. As a planned administrative city, Abuja benefits from relatively better infrastructure compared to many other urban centres in Nigeria. However, it still faces significant challenges related to grid instability, increasing urban population, and rising energy consumption in residential and governmental facilities (Marinakis et al. 2020). The presence of government institutions and ongoing urban expansion makes Abuja particularly relevant for assessing policy-driven adoption of smart energy systems and sustainable urban energy planning strategies (Oyedepo 2012; Pena-Bello et al. 2021). Port Harcourt is an important industrial and oil-producing city in the Niger Delta region and presents another distinct energy context. Despite its contribution to Nigeria's energy sector, the city suffers from frequent power supply disruptions, environmental pollution, and infrastructure degradation. Energy demand in Port Harcourt is strongly influenced by industrial operations, particularly in the oil and gas sector, alongside growing residential needs (Ndukwu et al. 2021; Huber et al. 2021). These conditions make the city an important case for exploring decentralised energy systems, renewable integration, and smart grid applications aimed at improving energy efficiency and environmental sustainability. Kano provides representation of Northern Nigeria and its distinctive commercial and infrastructural conditions, while Ibadan represents a major Southwestern inland city characterised by substantial population growth and expanding urban development.

Across these five cities, rapid urbanisation continues to exert pressure on already overstretched energy systems. Nigeria's national grid remains limited in capacity and reliability, resulting in a significant "energy access gap" that urban households and businesses often bridge through alternative energy sources. According to Oyedepo (2012), Nigeria's energy challenges are deeply rooted in infrastructural deficits, inefficient energy management, and overdependence on fossil-fuel-based backup systems, all of which justify the need for innovative technological interventions. By selecting Lagos, Abuja, Port Harcourt, Ibadan and Kano, this study captures a broad spectrum of socio-economic, infrastructural, and energy-use conditions within Nigeria's urban environment. This comparative urban framework provides a robust basis for evaluating the adoption, performance, and potential of AST in addressing the country's persistent urban energy challenges.

## Data collection methods

Data were collected using a structured questionnaire survey to ensure the systematic collection of reliable and quantifiable data on smart energy technology adoption in Nigerian urban centres. Before the main survey, the questionnaire was pre-tested with a small group of respondents to assess the clarity, relevance, and reliability of the measurement items. Following the pilot study and necessary revisions, the final questionnaire was administered to the target respondents. Respondent recruitment was undertaken using a purposive sampling approach, whereby households, energy providers, policymakers, and other relevant stakeholders with adequate knowledge and experience of AST were identified and invited to participate in the study. Participation was entirely voluntary, and respondents were informed of the academic purpose of the research, anonymity, confidentiality, and their right to withdraw at any stage without consequence. Questionnaire administration was conducted through a combination of face-to-face distribution and supervised self-completion to maximise response rates and minimise missing data. Trained research assistants were available to clarify questions where necessary while avoiding any influence on respondents' answers. The use of a structured survey instrument enabled the collection of standardised data suitable for subsequent descriptive, reliability, validity, and Structural Equation Modelling (SEM) analyses, consistent with recommendations for quantitative research involving complex socio-technical systems (Creswell and Plano Clark 2018; Hair et al. 2022).

The survey instrument (Supplementary Table S3) was designed to capture quantitative and perception-based information on adoption levels, user satisfaction, perceived benefits, operational challenges, and behavioural responses to AST. The structured format ensured comparability across respondents and facilitated statistical analysis of key variables influencing adoption and usage patterns. In addition, Likert-scale items, as supported by Likert (1932), were used to assess attitudes toward reliability, cost efficiency, and system usability, enabling a more nuanced understanding of user experiences within different urban contexts. Selected case studies of smart energy technology implementations were analysed to provide contextual and empirical insights into real-world applications.

## Sampling strategy

Given the absence of precise data regarding the total population of smart energy technology users and stakeholders across the selected Nigerian cities, the sample size for this study was determined using the Cochran formula for an unknown population (Higgins et al. 2011):

$$n0 = \frac{P\,(1-P)\;X\;Z^2}{\mathrm{e}^2} \tag{1}$$

where n0 represents the minimum sample size, Z is the standard normal deviate corresponding to the selected confidence level, P is the estimated population proportion, and e is the acceptable margin of error. Thus, Z = 1.96 at the 95% confidence level,

$P = 0.50$ represents the estimated population proportion, and $e = 0.05$ denotes the acceptable margin of error; the Cochran formula yields an initial minimum of approximately 384.16 (rounded up to 385); the final usable sample was 416 respondents. A value of $P = 0.50$ was adopted because no reliable prior estimate of the proportion of Nigerian stakeholders meeting the study's eligibility criteria or demonstrating a particular position toward smart energy technology adoption was available. The value of 0.50 represents the maximum-variability assumption, because it produces the largest required sample size when the population proportion is unknown. Consequently, its use provides a conservative basis for determining the initial target sample size and reduces the risk of underestimating the number of respondents required for the study. This assumption is methodological rather than an assertion that exactly 50% of Nigerian stakeholders adopt or support AST.

To enhance the statistical power of the Structural Equation Modelling (SEM) analysis and to accommodate potential non-responses and incomplete questionnaires, a total of 450 questionnaires were administered. Of these, 429 questionnaires were returned, representing a 95.3% response rate. Following data screening for missing values, inconsistent responses, and outliers, 13 questionnaires were excluded. Consequently, 416 valid questionnaires were retained for the final analysis, yielding a usable response rate of 92.4% based on the distributed questionnaires (or 97.0% of the returned questionnaires). This final sample exceeded the Cochran minimum of 385, although adequate power for individual PLS-SEM paths should be evaluated separately.

A city- and stakeholder-stratified recruitment framework was adopted to ensure balanced representation across the five selected case-study cities: Lagos, Abuja, Port Harcourt, Kano, and Ibadan. Stratified sampling is widely recommended in social science research where populations are heterogeneous, as it enables more precise representation of sub-groups within the population (Bryman and Buchanan 2018; Creswell and Plano Clark 2018). The population was divided into distinct strata, including residential users, industrial and commercial energy consumers, energy utility providers, regulatory agencies, and relevant policymakers. Respondents were recruited purposively or by convenience within the stakeholder groups; proportional random selection cannot be established from the reported recruitment procedure. This approach broadens the range of stakeholder perspectives but does not establish population representativeness (Bryman and Buchanan 2018; Hirzel and Guisan 2002). The final distribution comprised Lagos ($n = 104$), Abuja ($n = 84$), Port Harcourt ($n = 68$), Kano ($n = 80$), and Ibadan ($n = 80$), totalling 416 respondents to ensure adequate geographical and socio-economic representation across Nigeria's major urban centres. This sampling approach supported descriptive comparisons among sampled stakeholders regarding smart energy adoption and sustainability outcomes.

Within each stratum, respondents were recruited using a combination of purposive and convenience sampling, according to their relevance to the study objectives and accessibility. Purposive sampling was used to identify key informants, including institutional actors, policymakers, energy professionals, and technical experts with relevant knowledge of energy governance, infrastructure, and AST (Creswell and Plano Clark 2018). Convenience sampling was used primarily to recruit residential

and commercial users who were readily accessible and willing to participate within the available time and resource constraints (Hirzel and Guisan 2002).

The combination of these approaches enabled the study to capture both expert perspectives and user-level experiences of smart energy technology adoption. However, the researchers recognise that non-probability recruitment may introduce selection bias, particularly where more accessible, knowledgeable, or technology-aware respondents are more likely to participate. Accordingly, the findings are interpreted as representing the perceptions of the sampled stakeholders rather than statistically representative estimates of the wider Nigerian population. This limitation is explicitly acknowledged, and future studies are recommended to employ probability-based or stratified sampling where an appropriate sampling frame is available.

### Data presentation, model analysis, and hypothesis testing (SEM approach)

Survey data were analysed using statistical techniques to identify patterns, relationships, and determinants influencing the adoption and performance of AST. Descriptive statistics (such as frequencies, percentages, means, and standard deviations) were first used to summarise respondent characteristics and general trends. This was followed by using Partial Least Squares Structural Equation Modelling (PLS-SEM) implemented in SmartPLS to examine relationships between variables such as awareness levels, infrastructure quality, policy support, and technology adoption rates (Purwanto and Sudargini 2021). The analysis examines the relationships between Adoption of Smart Technologies (AST), Perceived Benefits (PB), Barriers (BR), and Sustainability Outcomes (SO). These techniques enabled the identification of statistically significant predictors of smart energy adoption and usage efficiency. PLS-SEM is particularly suitable for this study due to its ability to handle complex models with latent constructs, small-to-medium sample sizes, and non-normal data distributions (Hair et al. 2022). The analysis follows a two-step approach: (i) Assessment of the measurement model (validity and reliability of constructs); (ii) Evaluation of the structural model (hypothesis testing and path relationships).

### Model specification and hypotheses development

The model used in this research comprises both dependent and independent latent variables. Figure 3 shows the integrated conceptual and hypothesised structural model of AST and SO. Each is quantified by several indicators. The independent constructs include:

- Adoption of Smart Technologies (AST), measured by indicators AST1, AST2, and AST3, capturing smart grıds/meters, renewable integration. Digital monitoring system.
- Perceived Benefits (PB), measured by PB1, PB2, PB3, PB4 & PB5, reflecting energy efficiency, reliability, cost reduction, and environmental sustainability monitoring /control.
- Barriers (BR), measured by BR1, BR2, BR3, BR4 & BR5, represent constraints such as implementation cost, policy and regulatory framework, infrastructure,

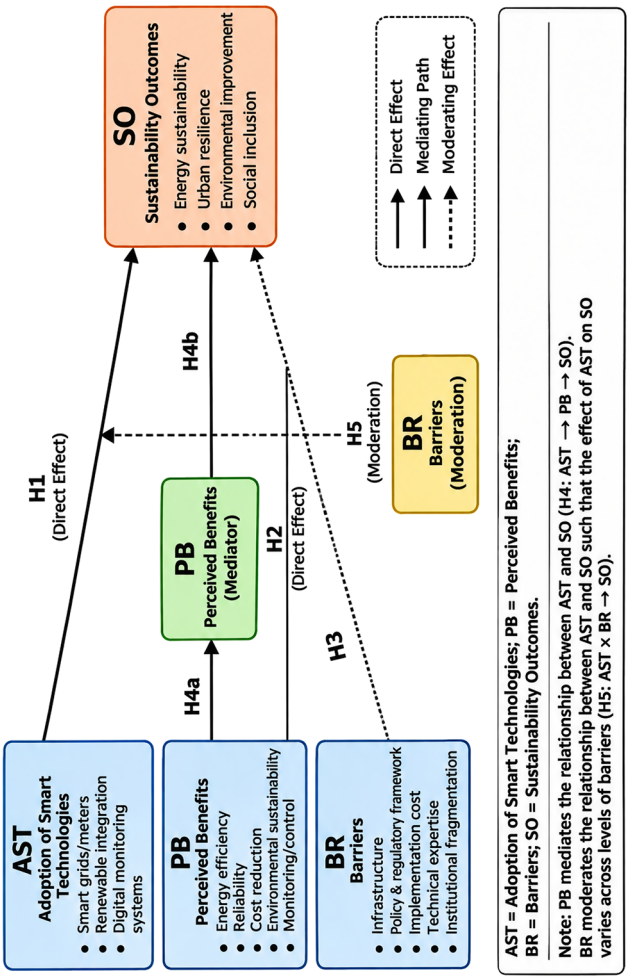


**Fig. 3** Integrated conceptual and hypothesised structural model of AST and SO.Source: Author's conceptualisation

technical expertise and institutional fragmentation.

The dependent construct is:

- Sustainability Outcomes (SO), measured by SO1, SO2, SO3, & SO4, which capture improvements in energy sustainability, urban resilience, environmental improvement, and social inclusion.

Based on the integrated conceptual and hypothesised structural model, the study specifies direct, mediating, and moderating relationships among Adoption of Smart Technologies (AST), Perceived Benefits (PB), Barriers (BR), and Sustainability Outcomes (SO). The framework recognises that the influence of smart technology adoption on sustainability outcomes may operate both directly and indirectly through perceived benefits, while the strength of this relationship may vary according to the level of adoption barriers. Accordingly, the following hypotheses are formulated:

- **$H_1$**: Adoption of Smart Technologies (AST) has a significant positive effect on Sustainability Outcomes (SO).
- **$H_2$**: Perceived Benefits (PB) have a significant positive effect on Sustainability Outcomes (SO).
- **$H_3$**: Barriers (BR) have a significant negative effect on Sustainability Outcomes (SO).
- **$H_4$**: Perceived Benefits (PB) significantly mediate the relationship between Adoption of Smart Technologies (AST) and Sustainability Outcomes (SO).
- **$H_5$**: Barriers (BR) significantly moderate the relationship between Adoption of Smart Technologies (AST) and Sustainability Outcomes (SO), such that higher levels of BR weaken the positive effect of AST on SO.

These hypotheses provide a coherent basis for testing the direct, mediating, and moderating mechanisms. Collectively, they recognise that the contribution of smart technology adoption to sustainable urban energy outcomes depends not only on the level of technological adoption but also on the benefits perceived by users and stakeholders and the institutional, infrastructural, financial, technical, and organisational barriers affecting implementation.

### Comparative case-study analysis and rating procedure

To ensure methodological transparency, consistency, and reproducibility, the comparative assessment of smart-energy technology implementation across five Nigerian cities Lagos, Abuja, Port Harcourt, Kano, and Ibadan by adopting a standardised composite indicator approach. This approach aligns with established methodological principles for constructing multidimensional indices, including systematic indicator selection, weighting, aggregation, and interpretation (Nardo et al. 2005; OECD and European Commission, Joint Research Centre 2008). The analysis utilised quantitative survey responses from 416 participants distributed across Lagos ($n=104$), Abuja ($n=84$), Port Harcourt ($n=68$), Kano ($n=80$), and Ibadan ($n=80$). The comparative

framework incorporated three principal dimensions, namely (i) Infrastructure Readiness (IR), (ii) Policy Support (PS), and (iii) Adoption Level (AL), operationalised through six (IR1–IR6), seven (PS1–PS7), and seven (AL1–AL7) questionnaire indicators, respectively, as presented in Supplementary Survey Questionnaire 4. Each indicator was assessed using a five-point Likert scale ranging from '1' (Very Low) to '5' (Very High), consistent with established quantitative approaches to measuring respondents' attitudes and perceptions (Likert 1932). For each city, indicator-level mean scores were calculated from the corresponding respondents' ratings and subsequently aggregated using arithmetic means to obtain composite scores. This procedure follows established composite indicator methodologies, which support linear aggregation when indicators are measured on comparable scales and the weighting assumptions are explicitly justified by Nardo et al. (2005) and OECD and European Commission, Joint Research Centre (2008). Relative Performance (RP) was subsequently conceptualised as an overall comparative indicator synthesising infrastructure readiness, policy support, and technology adoption, providing a consistent basis for evaluating variations in smart-energy implementation conditions across the selected cities. To calculate the City-Level Composite Scores for each city, the mean score of each indicator was first calculated from the responses of participants within that city using Eq. 2:

$$\overline{X}_{ic} = \frac{\sum_{j=1}^{n_c} X_{ijc}}{n_c} \tag{2}$$

Where $X_{ic}$ represent the mean score indicator $i$ for city c.

$X_{ijc}$ denotes the score assigned by respondent j to indicator $i$, in city c.

$n_c$ represent the total number of respondents in city c

$i$ = individual indicator (e.g., IR1, IR2, PS1, AL1).

j = individual respondent.

c = case-study city (Lagos, Abuja, Port Harcourt, Kano, or Ibadan).

For example, the mean score for Infrastructure Readiness indicator 1 (IR1) in Lagos would be:

$$IR_{1j,\text{Lagos}} = \frac{\sum_{j=1}^{104} IR_{1j,\text{Lagos}}}{104} \tag{3}$$

The resulting indicator-level means were subsequently aggregated to determine the composite scores for Infrastructure Readiness (IR), Policy Support (PS), and Adoption Level (AL) using Eq. 4 to 6 based on the arithmetic means of six Infrastructure Readiness indicators, seven Policy Support indicators, and seven Adoption Level indicators, respectively. The resulting composite scores were interpreted using the standardised five-point classification scale to facilitate consistent comparisons across the five selected Nigerian cities using the following equations as follows:

**Infrastructure readiness (IR)**

$$IR_c = \frac{IR_{1c} + IR_{2c} + IR_{3c} + IR_{4c} + IR_{5c} + IR_{6c}}{6} \quad (4)$$

**Policy support (PS)**

$$PS_c = \frac{PS_{1c} + PS_{2c} + PS_{3c} + PS_{4c} + PS_{5c} + PS_{6c} + PS_{7c}}{7} \quad (5)$$

**Adoption level (AL)**

$$AL_c = \frac{AL_{1c} + AL_{2c} + AL_{3c} + AL_{4c} + AL_{5c} + AL_{6c} + AL_{7c}}{7} \quad (6)$$

Assessment of the Relative Performance (RP) was subsequently derived using Eq. 7, which assigns equal weights to the three dimensions. It was conceptualised as a comparative synthesis indicator rather than an independently measured latent variable. For a reproducible composite assessment, an equal-weighted arithmetic mean of the three dimensions was adopted and calculated as follows:

$$RP_c = \frac{IR_c + PS_c + AL_c}{3} \quad (7)$$

Where:

- $IR_c$ = Infrastructure Readiness composite score for city *c*.
- $PS_c$ = Policy Support composite score for city *c*.
- AL*c*= Adoption Level composite score for city *c*.
- $IR_{ic}$ = Mean score of infrastructure readiness indicator *i* in city *c*.
- $PS_{ic}$ = Mean score of policy support indicator *i* in city *c*.
- $AL_{ic}$ = Mean score of adoption level indicator *i* in city *c*.
- *c*=Each of the five case-study cities: Lagos, Abuja, Port Harcourt, Kano, and Ibadan.
- RP*c*=Relative Performance composite score for city *c*.

Relative Performance (RPc) represents the overall comparative performance score for city (c), derived through the equal-weighted aggregation of Infrastructure Readiness (IR), Policy Support (PS), and Adoption Level (AL). This approach assigns equal importance to the three dimensions, avoiding unsupported assumptions regarding their relative contributions to smart-energy implementation. Accordingly, RP was treated as a composite comparative indicator rather than an independently measured latent construct. The resulting composite scores were retained to two deci-

mal places and interpreted using a standardised five-point classification scale: Very Low (1.00–1.80), Low (1.81–2.60), Moderate (2.61–3.40), High (3.41–4.20), and Very High (4.21–5.00). These intervals were applied consistently across the assessed dimensions to minimise subjective interpretation and facilitate meaningful comparisons among the selected cities. All city-level scores in this study are survey-derived, equal-weighted composite assessments of respondents' perceptions; they are not independently observed engineering, environmental, or municipal performance measurements.

To enhance methodological transparency and reproducibility, the city-level indicator means, calculated composite scores, and corresponding ratings were reported to enable independent verification of the comparative findings. Cities exhibiting consistently higher scores across infrastructure readiness, policy support, and technology adoption were considered to demonstrate stronger relative implementation conditions, whereas lower scores indicated comparatively weaker readiness and adoption capacity. The resulting classifications provide a descriptive assessment of smart-energy readiness and implementation conditions rather than direct measurements of technical energy performance or evidence of causal sustainability impacts.

This analytical procedure established a systematic framework for identifying spatial variations in smart-energy development across Lagos, Abuja, Port Harcourt, Kano, and Ibadan. By integrating infrastructural, institutional, and technological dimensions, the comparative assessment provides an empirical basis for examining differences in smart-energy adoption and identifying context-specific development priorities. In particular, it highlights areas where inadequate infrastructure, limited policy support, and low technology adoption may constrain sustainable urban energy transitions. Overall, the approach strengthens the transparency, consistency, and interpretability of the comparative findings while supporting evidence-based recommendations for improving smart-energy implementation across Nigerian cities.

## Results and findings

### Respondents' demographic characteristics and adoption profile

The socio-demographic profile of the 416 respondents (Table 3); indicates that the study captured perspectives from a diverse range of stakeholder groups relevant to smart energy technology adoption. Household respondents constituted the largest stakeholder category (40.4%, $n=168$). This household category represents general energy-system users rather than a narrowly defined residential-interest group. Following this are commercial users (22.1%, $n=92$), energy providers (13.9%, $n=58$), industrial stakeholders (13.0%, $n=54$), and policymakers (10.6%, $n=44$). This distribution provides representation from both end-users and institutional/technical stakeholders, allowing the study to examine smart energy adoption from multiple perspectives. Regarding gender, males represented 59.1% ($n=246$) of the respondents, while females accounted for 38.0% ($n=158$), with the remaining respondents not reporting gender. Although males constituted the majority, the participation of a

**Table 3** Demographic characteristics

| Variable | Category | Frequency (*n*) | Percentage (%) |
|---|---|---|---|
| Stakeholder Category | Household | 168 | 40.4 |
| | Commercial | 92 | 22.1 |
| | Industrial | 54 | 13.0 |
| | Energy Provider | 58 | 13.9 |
| | Policymaker | 44 | 10.6 |
| City | Lagos | 104 | 25.0 |
| | Abuja | 84 | 20.2 |
| | Port Harcourt | 68 | 16.3 |
| | Kano | 80 | 19.2 |
| | Ibadan | 80 | 19.2 |
| Gender | Male | 246 | 59.1 |
| | Female | 158 | 38.0 |
| Age Group | 18–25 | 72 | 17.3 |
| | 26–35 | 128 | 30.8 |
| | 36–45 | 110 | 26.4 |
| | 46–55 | 68 | 16.3 |
| | 56+ | 38 | 9.1 |
| Education Level | None | 14 | 3.4 |
| | Primary | 28 | 6.7 |
| | Secondary | 96 | 23.1 |
| | Diploma | 74 | 17.8 |
| | Bachelor's | 138 | 33.2 |
| | Postgraduate | 66 | 15.9 |
| Occupation | Public Sector | 102 | 24.5 |
| | Private Sector | 136 | 32.7 |
| | Self-employed | 92 | 22.1 |
| | Student | 54 | 13.0 |
| | Unemployed | 32 | 7.7 |
| Income Level | Low | 88 | 21.2 |
| | Lower-middle | 146 | 35.1 |
| | Upper-middle | 120 | 28.8 |
| | High | 62 | 14.9 |
| Years in City | < 1 year | 34 | 8.2 |
| | 1–5 years | 128 | 30.8 |
| | 6–10 years | 142 | 34.1 |
| | > 10 years | 112 | 26.9 |

($n = 416$)

substantial proportion of female respondents provides a meaningful gender perspective on perceptions of AST.

The age distribution demonstrates broad representation across adult age groups. Respondents aged 26–35 years constituted the largest group (30.8%, $n = 128$), followed by those aged 36–45 years (26.4%, $n = 110$) and 18–25 years (17.3%, $n = 72$). Respondents aged 46–55 years accounted for 16.3% ($n = 68$), while those aged 56 years and above represented 9.1% ($n = 38$). Overall, the distribution indicates that the

study captured perspectives from different adult age categories, providing a diverse basis for examining variations in awareness, adoption behaviour, and perceptions of AST among stakeholders in Nigerian cities. The distribution suggests that the study captured both younger and more experienced respondents, which is relevant because age may influence technology awareness, adoption behaviour, and perceptions of smart energy systems. The educational profile indicates a relatively well-educated sample. Respondents with a Bachelor's degree formed the largest group (33.2%, $n=138$), followed by those with secondary education (23.1%, $n=96$), diplomas (17.8%, $n=74$), postgraduate qualifications (15.9%, $n=66$), primary education (6.7%, $n=28$), and no formal education (3.4%, $n=14$). This distribution suggests that a substantial proportion of participants possessed educational backgrounds that could facilitate understanding of AST, although the inclusion of respondents with lower levels of formal education provides additional diversity.

In terms of occupation, private-sector employees represented the largest group (32.7%, $n=136$), followed by public-sector employees (24.5%, $n=102$), self-employed respondents (22.1%, $n=92$), students (13.0%, $n=54$), and unemployed respondents (7.7%, $n=32$). The occupational diversity is important because smart energy adoption is influenced by employment context, economic capacity, exposure to technology, and access to energy-related information and services. The income distribution shows that the largest proportion of respondents belonged to the lower-middle-income category (35.1%, $n=146$), followed by upper-middle-income respondents (28.8%, $n=120$), low-income respondents (21.2%, $n=88$), and high-income respondents (14.9%, $n=62$). This distribution provides representation across different economic circumstances. It is particularly relevant to the study because affordability and implementation cost were identified as important barriers to smart energy technology adoption. The inclusion of low- and middle-income respondents therefore enables these constraints to be considered from the perspective of users with potentially different financial capacities.

Finally, years of residence in the city indicate that most participants had relatively substantial experience with their respective urban environments. Respondents who had lived in their city for 6–10 years constituted 34.1% ($n=142$), followed by those with 1–5 years of residence (30.8%, $n=128$) and more than 10 years (26.9%, $n=112$). Only 8.2% ($n=34$) had lived in their city for less than one year. Thus, approximately 61.0% of respondents had lived in their respective cities for more than five years, suggesting that a large proportion had sufficient exposure to local energy infrastructure, service conditions, and urban development patterns to provide informed perceptions.

In connection with the city distributions, the sample comprised a purposively structured city distribution with respondents from five major Nigerian cities such as Lagos (25.0%), Abuja (20.2%), Port Harcourt (16.3%), Kano (19.2%), and Ibadan (19.2%). The inclusion of these cities provides broader geographical and contextual coverage of smart energy adoption across Nigeria. Lagos represents a highly urbanised commercial and technological environment; Abuja reflects the federal administrative and institutional context; Port Harcourt represents an important industrial and oil-producing centre; Kano provides representation of Northern Nigeria and its distinctive commercial and infrastructural conditions; while Ibadan represents a major Southwestern inland city characterised by substantial population growth and expand-

ing urban development. The distribution therefore facilitates comparative assessment across diverse urban, economic, infrastructural, and governance contexts.

### Level of adoption of smart energy technologies (AST)

The results in Table 4 provide a comprehensive picture of smart-energy technology adoption among the respondents in relation to objective 1. Overall, 67.8% ($n=282$) reported using AST, indicating a relatively substantial level of adoption, although the corresponding binary measure suggests that adoption is not yet universal. Among the reported technologies, smart grids (M = 3.98, SD = 0.84) and smart metering (M = 3.85, SD = 0.91) recorded the highest mean scores, suggesting relatively stronger uptake and recognition of these technologies. This may reflect their practical relevance in addressing unreliable electricity supply and improving energy monitoring and management. The extent of technology use (M = 3.29, SD = 1.21) indicates a moderate level of engagement, with 45.2% of respondents reporting high or very high usage. This variation suggests that adoption does not necessarily translate into intensive or consistent utilisation. Similarly, the duration of use (M = 2.37, SD = 1.02) indicates that adoption is relatively recent. In particular, 57.7% of respondents had used AST for three years or less, suggesting a growing but comparatively emerging adoption pattern. Other technologies, including EMS (M = 3.21, SD = 0.88) and

**Table 4** Level of adoption of smart energy technologies (AST)

| Variable | Category | Frequency (*n*) | Percentage (%) | Mean | Std. Dev. | Adoption Level | Interpretation |
|---|---|---|---|---|---|---|---|
| Use of Smart Energy Technology (B1) | Yes | 282 | 67.8 | 0.68 | 0.47 | Moderate | The majority of respondents have adopted smart technologies |
| | No | 134 | 32.2 | | | | |
| Types of Technology Usage (B2) | Smart grids | 86 | 20.7 | 3.98 | 0.84 | Moderate | Increasing adoption due to unreliable grid supply |
| | Smart meterings | 104 | 25.0 | 3.85 | 0.91 | Moderate | Widely adopted, especially in commercial settings |
| | Energy Management System | 58 | 13.9 | 3.21 | 0.88 | Moderate | Adoption is limited by technical awareness |
| | Renewable integration | 42 | 10.1 | 3.05 | 0.95 | Moderate | Growing among high-income households |
| Extent of Usage (B3) | Very Low | 36 | 8.7 | 3.29 | 1.21 | Moderate | Usage varies significantly across respondents |
| | Low | 68 | 16.3 | | | | |
| | Moderate | 124 | 29.8 | | | | |
| | High | 112 | 26.9 | | | | |
| | Very High | 76 | 18.3 | | | | |
| Duration of Use (B4) | <1 year | 94 | 22.6 | 2.37 | 1.02 | Moderate | Adoption is relatively recent but growing |
| | 1–3 years | 146 | 35.1 | | | | |
| | 4–6 years | 104 | 25.0 | | | | |
| | >6 years | 72 | 17.3 | | | | |

renewable-energy integration (M = 3.05, SD = 0.95), recorded comparatively lower mean scores. These patterns may reflect continuing constraints related to infrastructure, affordability, technical expertise, and implementation capacity. Overall, the findings indicate that smart-energy adoption is progressing in Nigerian urban contexts but remains moderate, relatively recent, and uneven across technology types and levels of use.

### Perceived benefits of smart technologies on efficiency

The results in Table 5 in connection with Research Objective 2 demonstrate that respondents have strongly positive perceptions of the benefits associated with AST, as all five benefit dimensions recorded mean scores above 3.80. Improved Energy Efficiency received the highest rating (Mean = 4.21), indicating that respondents primarily associate AST with more efficient energy consumption, reduced wastage, and improved system performance. This finding is particularly relevant in the Nigerian urban context, where improving energy efficiency can help address persistent supply constraints and rising energy demand.

Environmental Sustainability ranked second (Mean = 4.15), suggesting strong recognition of the contribution of AST to reducing environmental impacts and supporting cleaner energy systems. Enhanced Energy Reliability also received a high rating (Mean = 4.08), reflecting the importance of technologies that can improve monitor-

**Table 5** Perceived Benefits of Adoption of Smart Energy Technologies (AST)

| S/No | Benefit Dimension | Mean Score (1–5) | Std. Dev. | Rank | Level of Agreement | Interpretation | Adoption Implication |
|---|---|---|---|---|---|---|---|
| 1. | Improved Energy Efficiency | 4.21 | 0.78 | 1 | High | Strong agreement that smart technologies reduce energy wastage and optimise consumption | Key driver of adoption, especially among commercial and industrial users |
| 2. | Environmental Sustainability | 4.15 | 0.81 | 2 | High | Respondents recognise reduced emissions and improved resource conservation | Motivates adoption among environmentally conscious and policy-driven stakeholders |
| 3. | Enhanced Energy Reliability | 4.08 | 0.85 | 3 | High | Notable improvement in power stability and reduction in outages | Particularly important in urban areas with unstable grid supply |
| 4. | Demand-Side Management | 3.95 | 0.88 | 4 | Moderate | Improved ability to monitor and control energy consumption patterns | Supports behavioural change and efficient energy use |
| 5. | Cost Savings | 3.88 | 0.92 | 5 | Moderate | Financial benefits acknowledged despite high upfront investment | Adoption may depend on income level and financing options |

ing, energy management, and system stability in an environment characterised by electricity-supply challenges. Demand-Side Management recorded a mean score of 3.95, indicating that respondents recognise the value of smart technologies for monitoring and managing energy consumption, although this benefit may be less immediately visible than efficiency and reliability improvements. The comparatively lower rating may also reflect differences in users' familiarity with advanced demand-management functions and intelligent energy-control systems.

Cost Savings recorded the lowest mean score (Mean = 3.88), although the rating still indicates a generally positive perception. The lower ranking is particularly noteworthy given that high initial cost was identified as the most significant barrier to adoption (Mean = 4.35). This apparent contrast suggests that respondents may recognise the potential for long-term financial savings while remaining uncertain about the short-term economic returns of smart-energy investments. High purchase and installation costs, maintenance expenses, uncertain payback periods, equipment replacement, and fluctuations in energy prices may make financial benefits less immediately observable than efficiency or reliability improvements. Consequently, stakeholders may perceive smart technologies primarily as mechanisms for improving energy performance and reliability rather than as immediate cost-saving investments.

### Barriers to Adoption of Smart energy technologies (AST)

The results presented in Table 6 in relation to research objective 3, indicate that stakeholders identified several interrelated barriers to the adoption of AST, with mean scores ranging from 3.52 to 4.35. Inadequate infrastructure emerged as the most prominent barrier (M = 4.35, SD = 0.76), highlighting the constraints associated with unreliable electricity networks, limited grid capacity, inadequate digital connectivity, and insufficient supporting infrastructure. Weak policy and regulatory frameworks ranked second (M = 4.02, SD = 0.82), suggesting that regulatory uncertainty, limited incentives, and insufficient institutional support may reduce investor confidence and hinder large-scale deployment.

High implementation cost was the third-ranked barrier (M = 3.96, SD = 0.85), indicating that high initial investment and installation costs may restrict affordability, particularly among low- and middle-income users, households, and SMEs. Limited technical expertise (M = 3.74, SD = 0.89) further indicates that shortages of appropriately skilled personnel can constrain the installation, maintenance, and optimisation of smart energy systems. Finally, institutional fragmentation (M = 3.52, SD = 0.93) suggests that weak coordination among government agencies, regulators, energy providers, technology developers, and other stakeholders may create implementation gaps. Overall, the findings demonstrate that smart energy adoption is constrained not by a single factor but by the combined effects of infrastructure, policy, financial, technical, and institutional conditions, underscoring the need for coordinated interventions to support wider and sustainable adoption.

Generally, barriers are uniformly perceived as severe, with mean scores > 3.5 (moderate to very high), indicating that stakeholders perceive smart-energy adoption barriers as systemic rather than isolated challenges. Infrastructure deficiencies, regulatory weaknesses, financial constraints, limited technical expertise, and insti-

**Table 6** Barriers to Adoption of Smart Energy Technologies (AST)

| S/*N* | Barrier Category | Mean Score (1–5) | Std. Dev. | Rank | Level of Agreement | Key Issues Identified | Interpretation | Adoption Implication |
|---|---|---|---|---|---|---|---|---|
| 1 | Inadequate infrastructure | 4.35 | 0.76 | 1 | Moderate | Unreliable electricity networks, weak grid capacity, limited digital connectivity, and inadequate supporting infrastructure | Inadequate physical and digital infrastructure constrains the reliable integration and operation of AST. | Strongly constrains adoption, scalability, and effective system performance, particularly in underserved areas |
| 2 | Weak Policy and Regulatory Framework | 4.02 | 0.82 | 2 | Moderate | Limited policy incentives, regulatory uncertainty, weak enforcement mechanisms, and insufficient institutional support | Policy and regulatory uncertainty reduces investor confidence and discourages long-term investment in AST. | Restricts large-scale deployment, private-sector participation, and sustained technology diffusion |
| 3 | High Implementation Cost | 3.96 | 0.85 | 3 | Moderate | High initial investment, installation expenses, equipment costs, and limited access to affordable financing | High upfront and implementation costs create financial barriers for households, SMEs, and other potential adopters despite potential long-term benefits | Limits affordability and slows adoption, particularly among low- and middle-income users and smaller organisations |
| 4 | Limited Technical Expertise | 3.74 | 0.89 | 4 | Moderate | Shortage of skilled personnel for system design, installation, operation, maintenance, and troubleshooting | Insufficient technical capacity reduces the ability of organisations and users to effectively implement, maintain, and optimise smart energy systems | Slows technology adoption and may reduce reliability, maintenance capacity, and long-term system effectiveness |

**Table 6** (continued)

| S/*N* | Barrier Category | Mean Score (1–5) | Std. Dev. | Rank | Level of Agreement | Key Issues Identified | Interpretation | Adoption Implication |
|---|---|---|---|---|---|---|---|---|
| 5 | Institutional Fragmentation | 3.52 | 0.93 | 5 | Moderate | Poor coordination among government agencies, energy providers, technology developers, regulators, and other stakeholders | Fragmented institutional responsibilities and weak inter-organisational coordination create implementation gaps and hinder integrated smart-energy planning | Delays implementation, weakens coordination, and limits the effective scaling and diffusion of AST. |

tutional fragmentation are interconnected and reinforce one another. This uniform severity suggests that overcoming adoption challenges requires coordinated, multi-dimensional interventions rather than addressing individual barriers independently.

## Relationships between Adoption of Smart energy technologies (AST) and Sustainability Outcomes (SO)

### Results of the measurement model assessment and indicator purification

The measurement model was evaluated using Partial Least Squares Structural Equation Modelling (PLS-SEM) to establish the reliability and validity of the constructs associated with Research Objective 4. The assessment followed established PLS-SEM procedures, focusing on indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair et al. 2022). The initial measurement model (Table 7**)** comprised 17 observed indicators distributed across four reflective latent constructs: Adoption of Smart Technologies (AST), Perceived Benefits (PB), Barriers (BR), and Sustainability Outcomes (SO). Specifically, AST comprised three indicators (AST1–AST3), PB comprised five indicators (PB1–PB5), BR comprised five indicators (BR1–BR5), and SO comprised four indicators (SO1–SO4).

To ensure methodological transparency and measurement robustness, a systematic indicator purification procedure was applied before evaluating the final structural relationships. Indicator retention was primarily determined using standardised outer loadings, with values of 0.70 or higher considered acceptable, indicating that an indicator explains approximately 49% or more of its variance through the associated latent construct. Following the recommendations of Hair et al. (2022), indicators with outer loadings below 0.40 were considered unsuitable for retention, while indicators with loadings between 0.40 and 0.70 were evaluated for potential removal based on their contribution to composite reliability (CR), average variance extracted (AVE), and theoretical relevance.

The initial assessment identified 12 indicators with satisfactory outer loadings ranging from 0.78 to 0.88, while five indicators exhibited loadings below the recommended threshold. These were PB4 (0.37), PB5 (0.30), BR4 (0.22), BR5 (0.27),

**Table 7** Initial measurement model assessment and indicator retention decisions

| Construct | Indicator | Initial outer loading | Decision | Statistical justification |
|---|---|---|---|---|
| AST | AST1 | 0.81 | Retained | Loading≥0.70 |
| AST | AST2 | 0.84 | Retained | Loading≥0.70 |
| AST | AST3 | 0.78 | Retained | Loading≥0.70 |
| PB | PB1 | 0.82 | Retained | Loading≥0.70 |
| PB | PB2 | 0.86 | Retained | Loading≥0.70 |
| PB | PB3 | 0.83 | Retained | Loading≥0.70 |
| PB | PB4 | 0.37 | Excluded | Loading below 0.40 |
| PB | PB5 | 0.30 | Excluded | Loading below 0.40 |
| BR | BR1 | 0.79 | Retained | Loading≥0.70 |
| BR | BR2 | 0.83 | Retained | Loading≥0.70 |
| BR | BR3 | 0.81 | Retained | Loading≥0.70 |
| BR | BR4 | 0.22 | Excluded | Loading below 0.40 |
| BR | BR5 | 0.27 | Excluded | Loading below 0.40 |
| SO | SO1 | 0.85 | Retained | Loading≥0.70 |
| SO | SO2 | 0.87 | Retained | Loading≥0.70 |
| SO | SO3 | 0.80 | Retained | Loading≥0.70 |
| SO | SO4 | 0.33 | Excluded | Loading below 0.40 |

Note: AST = Adoption of Smart Technologies; PB = Perceived Benefits; BR = Barriers; SO = Sustainability Outcomes. Indicators with outer loadings below 0.40 were excluded. Values are based on the supplied initial measurement model

and SO4 (0.33). Four indicators (PB4, PB5, BR4, and BR5) had loadings below 0.40 and were therefore excluded because of their limited ability to represent their respective latent constructs. The remaining indicator, SO4 (0.33), fell within the conditional deletion range of less than 0.40. Its exclusion was justified by its relatively weak association with Sustainability Outcomes and the need to achieve an acceptable level of convergent validity while retaining the construct's principal theoretical dimensions.

The purification process therefore involved the exclusion of five underperforming indicators, representing 29.4% of the initial measurement items. Importantly, indicator deletion was guided by statistical adequacy and conceptual relevance rather than the exclusive objective of maximising reliability coefficients. The retained indicators continued to represent the principal dimensions of each construct, including smart energy technology adoption, perceived operational and economic benefits, infrastructure and institutional barriers, and environmental and social sustainability outcomes. This approach maintained the theoretical coherence of the measurement framework while reducing measurement error associated with weak indicators.

Following indicator purification, the PLS-SEM measurement model was re-estimated using the 12 retained indicators, comprising AST1–AST3, PB1–PB3, BR1–BR3, and SO1–SO3. Each of the four latent constructs was therefore represented by three observed indicators. As presented in Table 8, the purification process reduced the initial 17-indicator model to a more parsimonious 12-indicator measurement structure without eliminating any of the four theoretically established constructs.

**Table 8** Summary of indicator purification and final measurement model composition

| Construct | Initial indicators | Retained indicators | Excluded indicators | Initial number | Final number |
|---|---|---|---|---|---|
| Adoption of Smart Technologies (AST) | AST1–AST3 | AST1–AST3 | None | 3 | 3 |
| Perceived Benefits (PB) | PB1–PB5 | PB1–PB3 | PB4, PB5 | 5 | 3 |
| Barriers (BR) | BR1–BR5 | BR1–BR3 | BR4, BR5 | 5 | 3 |
| Sustainability Outcomes (SO) | SO1–SO4 | SO1–SO3 | SO4 | 4 | 3 |
| Total | 17 | 12 | 5 | 17 | 12 |

Note: The purification process resulted in the removal of five indicators (29.4%) and retention of 12 indicators (70.6%). All four latent constructs were maintained in the final model

**Table 9** Discriminant validity assessment using the Fornell–Larcker criterion

| Construct | AST | PB | BR | SO |
|---|---|---|---|---|
| Adoption of Smart Technologies (AST) | 0.80 | | | |
| Perceived Benefits (PB) | 0.62 | 0.82 | | |
| Barriers (BR) | −0.55 | −0.48 | 0.81 | |
| Sustainability Outcomes (SO) | 0.68 | 0.71 | −0.52 | 0.83 |

Note: Bold diagonal values represent the reported square roots of AVE. These exceed the corresponding absolute interconstruct correlations, supporting discriminant validity under the Fornell–Larcker criterion. The diagonal values should be updated using the final verified AVE estimates

The final measurement model demonstrated satisfactory indicator reliability, with reported outer loadings ranging from 0.78 to 0.87. Internal consistency reliability was evaluated using composite reliability (CR), with values ranging from 0.851 to 0.878, exceeding the recommended minimum threshold of 0.70. Convergent validity was assessed using AVE, with reported values ranging from 0.656 to 0.706, exceeding the recommended threshold of 0.50 (Hair et al. 2022). These results indicate that the retained indicators adequately represent their respective latent constructs and that each construct explains more than half of the variance in its indicators.

Discriminant validity was evaluated using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. Under the Fornell–Larcker criterion, the square root of each construct's AVE should exceed its correlations with other latent constructs (Fornell and Larcker 1981). As presented in Table 9, the reported diagonal values exceed the corresponding interconstruct correlations, providing preliminary support for discriminant validity. However, the HTMT results are reported to establish whether the constructs satisfy the recommended discriminant validity thresholds.

Overall, the indicator purification process provides a transparent explanation of the transition from the initial 17-indicator model to the final 12-indicator measurement structure. The exclusion of five weakly performing indicators improved the conceptual clarity and parsimony of the model, while the reported reliability and conver-

**Table 10** Retained indicators in the final PLS-SEM model

| Construct | Code | Measurement variable/indicator | Reported final outer loading |
|---|---|---|---|
| AST | AST1 | Smart grids/meters | 0.81 |
| AST | AST2 | Renewable energy integration | 0.84 |
| AST | AST3 | Digital monitoring systems | 0.78 |
| PB | PB1 | Energy efficiency | 0.82 |
| PB | PB2 | Reliability | 0.86 |
| PB | PB3 | Cost reduction | 0.83 |
| BR | BR1 | Infrastructure | 0.79 |
| BR | BR2 | Policy and regulatory framework | 0.83 |
| BR | BR3 | Implementation/technical constraints | 0.81 |
| SO | SO1 | Energy sustainability | 0.85 |
| SO | SO2 | Urban resilience/environmental performance | 0.87 |
| SO | SO3 | Social inclusion | 0.80 |

**Table 11** Reported reliability and convergent validity of the final measurement model

| Construct | Number of indicators | Outer loading range | Reported AVE | Reported CR |
|---|---|---|---|---|
| AST | 3 | 0.78–0.84 | 0.724 | 0.851 |
| PB | 3 | 0.82–0.86 | 0.700 | 0.875 |
| BR | 3 | 0.79–0.83 | 0.752 | 0.851 |
| SO | 3 | 0.80–0.87 | 0.706 | 0.878 |

gent validity statistics indicate satisfactory measurement properties. Consequently, the retained measurement structure provides a basis for examining the hypothesised direct, mediating, and moderating relationships between smart technology adoption, perceived benefits, adoption barriers, and sustainability outcomes.

## Final structural model evaluation

Following measurement model purification and assessment, the final PLS-SEM model comprised four latent constructs: Adoption of Smart Technologies (AST), Perceived Benefits (PB), Barriers (BR), and Sustainability Outcomes (SO). Each construct was operationalised using three retained indicators, producing a final measurement structure of 12 indicators. The model was subsequently employed to examine the hypothesised direct relationships, mediation effect, and moderation effect associated with smart energy technology adoption and sustainability outcomes. The final measurement model demonstrated acceptable reported indicator reliability, internal consistency, and convergent validity. As summarised in Tables 10 and 11, the retained indicators exhibited outer loadings above 0.70, while the reported composite reliability and AVE values exceeded the recommended minimum thresholds of 0.70 and 0.50, respectively (Hair et al. 2022). These measurement properties provided a basis for estimating the relationships among the latent constructs.

Following the purification and validation of the measurement model, the final 12-indicator PLS-SEM framework was employed to examine the hypothesised relationships among Adoption of Smart Technologies (AST), Perceived Benefits (PB), Barriers (BR), and Sustainability Outcomes (SO). The structural model comprised three direct relationships, one mediating relationship, and one moderating relationship. The statistical significance of the hypothesised paths was evaluated through bootstrapping, using standardised path coefficients (β), t-statistics, p-values, and, where available, 95% confidence intervals. Bootstrapping is particularly appropriate for PLS-SEM because it provides a non-parametric approach to statistical inference without imposing strict distributional assumptions on the data (Hair et al. 2022).

The structural model assessment was conducted using the four validated latent constructs, each represented by three retained measurement indicators. The reported final outer loadings ranged from 0.78 to 0.87, indicating satisfactory indicator reliability. Following confirmation of the measurement properties, the analysis focused on determining the magnitude, direction, and statistical significance of the hypothesised structural relationships. As illustrated in Fig. 4 and summarised in Table 12, AST and PB demonstrated positive relationships with SO, whereas BR exhibited a negative relationship. Furthermore, the mediation and moderation analyses identified the mechanisms and contextual conditions through which smart technology adoption is associated with sustainability outcomes.

i. Direct Effects

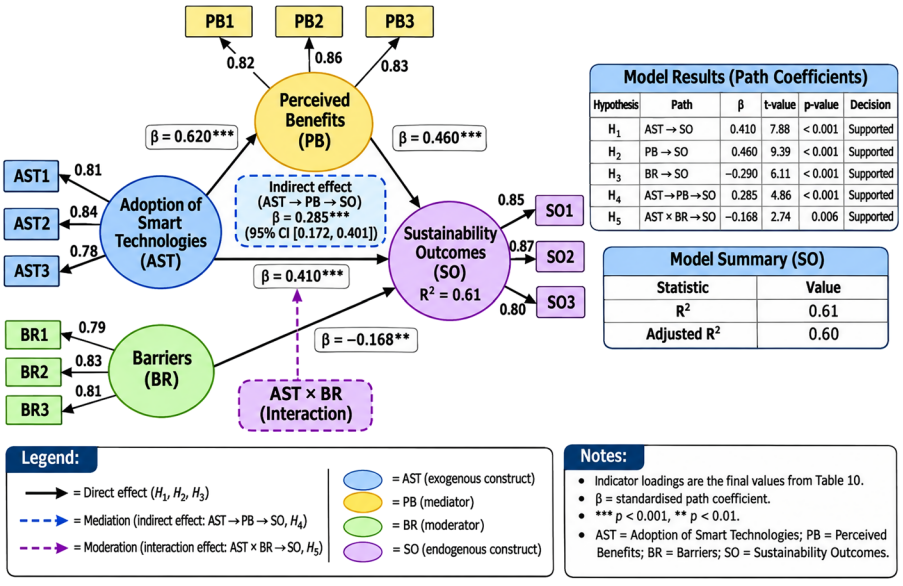


**Fig. 4** Integrated PLS-SEM structural model showing direct, mediating, and moderating effects on sustainability outcomes

**Table 12** Direct, mediating, and moderating effects in the final PLS-SEM structural model

| Hypothesis | Structural relationship | Path coefficient (β) | t-statistic | *p*-value | Decision |
|---|---|---|---|---|---|
| $H_1$ | AST → SO | 0.410 | 7.88 | <0.001 | Supported |
| $H_2$ | PB → SO | 0.460 | 9.39 | <0.001 | Supported |
| $H_3$ | BR → SO | −0.290 | 6.11 | <0.001 | Supported |
| $H_4$ | AST → PB → SO | 0.285 | 4.86 | <0.001 | Supported |
| $H_5$ | AST × BR → SO | −0.168 | 2.74 | 0.006 | Supported |

Note: AST = Adoption of Smart Technologies; PB = Perceived Benefits; BR = Barriers; SO = Sustainability Outcomes. β represents the standardised path coefficient. The t-statistics and p-values are based on the reported bootstrapping results. The *p*-values for $H_1$–$H_3$ have been expressed as $p < 0.001$, consistent with the reported t-statistics under conventional two-tailed large-sample inference

**$H_1$: Adoption of Smart Technologies (AST) positively influences Sustainability Outcomes (SO).** The results revealed a positive and statistically significant relationship between AST and SO (β = 0.410, t = 7.88, $p < 0.001$). This finding indicates that greater adoption of AST is associated with improved sustainability outcomes. Specifically, the integration of smart grids and meters, renewable energy technologies, and digital monitoring systems may contribute to more efficient energy management, enhanced environmental performance, improved system reliability, and greater urban resilience. The positive coefficient suggests that smart technology adoption constitutes an important enabling factor in achieving sustainability objectives. Accordingly, $H_1$ is supported.

**$H_2$: Perceived Benefits (PB) positively influence Sustainability Outcomes (SO).** The relationship between PB and SO was positive and statistically significant (β = 0.460, t = 9.39, $p < 0.001$), representing the strongest positive direct association among the examined predictors. This result indicates that stakeholders' perceptions of energy efficiency, operational reliability, and cost reduction are strongly associated with favourable sustainability outcomes. The finding suggests that recognising the practical and economic advantages of AST may reinforce their effective utilisation and contribution to sustainability performance. Consequently, $H_2$ is supported.

**$H_3$: Barriers (BR) negatively influence Sustainability Outcomes (SO).** The analysis identified a statistically significant negative relationship between BR and SO (β = −0.290, t = 6.11, $p < 0.001$). The negative coefficient indicates that greater implementation barriers are associated with lower sustainability performance. These barriers include inadequate infrastructure, limitations in policy and regulatory frameworks, and implementation-related technical constraints. Such challenges may restrict the effective deployment, integration, and operation of AST, thereby reducing their potential environmental, economic, and social benefits. The finding emphasises the

importance of addressing institutional, infrastructural, and technical constraints to strengthen sustainability outcomes. Therefore, $H_3$ is supported.

ii. Mediation Effect

**$H_4$: Perceived Benefits (PB) mediate the relationship between Adoption of Smart Technologies (AST) and Sustainability Outcomes (SO).** The mediation analysis examined whether PB provides an indirect pathway through which AST is associated with SO. The bootstrapping results revealed a positive and statistically significant indirect effect ($\beta = 0.285$, $t = 4.86$, $p < 0.001$, 95% CI [0.172, 0.401]). Since the confidence interval excludes zero, the indirect relationship is statistically significant, confirming the mediating role of PB. The findings suggest that the contribution of smart technology adoption to sustainability outcomes operates partly through stakeholders' recognition of the benefits associated with these technologies. In particular, perceived improvements in energy efficiency, reliability, and cost-effectiveness may reinforce the positive relationship between technological adoption and sustainability performance. Furthermore, the direct relationship between AST and SO remained statistically significant ($\beta = 0.410$, $p < 0.001$) alongside the significant positive indirect effect, indicating a pattern consistent with complementary partial mediation. This suggests that smart technology adoption is associated with sustainability outcomes both directly and indirectly through perceived benefits. Accordingly, $H_4$ is supported.

iii. Moderation Effect

**$H_5$: Barriers (BR) significantly moderate the relationship between Adoption of Smart Technologies (AST) and Sustainability Outcomes (SO).** The moderation analysis assessed whether implementation barriers alter the strength of the relationship between AST and SO. The interaction term (AST × BR → SO) demonstrated a statistically significant negative coefficient ($\beta = -0.168$, $t = 2.74$, $p = 0.006$, 95% CI [−0.286, −0.049]). The exclusion of zero from the bootstrap confidence interval confirms the statistical significance of the moderating effect. The negative interaction coefficient indicates that higher levels of adoption barriers weaken the positive relationship between smart technology adoption and sustainability outcomes. Consequently, the association between technological adoption and sustainability performance varies according to the severity of implementation constraints. Under relatively favourable infrastructural, regulatory, and technical conditions, smart technology adoption is expected to demonstrate a stronger positive association with sustainability outcomes. Conversely, inadequate infrastructure, restrictive regulatory conditions, and limited technical capacity may diminish the sustainability benefits associated with technology adoption. This finding highlights the importance of considering contextual implementation conditions when evaluating the sustainability contributions of AST. It also suggests that technological investment alone may be insufficient to achieve optimal sustainability performance without complementary institutional support, infrastructure development, and technical capacity enhancement. Therefore, $H_5$ is supported.

iv. Overall Structural Relationships and Hypothesis Evaluation

The structural model results provide statistical support for all five proposed hypotheses, demonstrating the complementary roles of technological adoption, perceived benefits, and implementation barriers in explaining sustainability outcomes. Among the direct relationships, PB exhibited the strongest positive association with SO (β = 0.460), followed by AST (β = 0.410), while BR demonstrated a significant negative association (β = −0.290). These findings indicate that sustainability outcomes are associated not only with the AST, but also with stakeholders' recognition of their benefits and the contextual constraints affecting their implementation.

The mediation analysis further established that PB constitutes a significant indirect pathway linking AST to SO (β = 0.285, $p < 0.001$), suggesting that perceived technological benefits help explain the positive relationship between adoption and sustainability performance. Meanwhile, the significant negative moderation effect (β = −0.168, $p = 0.006$) indicates that implementation barriers weaken this positive relationship. Collectively, the findings support an integrated interpretation in which technological adoption, perceived benefits, and implementation conditions jointly contribute to variations in sustainability outcomes. The results therefore provide empirical support for the proposed structural framework and highlight the importance of combining technological interventions with supportive institutional, infrastructural, and policy environments.

v. Explanatory Power and Structural Model Assessment

The explanatory power of the structural model was assessed using the coefficient of determination ($R^2$), which indicates the proportion of variance in the endogenous construct explained by its predictors. As presented in Table 13, the reported model yielded an $R^2$ value of 0.610 and an adjusted $R^2$ of 0.600 for Sustainability Outcomes. This indicates that approximately 61% of the variance in SO is explained by the predictors included in the estimated model, with the adjusted value suggesting that the model retains substantial explanatory capacity after accounting for model complexity.

The explanatory relationships are primarily associated with AST, PB, and BR, together with the specified interaction effect between AST and BR. The positive coefficients for AST and PB indicate their favourable associations with sustainability outcomes, while the negative coefficients for BR and its interaction with AST demonstrate the constraining influence of implementation barriers. The $R^2$ value therefore suggests that the structural framework captures a substantial proportion of the observed variation in sustainability outcomes.

The reported R value of 0.78 is approximately consistent with the square root of $R^2$ and indicates a strong association between the model's predicted and observed

**Table 13** Explanatory power of the final PLS-SEM structural model

| Endogenous construct | $R^2$ | Adjusted $R^2$ | Interpretation |
|---|---|---|---|
| Sustainability Outcomes (SO) | 0.610 | 0.600 | Substantial in-sample explanatory power |

Note: $R^2$ represents the proportion of variance explained in the endogenous construct, while adjusted $R^2$ accounts for model complexity. The values are reproduced from the results of the final 12-indicator SmartPLS model

sustainability outcome scores. However, in PLS-SEM, the $R^2$ statistic is the principal measure of in-sample explanatory power and should not be interpreted independently as evidence of predictive validity. Similarly, the reported F-statistic of 182.45 ($p < 0.001$), if obtained from a separate conventional regression analysis, should not be presented as a standard PLS-SEM global model-fit statistic. Instead, PLS-SEM structural assessment primarily considers the significance and relevance of path coefficients, explanatory power ($R^2$), collinearity diagnostics, effect sizes ($f^2$), and out-of-sample predictive performance where appropriate (Hair et al. 2022).

Although the reported $R^2$ indicates substantial in-sample explanatory power, additional predictive assessment using procedures such as PLSpredict would be necessary to establish the model's out-of-sample predictive performance. Overall, the reported findings demonstrate that the proposed framework provides a meaningful explanation of sustainability outcomes, with perceived benefits emerging as the strongest positive direct predictor, technology adoption contributing positively, and implementation barriers exerting both direct and moderating constraints.

### Assessment of model quality, predictive relevance, and effect sizes

The assessment of the PLS-SEM model in terms of discriminant validity, collinearity, predictive relevance, effect sizes, explanatory power, and model fit is presented in Table 14. The HTMT values range from 0.471 to 0.734, all below the recommended threshold of 0.85, confirming satisfactory discriminant validity among the constructs (Henseler et al. 2015; Hair et al. 2022). This indicates that AST, PB, BR, and SO represent empirically distinct constructs within the revised model. The inner VIF values range from 1.00 to 1.92, remaining well below the conservative threshold of 3.30. This demonstrates that problematic multicollinearity is not present among the predictor constructs and the interaction term. The model therefore provides an adequate basis for estimating the structural relationships without substantial redundancy among predictors. The predictive relevance results are also satisfactory. The $Q^2$ values for PB (0.351) and SO (0.438) are both greater than zero, indicating that the model possesses predictive relevance for both endogenous constructs. The effect-size assessment further shows that AST → PB ($f^2 = 0.287$) and PB → SO ($f^2 = 0.268$) have medium effects, whereas BR → SO ($f^2 = 0.134$) and AST × BR → SO ($f^2 = 0.083$) demonstrate small effects. These results suggest that AST and PB make comparatively stronger contributions to the explained variance of the endogenous constructs, while barriers have a smaller but meaningful direct and moderating influence.

The model also demonstrates substantial explanatory power for Sustainability Outcomes, with $R^2 = 0.61$ and Adjusted $R^2 = 0.60$. Thus, approximately 61% of the variance in SO is explained by the predictors included in the structural model, indicating substantial explanatory capability. Regarding approximate model fit, the SRMR value of 0.056 is below the recommended threshold of 0.08, indicating acceptable fit. Similarly, NFI = 0.928 exceeds the 0.90 criterion, indicating good comparative fit, while RMS Theta = 0.081 remains below the recommended threshold of 0.12. Collectively, these results demonstrate that the revised PLS-SEM model has satisfactory measurement and structural quality. Overall, the results provide empirical support for the revised framework linking Adoption of Smart Technologies (AST),

**Table 14** Summary of PLS-SEM model quality and structural assessment

| Assessment Category | Measure | Relationship/Construct | Value | Criterion | Interpretation |
|---|---|---|---|---|---|
| Discriminant Validity | HTMT | AST–BR | 0.482 | <0.85 | Satisfactory* |
| | HTMT | AST–PB | 0.671 | <0.85 | Satisfactory* |
| | HTMT | AST–SO | 0.612 | <0.85 | Satisfactory* |
| | HTMT | BR–PB | 0.593 | <0.85 | Satisfactory* |
| | HTMT | BR–SO | 0.471 | <0.85 | Satisfactory* |
| | HTMT | PB–SO | 0.734 | <0.85 | Satisfactory* |
| Collinearity | Inner VIF | AST → PB | 1.00 | <3.30 | No critical collinearity* |
| | Inner VIF | AST → SO | 1.86 | <3.30 | No critical collinearity* |
| | Inner VIF | PB → SO | 1.92 | <3.30 | No critical collinearity* |
| | Inner VIF | BR → SO | 1.74 | <3.30 | No critical collinearity* |
| | Inner VIF | AST × BR → SO | 1.58 | <3.30 | No critical collinearity* |
| Predictive Relevance | $Q^2$ | PB | 0.351 | >0 | Predictive relevance* |
| | $Q^2$ | SO | 0.438 | >0 | Predictive relevance* |
| Effect Size | $f^2$ | AST → PB | 0.287 | 0.02/0.15/0.35 | Medium effect* |
| | $f^2$ | AST → SO | 0.210 | 0.02/0.15/0.35 | Medium effect* |
| | $f^2$ | PB → SO | 0.268 | 0.02/0.15/0.35 | Medium effect* |
| | $f^2$ | BR → SO | 0.134 | 0.02/0.15/0.35 | Small effect* |
| | $f^2$ | AST × BR → SO | 0.083 | 0.02/0.15/0.35 | Small effect* |
| Mediation | Indirect effect | AST → PB → SO | β = 0.285 | CI excludes 0 | Significant mediation |
| Moderation | Interaction effect | AST × BR → SO | β = −0.168 | CI excludes 0 | Significant negative moderation |
| Model Explanatory Power | $R^2$ | SO | 0.61 | Higher values preferred | Substantial explanatory power |
| | Adjusted $R^2$ | SO | 0.60 | — | Strong explanatory power |
| Model Fit | SRMR | Model | 0.056 | <0.08 | Acceptable fit* |
| | NFI | Model | 0.928 | >0.90 | Good fit* |
| | RMS Theta | Model | 0.081 | <0.12 | Acceptable* |

Note: HTMT = Heterotrait–Monotrait Ratio; VIF = Variance Inflation Factor; $Q^2$ = Stone–Geisser predictive relevance; $f^2$ = Cohen's effect size; SRMR = Standardised Root Mean Square Residual; NFI = Normed Fit Index; RMS Theta = Root Mean Square Theta

Perceived Benefits (PB), Barriers (BR), and Sustainability Outcomes (SO). The structural results indicate positive relationships between AST and PB and between AST and SO, while PB positively contributes to SO. Conversely, BR has a negative effect on SO and significantly weakens the AST–SO relationship through the interaction effect. The significant indirect pathway AST → PB → SO (β = 0.285) further

demonstrates the mediating role of perceived benefits. Importantly, the previously reported BR → PB effect has been excluded because this pathway is not specified in the revised conceptual and structural model. Collectively, these findings strengthen the empirical validity of the revised framework and demonstrate that sustainability outcomes depend not only on smart-energy adoption but also on perceived benefits and the structural conditions surrounding implementation.

### Comparative synthesis across case studies

The comparative analysis assessed variations in smart-energy technology implementation across five Nigerian cities such as Lagos, Abuja, Port Harcourt, Kano, and Ibadan using four interrelated dimensions: Infrastructure Readiness (IR), Policy Support (PS), Adoption Level (AL), and Relative Performance (RP). Drawing on quantitative survey responses from 416 participants and the standardised composite rating procedure, the assessment identified distinct patterns of technological readiness, institutional capacity, and adoption across the selected urban contexts. As presented in Table 15, Lagos and Abuja exhibited relatively high levels of infrastructure readiness, policy support, and technology adoption, while Port Harcourt demonstrated moderate performance. Conversely, Kano and Ibadan recorded comparatively lower ratings, indicating less favourable conditions for smart-energy technology implementation. These variations reinforce the understanding that smart-city development is shaped by the interaction of technological, institutional, economic, and governance factors rather than technological availability alone (Chourabi et al. 2012; Neirotti et al. 2014; Albino et al. 2015).

The comparative assessment distinguished between numerical composite scores and their corresponding categorical ratings to facilitate consistent interpretation of city-level differences. Infrastructure Readiness reflected the availability and reliability of physical and digital energy infrastructure, while Policy Support captured regulatory effectiveness, institutional commitment, and governance conditions. Adoption Level measured the deployment and AST, whereas Relative Performance represented an aggregated comparative indicator of overall implementation readiness. Although Lagos and Abuja received identical categorical ratings of 4 for IR, PS, and AL, their reported RP classifications differed. This distinction requires examination of the underlying unrounded composite scores and the specified aggregation procedure to establish whether the difference is mathematically justified. Accordingly, the comparative results should be interpreted as descriptive indicators of implementation conditions rather than direct measurements of technical energy performance or evidence of causal relationships.

Lagos and Abuja emerged as the relatively stronger urban contexts for smart-energy implementation, although their enabling conditions reflected different development characteristics. Lagos demonstrated comparatively favourable infrastructure readiness and technology adoption, potentially supported by its extensive commercial activities, economic capacity, and demand for innovative energy solutions. These characteristics are consistent with previous studies identifying technological infrastructure, market opportunities, and digital readiness as important drivers of smart-city development (Chourabi et al. 2012; Neirotti et al. 2014; Albino et al.

**Table 15** Comparative synthesis of quantitative findings across case study cities ($n$=416)

| Case Study City | Sample ($n$) | Infrastructure Readiness (mean score) | Policy Support (mean score) | Adoption Level (mean score) | Relative Performance (mean score) | Evidence-Based Interpretation |
|---|---|---|---|---|---|---|
| 1. Lagos | 104 | 4 – Relatively high | 4 – High | 4 – High | 5 – Highest | Quantitative results indicate that stronger infrastructure and market demand are associated with higher adoption levels. |
| 2. Abuja | 84 | 4 – High | 4 – Relatively high | 4 – High | 4 – High | Results indicate that stronger institutional and policy support is associated with relatively high implementation levels. |
| 3. Port Harcourt | 68 | 3 – Moderate | 3 – Moderate | 3 – Moderate | 3 – Moderate | The findings indicate partial adoption, supported by the city's industrial and infrastructure base. |
| 4. Kano | 80 | 2 – Low–moderate | 2 – Low–moderate | 2 – Low–moderate | 2 – Low | Quantitative findings indicate that infrastructure and institutional constraints are associated with lower adoption. |
| 5. Ibadan | 80 | 1 – Low | 1 – Low | 1 – Low | 1 – Low | The results indicate relatively limited adoption in association with weaker infrastructure and institutional support. |

2015). Abuja, meanwhile, exhibited relatively strong institutional and policy support, highlighting the potential importance of regulatory frameworks, administrative coordination, and governance capacity in facilitating smart-energy initiatives. This interpretation aligns with Höjer and Wangel (2015) and Anthopoulos (2017), who emphasised the importance of governance structures and institutional arrangements in sustainable smart-city development.

Port Harcourt occupied an intermediate position, characterised by moderate infrastructure readiness, policy support, and technology adoption. This pattern suggests that partial technological and institutional preparedness may be associated with intermediate levels of smart-energy implementation. Such findings are consistent with the socio-technical perspective that urban innovation depends on the interaction of infrastructure provision, institutional effectiveness, and socio-economic conditions (Chourabi et al. 2012; Neirotti et al. 2014). In contrast, Kano and Ibadan exhibited comparatively lower ratings across the assessed dimensions, indicating potential constraints associated with inadequate infrastructure, limited institutional support, and weaker technology adoption capacity. These conditions reflect challenges identified in the broader smart-city literature, where infrastructural deficiencies and governance limitations can restrict technological diffusion and sustainable urban transformation (Albino et al. 2015; Höjer and Wangel 2015).

Overall, the comparative findings highlight the multidimensional and context-dependent nature of smart-energy technology implementation in Nigerian cities. Although effective policy frameworks and institutional coordination can facilitate technological adoption, their contributions may be constrained where substantial deficiencies persist in electricity infrastructure, digital connectivity, technical expertise, and investment capacity. This observation supports the socio-technical understanding that sustainable urban transformation requires coordinated improvements in technological infrastructure, institutional governance, economic resources, and stakeholder participation (Chourabi et al. 2012; Zakka et al. 2025). Consequently, smart-energy development strategies should reflect the specific conditions of individual cities rather than adopting uniform implementation approaches. For Lagos and Abuja, priorities may include scaling advanced smart-energy systems and strengthening integrated energy management, while Port Harcourt may benefit from targeted infrastructure improvements and institutional coordination. In Kano and Ibadan, greater emphasis may be required on foundational energy infrastructure, affordable technologies, technical capacity development, and supportive regulatory mechanisms. Such differentiated interventions could strengthen smart-energy adoption, improve implementation readiness, and contribute to more inclusive and sustainable urban energy transitions (Albino et al. 2015; Höjer and Wangel 2015).

## Discussion

### Adoption of smart energy technologies (AST)

The findings on the AST in Nigerian urban centres (research objective 1) provide important insights when interpreted through theoretical, socio-technical, and com-

parative lenses. Overall, the relatively high adoption rate (67.8%), coupled with the strong performance of widely used technologies such as smart meters, suggests that adoption is no longer nascent but is gaining meaningful traction across urban contexts. From a theoretical perspective, the high mean scores (approaching 4.0) for commonly adopted technologies indicate that users recognise clear functional benefits, particularly in improving energy reliability and efficiency. This is consistent with prior studies that demonstrate how perceived value significantly shapes user acceptance in energy systems (Al-Emran 2023; Edomah 2021). Furthermore, the moderate level of actual usage (Mean = 3.29) suggests that adoption extends beyond awareness or symbolic acceptance to practical utilisation. This finding reinforces behavioural theories such as the Theory of Planned Behaviour, which posit that behavioural intention shaped by attitudes and perceived control translates into real-world actions (Agboola and Alsharif 2026).

However, the uneven adoption pattern, particularly the limited uptake of advanced technologies such as integrated EMS and smart grid infrastructure, highlights the limitations of purely perception-based models. In this regard, the findings resonate with socio-technical transition perspectives, particularly the Multi-Level Perspective, which emphasises that technological change is shaped by interactions between users, institutions, infrastructure, and broader socio-economic conditions. The persistence of barriers such as cost, infrastructure deficits, and limited technical capacity suggests that adoption is not solely determined by perceived benefits but also by systemic constraints. This supports a more holistic understanding in which enabling and constraining factors jointly influence adoption outcomes. From a socio-technical standpoint, the results point to an ongoing transition characterised by increasing reliance on decentralised and hybrid energy systems. The notable proportion of users adopting multiple technologies (30.3%) reflects a shift away from dependence on a single energy source toward more diversified and resilient energy configurations. This pattern is consistent with the concept of "bottom-up innovation" in socio-technical systems, where users actively adapt to infrastructural deficiencies by integrating alternative solutions (Geels 2002; Edomah 2021; Mariscal et al. 2026). In the Nigerian context, where grid electricity remains unreliable, such adaptive behaviour underscores the agency of users in shaping energy transitions. Nevertheless, the relatively recent adoption levels (Mean = 2.37) indicate that this transition is still emerging. The limited penetration of advanced systems further suggests that while user demand exists, the supporting ecosystem comprising infrastructure, policy frameworks, and technical expertise remains underdeveloped.

In comparison with global studies, the findings exhibit both convergence and divergence. The growing adoption of digital monitoring energy systems aligns with trends observed across developing regions, where unreliable grid infrastructure drives the uptake of off-grid and hybrid systems. For instance, reports by the International Energy Agency (2021) highlight similar patterns in Sub-Saharan Africa and South Asia, where decentralised energy solutions are increasingly used to bridge supply gaps. However, the Nigerian case contrasts with developed economies, where adoption is characterised by widespread integration of advanced smart technologies, including automated EMS and fully developed smart grids. Studies from OECD countries, such as those by the Organisation for Economic Co-operation and Devel-

opment, show that strong institutional frameworks, advanced infrastructure, and supportive policies facilitate deeper technological integration (OECD and European Commission, Joint Research Centre 2008).

The relatively low adoption of such advanced systems in this study, therefore, reflects a persistent technological and infrastructural gap between developed and developing contexts. Additionally, while moderate usage levels in Nigeria indicate growing engagement, they remain below the levels observed in highly digitised energy systems, where smart technologies are seamlessly embedded into everyday operations. This suggests that adoption in Nigerian cities is currently more functional, focused on addressing immediate energy needs rather than systemic, where technologies are fully integrated into interconnected and intelligent energy networks. Overall, the discussion highlights that while smart energy adoption in Nigeria is progressing and supported by strong user acceptance, it remains constrained by broader socio-technical and institutional factors. Bridging this gap will require not only sustained user engagement but also significant improvements in infrastructure, policy support, and system integration to enable a transition from basic adoption to advanced, fully integrated smart energy systems.

### Perceived benefits of adoption of smart technologies (AST)

The findings for research objective 2 indicate that stakeholders perceive AST as highly beneficial, particularly in improving energy efficiency, enhancing reliability, and supporting environmental sustainability. These positive perceptions are evident in the high mean scores and relatively low variability across responses, suggesting a strong and consistent recognition of value among users. Such outcomes highlight the growing acceptance of smart energy solutions within urban Nigeria and underscore their perceived relevance in addressing persistent energy challenges.

From a theoretical standpoint, these results align closely with established adoption frameworks that emphasise perceived usefulness and expectancy as key determinants of technology acceptance (Al-Emran 2023; Mariscal et al. 2026). In this study, stakeholders' strong recognition of benefits such as reduced energy wastage, improved efficiency, and enhanced supply reliability directly reflects perceived usefulness, reinforcing its central role in shaping adoption behaviour. This is further supported by behavioural insights from the Theory of Planned Behaviour, which suggests that individuals are more inclined to adopt technologies that increase their control over outcomes (Ajzen 1991). The ability of smart technologies to enable demand-side management and optimise energy use illustrates this sense of control.

At the same time, the relatively consistent perceptions across stakeholder groups strengthen the robustness of the PB construct within the structural model. However, the slightly higher variation in responses related to cost highlights the continued importance of economic considerations. This suggests that while users broadly acknowledge the benefits, financial constraints may moderate how these perceptions translate into actual adoption, thereby supporting the inclusion of barriers as a countervailing factor in the overall model. From a socio-technical perspective, the findings point to an ongoing transition in urban energy systems, where technological innovation is closely intertwined with social needs and institutional contexts. The

emphasis on efficiency and reliability indicates that AST are not merely technical upgrades but practical solutions embedded in everyday energy use. In a context characterised by unstable grid supply, the perceived reliability benefits are particularly significant, as users adopt these technologies to mitigate service disruptions. This reflects bottom-up adaptation processes within socio-technical systems, as described in the Multi-Level Perspective (Geels 2002).

Moreover, the recognition of environmental benefits suggests an emerging awareness of sustainability concerns among stakeholders. This is important for long-term transitions, as positive environmental perceptions can shape behavioural change, strengthen public support for clean energy policies, and encourage broader societal engagement with sustainability goals. However, the variation in cost perceptions also reveals the influence of socio-economic disparities. While many stakeholders recognise the long-term benefits of AST, particularly improved efficiency, reliability, and environmental performance, high upfront costs, installation expenses, and limited access to affordable financing may restrict adoption among lower-income households and small businesses. Consequently, perceived benefits do not automatically translate into equitable adoption. Without targeted subsidies, flexible financing mechanisms, and inclusive implementation strategies, smart-energy transitions may primarily benefit higher-income users and potentially reinforce existing energy inequalities. Ensuring affordability and accessibility is therefore essential for achieving an inclusive and socially just energy transition.

In comparison with global evidence, the findings are broadly consistent with trends reported by the International Energy Agency (2023), which show that users across both developed and developing regions are more likely to AST when clear efficiency, reliability, and environmental benefits are evident. Similarly, research from the Organisation for Economic Co-operation and Development (OECD 2020) highlights that in developed economies, these perceived benefits are reinforced by advanced infrastructure, integrated smart grid systems, and supportive policy environments. However, a key distinction emerges in the Nigerian context: while stakeholder perceptions are comparably positive, the actual deployment of advanced systems remains limited.

This gap between perception and implementation reflects broader structural challenges, including infrastructural deficits, regulatory inconsistencies, and financial constraints. The observed variability in cost-related perceptions is also consistent with findings from other developing regions, where affordability and access to financing play a decisive role in shaping adoption decisions (IEA, 2022; OECD 2020). Consequently, the results suggest that although positive perceptions are a necessary condition for adoption, they are not sufficient on their own. Realising the full potential of AST requires complementary investments in infrastructure, supportive policy frameworks, and inclusive financing mechanisms. Overall, the discussion demonstrates that perceived benefits are a critical driver of smart energy adoption in urban Nigeria, reinforcing theoretical expectations and aligning with global trends. However, translating these positive perceptions into widespread and sustained adoption will depend on addressing the broader socio-economic and institutional conditions that shape access, affordability, and system integration.

### Discussion of barriers to adoption of smart technologies (AST)

The findings in relation to research objective 2 are consistent with previous research showing that smart-energy transitions are constrained by interconnected economic, infrastructural, technical, and institutional barriers. Studies of smart-grid implementation similarly identify financing limitations, regulatory uncertainty, knowledge gaps, and institutional weaknesses as major constraints on technology deployment. The present study extends this evidence by demonstrating the severity and structural consequences of these barriers in Nigerian urban contexts. In particular, inadequate infrastructure (M = 4.35), weak policy and regulatory frameworks (M = 4.02), and high implementation costs (M = 3.96) emerged as the most prominent barriers. These findings are consistent with research identifying financial, regulatory, market, and infrastructure constraints as major obstacles to sustainable energy development in developing countries. Limited technical expertise (M = 3.74) and institutional fragmentation (M = 3.52) further demonstrate that smart-energy adoption requires not only technological investment but also appropriate human and organisational capacity.

Importantly, the negative relationship between BR and SO ($\beta = -0.29$) provides empirical evidence that increasing implementation constraints are associated with poorer sustainability performance. This extends previous studies that primarily identify barriers descriptively by demonstrating their direct structural effect on sustainability outcomes. The result suggests that infrastructure deficiencies, high costs, weak regulation, and limited technical capacity can prevent adopted technologies from delivering their expected benefits. More importantly, the significant AST × BR interaction ($\beta = -0.168$, $t = 2.74$, $p = 0.006$) demonstrates that barriers weaken the positive relationship between smart-technology adoption and sustainability outcomes. Thus, technology adoption alone does not guarantee improved sustainability. Where infrastructure is unreliable, financing is inadequate, regulations are weak, and technical expertise is limited, the contribution of smart technologies is substantially reduced. This finding advances existing literature by showing that barriers do not merely restrict adoption; they condition the effectiveness of adoption after implementation.

The findings demonstrate that smart-energy adoption in Nigerian urban centres is constrained by interconnected economic, institutional, infrastructural, technical, and socio-cognitive barriers. High implementation costs, inadequate infrastructure, weak regulatory frameworks, limited technical expertise, and institutional fragmentation indicate that adoption depends not only on perceived benefits but also on the conditions supporting implementation. This interpretation is consistent with the Technology Acceptance Model, which recognises the role of external facilitating conditions in translating perceived usefulness into actual use (Al-Emran 2023), and UTAUT, which emphasises financial, technical, and infrastructural support as important facilitating conditions (Mariscal et al. 2026).

The findings also support Diffusion of Innovation Theory, particularly its emphasis on relative advantage, complexity, and compatibility. High upfront costs can reduce the perceived relative advantage of AST especially for lower-income users, while policy uncertainty and weak regulation can discourage investment and slow diffusion. Similarly, evidence from developing economies identifies inadequate

infrastructure and financing as persistent constraints on smart and renewable-energy adoption (IEA, 2022). In contrast, stronger institutional frameworks, incentives, subsidies, and financing mechanisms have supported wider adoption in many developed economies (OECD 2020). The infrastructure challenges identified, particularly unreliable electricity networks and limited digital connectivity, are consistent with broader Sub-Saharan African evidence (IEA, 2022). However, the strong respondent agreement suggests that these barriers are interconnected and require integrated rather than isolated interventions. Infrastructure investment, affordable financing, regulatory reform, institutional coordination, technical training, and stakeholder awareness should therefore be pursued simultaneously.

These findings have direct implications for the Sustainable Development Goals. Addressing affordability, reliability, and efficiency supports SDG 7 (Affordable and Clean Energy); strengthening digital and energy infrastructure advances SDG 9 (Industry, Innovation and Infrastructure); integrating smart-energy systems into resilient urban development contributes to SDG 11 (Sustainable Cities and Communities); and improving energy efficiency and renewable-energy integration supports SDG 13 (Climate Action) (United Nations, 2015). Thus, overcoming Nigeria's smart-energy barriers is essential not only for technological adoption but also for achieving broader sustainable urban-development and climate objectives.

### SEM results of the interrelationships between AST and SO

The results in connection with research objective 4, demonstrate a positive and substantial relationship between Adoption of Smart Technologies (AST) and Sustainability Outcomes (SO) ($\beta = 0.41$, $p < 0.05$), indicating that greater AST is associated with improved energy efficiency, environmental performance, system reliability, and urban resilience. Smart meters, intelligent monitoring, automated controls, renewable-energy systems, and data-driven energy management can improve demand management, reduce inefficiencies, and enhance the responsiveness of urban energy systems. This finding is consistent with the International Energy Agency (2023), which identifies digitalisation as an important enabler of energy efficiency, system flexibility, demand management, and renewable-energy integration. It also supports Agboola (2024) and Baby et al. (2026), who highlight the potential of AI, IoT, and intelligent technologies to improve resource efficiency and urban sustainability.

Beyond immediate benefits, AST can strengthen long-term urban resilience by improving cities' capacity to respond to climate-related disruptions, population growth, and increasing energy demand. Renewable and decentralised systems can reduce dependence on centralised grids, while real-time monitoring and automated controls can support rapid responses to energy disruptions. However, these benefits depend on reliable infrastructure, financing, technical capacity, and supportive governance. Therefore, smart-energy adoption should be integrated into climate-responsive buildings, resilient neighbourhoods, infrastructure upgrading, and long-term urban planning to support adaptive, reliable, and sustainable Nigerian cities.

The positive AST–SO relationship can further be interpreted through Diffusion of Innovation Theory, particularly the principle of relative advantage (Rogers 2003). When stakeholders recognise tangible improvements in efficiency, reliability,

environmental performance, and energy management, smart technologies become more attractive for adoption. The present study extends previous research by providing empirical evidence that this adoption is positively associated with sustainability outcomes in Nigerian urban contexts. However, the findings also demonstrate that technological adoption is dependent on the wider socio-technical environment. Nigerian cities continue to face infrastructure deficiencies, high investment costs, limited technical expertise, regulatory weaknesses, and institutional fragmentation. These challenges are consistent with the IEA (2022), which identifies inadequate infrastructure, financing constraints, and weak enabling environments as persistent barriers to energy-transition technologies in developing economies. Importantly, the significant negative moderation effect of AST × BR on SO ($\beta = -0.168$, $p = 0.006$) demonstrates that these barriers weaken the sustainability benefits of technology adoption. Thus, adoption alone does not guarantee improved outcomes; appropriate institutional, financial, infrastructural, and technical conditions are required to realise its full potential.

The findings are further supported by Agboola et al. (2023); Agboola et al. (2024); and Alabdali et al. (2023), who emphasise coordinated planning, professional capacity, and institutional support in developing climate-responsive and sustainable built environments. From an architectural and urban-planning perspective, AST should therefore be incorporated from the earliest stages of design. Intelligent building-management systems, smart meters, renewable-energy technologies, and automated controls should complement passive strategies such as appropriate orientation, shading, daylight optimisation, natural ventilation, and climate-responsive envelopes. Such integration can reduce energy demand while improving occupant comfort, operational efficiency, and environmental performance. Consequently, the study confirms that smart technologies can accelerate sustainable urban transformation, but their benefits depend on the infrastructure, policies, financing, skills, and institutional capacity available to support their implementation.

At the neighbourhood and city scales, the findings have direct implications for SDG 7 (Affordable and Clean Energy) through improved energy efficiency, reliability, access, and the integration of renewable and AST (United Nations, 2015; Fayiah and Kallon 2025). They also contribute to SDG 9 (Industry, Innovation and Infrastructure) by demonstrating the importance of digital energy infrastructure, grid modernisation, and technological innovation in strengthening urban energy systems. Furthermore, the findings support SDG 11 (Sustainable Cities and Communities), as smart-energy systems can enhance the efficiency, resilience, and sustainability of rapidly urbanising Nigerian cities when integrated with broader urban planning and infrastructure strategies (United Nations, 2015; UN-Habitat 2022; Edomah 2021). The positive relationship between smart-technology adoption and sustainability outcomes also contributes to SDG 13 (Climate Action) by supporting more efficient energy consumption, renewable-energy integration, and potentially lower carbon emissions (IPCC, 2022).

Overall, the findings extend previous research by demonstrating a significant positive effect of AST on SO ($\beta = 0.41$), while the significant negative moderation effect of barriers indicates that this contribution is conditional on the implementation context. This suggests that smart technologies alone cannot guarantee sustainable

outcomes. Consistent with the socio-technical perspective of sustainable transitions (Geels 2002), Nigerian cities require an integrated approach combining smart technologies, sustainable architectural design, resilient infrastructure, supportive governance, appropriate financing, technical capacity, and stakeholder participation. Such an approach can help translate technological innovation into tangible progress towards SDGs 7, 9, 11, and 13, while supporting a more inclusive and resilient urban energy transition.

### Discussion on the comparative analysis across case studies

The comparative findings demonstrate that smart-energy adoption and sustainability performance are strongly context-dependent, varying with infrastructure readiness, policy support, and adoption capacity across the five Nigerian cities. Lagos records the highest relative performance, supported by relatively high infrastructure readiness, strong policy support, and high adoption. Abuja also demonstrates high performance, although its results appear more closely associated with institutional and policy capacity. Port Harcourt occupies an intermediate position, whereas Kano and Ibadan record comparatively lower levels across the assessed dimensions. These patterns support previous research showing that smart-city and energy transitions are embedded within specific socio-technical, institutional, and infrastructural contexts rather than following uniform trajectories (Joss and Molella 2013; Geels 2002; Agboola & Ahmadnia, 2025).

Lagos's strong performance may be associated with its relatively developed infrastructure, substantial economic base, and strong market demand, which create favourable conditions for smart-energy investment. Abuja, in contrast, highlights the importance of institutional and policy capacity, suggesting that effective governance can facilitate technology implementation. This interpretation is consistent with socio-technical transition theory, which emphasises interactions among technological systems, institutions, and socio-economic conditions (Geels 2002). Previous studies similarly identify regulatory stability, institutional coordination, and policy support as important conditions for urban technology adoption (Giwah et al. 2020). Thus, infrastructure and policy support should be regarded as complementary enabling conditions.

Port Harcourt's moderate performance provides further evidence of this relationship. Its moderate infrastructure readiness, policy support, and adoption correspond with moderate relative performance, suggesting that partial system readiness may produce partial sustainability benefits. This supports evidence that smart-urban technologies are more effective where technological infrastructure, institutional capacity, and supportive governance develop simultaneously (Tan and Taeihagh 2020). Incremental strategies that strengthen these dimensions together may therefore be appropriate for transitional cities. The lower performance observed in Kano and Ibadan further illustrates the consequences of weaker enabling conditions. Their relatively limited infrastructure, policy support, and adoption are associated with lower overall performance, consistent with research identifying infrastructural deficiencies, institutional weaknesses, and limited implementation capacity as major constraints in developing urban contexts (Tan and Taeihagh 2020; Agboola and AhmadNia 2025).

The cross-city findings also reinforce the PLS-SEM results concerning PB and BR. The positive relationship between PB and SO indicates that recognising benefits such as efficiency, reliability, cost savings, and environmental performance can support favourable outcomes, consistent with technology-acceptance research (Al-Emran 2023; Mariscal et al. 2026). Conversely, the negative relationship between BR and SO ($\beta = -0.29$) and the significant negative AST × BR → SO interaction indicate that infrastructure deficiencies, high costs, weak policies, limited technical expertise, and institutional fragmentation can reduce the sustainability benefits of smart-energy adoption. The findings confirm that technological adoption must be accompanied by supportive infrastructure, effective governance, adequate financing, and institutional capacity to achieve meaningful and equitable urban sustainability outcomes.

Overall, the comparative analysis extends previous research by demonstrating that smart-energy performance in Nigerian cities reflects the combined influence of infrastructure readiness, policy support, adoption capacity, perceived benefits, and contextual barriers. Lagos and Abuja illustrate the advantages of relatively stronger enabling environments; Port Harcourt demonstrates the outcomes associated with moderate system readiness, while Kano and Ibadan highlight the consequences of persistent structural constraints. The findings therefore support a context-sensitive and integrated urban energy-transition approach, in which investment in digital and physical infrastructure is accompanied by effective governance, capacity building, financial support, and stakeholder engagement. Such an approach is more likely to translate smart-energy adoption into measurable improvements in sustainability, resilience, and long-term urban development.

## Conclusions and key contributions

This study examined the AST and their implications for urban sustainability across selected Nigerian cities. The findings demonstrate that smart technologies can improve energy efficiency, environmental performance, reliability, and urban resilience, but their effectiveness depends on the economic, infrastructural, institutional, and policy conditions within which they are implemented. A major contribution is the empirical validation of an integrated socio-technical framework linking AST, PB, BR, and SO through direct, mediating, and moderating relationships.

The first objective examined smart-energy adoption across Nigerian urban centres. Adoption is increasing but remains uneven. Smart meters demonstrate relatively higher uptake, whereas integrated energy-management systems, smart grids, and other advanced intelligent building technologies remain less widespread. This variation reflects differences in affordability, infrastructure readiness, technical capacity, institutional support, and market maturity. The findings suggest that AST should be integrated into buildings, neighbourhoods, infrastructure networks, and wider urban-development strategies rather than treated as isolated technological solutions. For architecture and urban planning, this requires incorporating renewable-energy systems, intelligent controls, and energy-monitoring technologies from the early design stage to support efficient buildings, resilient infrastructure, and climate-responsive urban development.

The second objective investigated perceived benefits. Stakeholders reported positive perceptions of energy efficiency, reliability, environmental sustainability, monitoring, cost management, and resilience. The positive influence of PB on SO confirms the importance of perceived usefulness in technology acceptance and utilisation. However, perceived benefits alone cannot ensure equitable adoption because affordability, infrastructure, financing, technical support, and institutional capacity remain important. User-centred design should therefore integrate smart systems with passive strategies such as appropriate orientation, shading, daylight optimisation, and natural ventilation to improve efficiency, comfort, and sustainability.

The third objective examined adoption barriers. Inadequate infrastructure was the most prominent barrier (M = 4.35), followed by high implementation costs, weak policy and regulatory frameworks, limited technical expertise, and institutional fragmentation. The negative relationship between BR and SO ($\beta = -0.29$) confirms that increasing barriers are associated with poorer sustainability outcomes. Moreover, the significant negative moderation effect of AST × BR ($\beta = -0.168$, $p = 0.006$) demonstrates that barriers weaken the positive contribution of smart-technology adoption. Thus, technology adoption alone cannot guarantee sustainability; supportive infrastructure, financing, regulation, technical capacity, and institutional coordination are essential. In Kano and Ibadan, priority should therefore be given to foundational infrastructure and institutional strengthening, whereas Lagos and Abuja offer stronger conditions for scaling advanced solutions.

The fourth objective examined the determinants of sustainability outcomes. The PLS-SEM results confirm a positive relationship between AST and SO ($\beta = 0.41$, $p < 0.05$), demonstrating that greater smart-technology adoption is associated with improved sustainability performance. The findings further show that perceived benefits and implementation barriers provide important explanatory mechanisms within this relationship.

Methodologically, the study contributes by moving beyond a simple adoption–outcome model and demonstrating the value of an integrated PLS-SEM framework incorporating direct, mediating, and moderating mechanisms. The study establishes that AST can support sustainable urban transformation in Nigeria, but their benefits will be maximised only through context-sensitive planning, inclusive financing, reliable infrastructure, supportive governance, and coordinated institutional action.

The comparative analysis reveals substantial spatial variation across the five cities. Lagos and Abuja demonstrate the strongest overall performance, supported by relatively stronger infrastructure, policy support, institutional capacity, and market conditions. Port Harcourt represents a moderate or transitional context, while Kano and Ibadan show comparatively lower readiness and adoption. These differences have important implications for SDG 7 (Affordable and Clean Energy) and SDG 11 (Sustainable Cities and Communities), which emphasise accessible energy and sustainable urban development (United Nations, 2015; IEA, 2023). Rather than applying a uniform national strategy, interventions should reflect local conditions. Lagos and Abuja could serve as demonstration and scaling centres, whereas Kano and Ibadan require greater investment in infrastructure, affordability, institutional capacity, and technical skills.

The findings also support SDG 9 (Industry, Innovation and Infrastructure) through the integration of smart technologies and resilient digital and physical infrastructure, while improved energy efficiency and renewable-energy integration contribute to SDG 13 (Climate Action) by supporting reduced energy consumption and emissions (United Nations, 2015; IEA, 2023). The positive relationship between AST and SO ($\beta = 0.41$) confirms the contribution of smart technologies to sustainable urban transformation. However, the significant negative moderation effect (AST × BR → SO: $\beta = -0.168$, $p = 0.006$) shows that infrastructure, financial, policy, and technical barriers weaken this contribution.

Overall, the findings contribute theoretically by integrating technology-adoption and socio-technical perspectives, empirically through comparative evidence from five Nigerian cities, and practically by demonstrating the need for coordinated interventions in architecture, urban planning, infrastructure, financing, governance, and technical capacity. Smart technologies can advance SDGs 7, 9, 11, and 13, but their transformative potential depends on reliable infrastructure, affordable financing, supportive policies, technical expertise, and context-sensitive urban planning.

## Policy and practical implications for urban energy systems and planning in Nigeria

The policy recommendations are derived directly from the empirical findings, particularly the high perceived barriers to smart-energy adoption, the positive effect of technology adoption on sustainability outcomes ($\beta = 0.41$), the negative effect of barriers on sustainability outcomes ($\beta = -0.29$), and the significant moderating effect of barriers on the AST–SO relationship ($\beta = -0.168$, $p = 0.006$). The recommendations are therefore prioritised according to the principal constraints identified in the study and differentiated according to urban context and stakeholder responsibility.

### Priorities for policymakers and government agencies

- First priority vis-a-vis affordability barriers: The highest-rated barrier was inadequate infrastructure (Mean = 4.35). Federal and state governments should therefore prioritise targeted financing mechanisms, including concessional loans, consumer financing, tax incentives and carefully targeted subsidies for smart meters, energy-monitoring systems and other appropriate technologies. Such measures should particularly target low- and middle-income households and SMEs to prevent smart-energy adoption from widening existing energy inequalities.
- Second priority vis-à-vis strengthening policy and regulatory coordination: The relatively high score for weak policy and regulatory frameworks (Mean = 4.02) indicates the need for clearer regulations, stable investment rules and coordinated institutional responsibilities. These interventions should be aligned with Nigeria's Energy Transition Plan (ETP), which prioritises improved energy access, renewable-energy deployment, smart metering, resilient power infrastructure and a just transition toward net-zero emissions by 2060. The recommendations are

also consistent with the objectives of Nigeria's Medium-Term National Development Plan, which identifies transmission and distribution improvements, renewable energy, mini-grids, regulatory support and improved energy-sector governance as important priorities.

- Third priority vis-a-vis institutionalising implementation mechanisms: A dedicated inter-agency smart-energy implementation mechanism should coordinate energy regulators, utilities, state governments, ICT agencies, financial institutions and local authorities. Clear responsibilities, implementation timelines, monitoring indicators and annual performance reviews should accompany the policy framework.

### City-specific strategies

The comparative results indicate that a single national implementation model would be inappropriate.

- Lagos: Given its relatively high infrastructure readiness and adoption level, Lagos should function as a scaling and demonstration environment for advanced smart metering, digital energy monitoring, demand management and building-level energy-management systems.
- Abuja: Given its relatively strong policy and institutional environment, Abuja should prioritise policy-led demonstration projects, integrated public-building energy management and coordinated smart-energy planning.
- Port Harcourt: As a moderate/transitional case, investment should focus on strengthening infrastructure and institutional capacity simultaneously, particularly through decentralised energy systems for commercial and industrial users.
- Kano: Given its low–moderate infrastructure and policy readiness, initial intervention should prioritise basic infrastructure upgrading, affordable smart metering and technical training before introducing more complex systems.
- Ibadan: Given its low infrastructure readiness, policy support and adoption level, interventions should begin with foundational infrastructure, affordable decentralised energy, institutional strengthening and awareness programmes rather than expensive advanced smart-city technologies.

This differentiated approach is consistent with the study's finding that infrastructure and policy conditions vary considerably among Nigerian cities.

### Strategies for scaling adoption of smart energy technologies

- The relatively strong adoption of basic technologies such as smart meters and energy-monitoring systems provides a practical foundation for progressive technological scaling. Rather than attempting immediate deployment of complex integrated smart grids, cities with lower readiness should adopt a phased pathway: basic smart meters and distributed renewable energy → digital monitoring → automated demand management → integrated smart-energy systems.

- High-performing cities such as Lagos and Abuja can provide demonstration models, but their approaches should be adapted rather than directly replicated in Kano, Ibadan and other lower-readiness cities. The national ETP already identifies smart metering, transmission and distribution improvements, renewable energy and resilient power systems as important components of the country's energy-transition pathway.

### Investment, infrastructure and private-sector participation

- The infrastructure barrier (Mean = 4.35) and implementation-cost barrier (Mean = 3.96) indicate that technological deployment cannot be separated from investment in enabling infrastructure. Priority investment should therefore target grid modernisation, distribution networks, digital connectivity, smart metering and decentralised renewable-energy infrastructure.
- Private-sector participation should be encouraged through predictable regulations, transparent procurement, risk-sharing mechanisms, green-finance instruments and public–private partnerships. This is particularly relevant because Nigeria's ETP identifies substantial financing requirements and explicitly recognises private-sector participation as important to closing the energy-transition investment gap.

### Recommendations for utilities and energy providers

- Energy providers should prioritise smart-meter deployment, digital monitoring, loss reduction and demand-side management. Utilities should establish interoperable digital platforms that allow energy consumption to be monitored in real time and used for improved load management. In low-readiness cities, utilities should initially concentrate on improving reliability and metering coverage before introducing more sophisticated automated systems.

### Recommendations for households and commercial users

- Households and commercial users should be supported to adopt affordable technologies through consumer financing, pay-as-you-go models, energy audits and awareness programmes. Given that household respondents in this study provided feedback on the broader energy system rather than representing only a residential perspective, engagement should focus on users as active participants in the wider energy transition. Demonstrating measurable benefits such as reduced energy expenditure, improved reliability and better energy management can strengthen acceptance and continued utilisation.

### Technical capacity and awareness

- Limited technical expertise (Mean = 3.74) should be addressed through certified training programmes for installers, architects, engineers, facility managers and energy professionals. Universities, professional bodies, utilities and technology providers should collaborate on training and continuing professional development. Public awareness programmes should communicate not only the environmental benefits but also the financial, reliability and efficiency benefits of AST.

### Implementation prioritisation

Given Nigeria's resource constraints, implementation should follow a three-stage priority framework:

- Immediate: reduce affordability barriers, strengthen regulation, improve awareness and expand basic smart metering and decentralised renewable energy.
- Medium term: modernise distribution infrastructure, develop technical capacity, expand digital monitoring and establish city-level demonstration projects.
- Long term: integrate smart grids, automated demand management, energy storage, renewable-energy integration and resilient urban-energy systems.

This sequencing is important because the study's moderation result demonstrates that high barriers weaken the sustainability benefits of technology adoption. Consequently, investment in smart technologies without simultaneous investment in infrastructure, financing, institutional capacity and technical skills may produce limited sustainability gains.

## Limitations of the study and suggestions for future research

- This study provides important insights into the adoption and impact of AST in urban Nigeria; however, several limitations should be acknowledged. First, the study is largely based on cross-sectional data, which limits the ability to capture dynamic changes in technology adoption and sustainability outcomes over time. Given that smart energy systems are evolving rapidly, longitudinal studies would provide a more robust understanding of how adoption patterns, user perceptions, and system performance develop. Second, the reliance on self-reported data may introduce response bias, particularly in assessing perceived benefits, barriers, and sustainability outcomes. Future studies could incorporate objective performance data, such as energy consumption records or system efficiency metrics, to strengthen validity.
- While the study captures key urban centres, variations in infrastructure readiness, socio-economic conditions, and governance structures across cities may limit the generalisability of the findings to all contexts in Nigeria or other develop-

ing countries. The observed differences in affordability, policy environments, and technical capacity suggest that localised factors play a significant role, which may not be fully captured in the current model. Furthermore, although the model explains a substantial proportion of variance in sustainability outcomes, other potentially relevant factors such as behavioural dynamics, private sector innovation, and informal energy systems were not explicitly included.

- Given these constraints, to improve generalizability and distinguish context-specific versus universal adoption determinants, future research should concentrate on study comparisons across different geographic areas or nations. Future work could further explore advanced smart technologies and their integration into decentralised energy systems, particularly in relation to grid modernisation and digital infrastructure. Moreover, in-depth investigations into financing mechanisms, policy interventions, and capacity-building strategies would be valuable, especially in addressing affordability and technical gaps. Finally, future studies should consider developing more comprehensive models that incorporate additional socio-economic, institutional, and technological variables to better reflect the complexity of sustainable urban energy transitions.

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## Declarations

**Ethical approval** Ethical approval was waived for the study. It was a non-interventional online survey with anonymous and voluntary participation, collecting no sensitive or identifying information, in accordance with institutional and national regulations.

**Consent to participate** Informed consent was obtained from all individual participants included in the study.

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