MULTIDIMENSIONAL DIGITAL TRUST AS A DRIVER OF USER ADOPTION IN SMART ENERGY SERVICES SUSTAINABILITY

ÎNCREDEREA DIGITALĂ MULTIDIMENSIONALĂ CA FACTOR DETERMINANT AL ADOPTĂRII UTILIZATORILOR ÎN SUSTENABILITATEA SERVICIILOR ENERGETICE INTELIGENTE

Soufyane BOUALI[1], Oklander MYKHAILO[2], Selma DOUHA[3]

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Abstract: *This study presents a multidimensional view of digital trust in smart energy services that includes aspects such as reliability, data integrity, privacy, security, transparency, usability, explainability, and user empowerment. Using empirical data from 12345 respondents, the study proves that trust is an important mediator between them and adoption intentions. It also updates existing models like TAM and UTAUT by providing a novel integration of digital trust dimensions with adoption behaviors. Results will give practical guidance to energy providers and policymakers for better user engagement to fast-track the shift toward sustainable user-centered smart energy systems.*

Keywords: Digital trust, Smart energy services, Adoption intention, Technology Acceptance Model, Energy sector innovation.

Rezumat: *Acest studiu prezintă o perspectivă multidimensională asupra încrederii digitale în serviciile energetice inteligente, incluzând aspecte precum fiabilitatea, integritatea datelor, confidențialitatea, securitatea, transparența, ușurința în utilizare, explicabilitatea și împuternicirea utilizatorilor. Pe baza datelor empirice provenite de la 12.345 de respondenți, rezultatele*

[1] Prof., Dept of Commerce, Ferhat Abbas Universit Setif 1, Algeria, e-mail: soufiane.bouali@univ-setif.dz, *ORCID ID: 0000-0002-2621-8329*
[2] Prof., Dept of Marketing, Odesa Polytechnic National University, Ukraine, e-mail: imt@te.net.ua, *ORCID ID: 0000-0002-1268-6009*
[3] Prof., Dept of Commerce, University of Batna 1, Algeria, e-mail: selma.douha@univ-batna.dz, *ORCID ID: 0000-0001-5231-9636*

demonstrează că încrederea digitală acționează ca un mediator important între caracteristicile sistemelor și intențiile de adoptare ale utilizatorilor. Studiul actualizează, de asemenea, modele existente precum TAM și UTAUT, prin integrarea unor dimensiuni extinse ale încrederii digitale cu comportamentele de adoptare. Concluziile oferă recomandări practice pentru furnizorii de energie și factorii de decizie, facilitând o implicare mai bună a utilizatorilor și accelerând tranziția către sisteme energetice inteligente durabile, centrate pe utilizator.

Cuvinte cheie: Încredere digitală, Servicii energetice inteligente, Intenția de adoptare, Modelul de Acceptare a Tehnologiei, Inovație în sectorul energetic.

1. Introduction

Digital innovations are dramatically transforming the energy sector by pushing it toward two main goals: decarbonization and democratization. Decarbonization means cutting down carbon emissions by using cleaner, renewable energy sources and enhancing energy efficiency. Meanwhile, democratization involves giving more users the power to take part in producing, managing, and consuming energy. This changing environment is giving rise to new energy services that aim to involve users in a more active and dynamic role within energy systems. These smart energy services allow users not just to consume energy but also to produce it—often using solar panels or other renewable sources—store it efficiently through batteries or other technologies, trade energy in decentralized markets, and adjust their consumption flexibly based on real-time data and incentives.

These smart energy services are a combination of different elements: physical devices like smart meters, sensors, and energy storage hardware; digital platforms that offer interfaces for monitoring, controlling, and trading energy; and other services such as data analytics, customer support, and financial mechanisms that make everything work well together and easy for users. Even though they have great potential to change how energy is managed and consumed, the adoption of these smart energy services on a large scale is still limited [1]. This limited uptake signals the need for deeper exploration into the factors that influence users' acceptance and willingness to engage with these technologies [2]. One key factor influencing adoption is digital trust. Digital trust refers to the confidence users place in digital technologies and platforms to work reliably, securely, and transparently [3].

This trust helps create positive trust beliefs that lower perceived risks associated with technology use—like fears of privacy breaches, misuse of data, or system failures[4]. Many elements shape whether users will develop this trust: perceived security of technology; transparency about data practices; usability; and reputation of service providers. Current studies increasingly focus on smart energy services to identify core constructs that define digital trust in this context[5]. These efforts theorize how these constructs together promote acceptance by users as well as continued engagement with smart energy technologies[6].

Yet, even though this area has been gaining attention, there is still a major gap in research on fully understanding what exactly affects digital trust in smart energy services and how these factors directly impact adoption behaviors [7]. Current studies usually talk about digital trust in wider technology situations and do not go into detail about the special challenges of smart energy systems that combine physical, digital, and social parts. Additionally, empirical evidence about the interaction of digital trust with other behavioral and contextual factors in this sector is limited. This prevents designing targeted interventions and strategies to effectively build trust and encourage widespread adoption.

Filling this research gap is crucial since it relates to understanding how digital trust impacts adoption theoretically, thus enriching academic knowledge regarding the role of trust in the diffusion of innovative digital services within critical sectors like energy. It also has practical significance by informing how smart energy services are designed and implemented based on user concerns to enhance trust and speed up the energy transition. Service providers, policymakers, and technology developers can enable higher levels of digital trust to realize the complete capacity of digital innovations for a more sustainable, user-centered, and decarbonized energy future.

2. Literature Review

2.1. Conceptual foundations of digital trust

Digital technologies and data-driven applications are increasingly reshaping energy systems and services by enabling new forms of interactions and real-time functionalities. Smart meters, sensors, and connected devices now create an environment for remote continuous monitoring of energy consumption and bi-directional information exchange between consumers and grid operators[8]. The data generated from these devices provide insights into consumption patterns, price forecasts, or incentives for demand response or energy flexibility programs. These digital services empower users to take part in an energy flexibility project that contributes to the stability of the grid in return for financial or non-financial benefits.

These technological systems are not evolving at the same pace as user participation in digital energy programs[9]. The European Union has reported that only about 35% of its citizens use smart meters actively even though they have been deployed widely [10]. This proves that technical availability does not ensure user adoption; psychological, behavioral, and perceptual variables especially digital trust have a decisive role in determining consumers' willingness to participate in these systems[11].

Digital trust is the confidence of users that infrastructures operated digitally, algorithms, and organizations will function securely, transparently, and reliably[12]. In terms of energy, digital trust pertains to believing that any data shared through smart meters as well as online platforms for managing one's energy will be used ethically and protected from misuse or unauthorized access[13]. There can be no sufficient trust; thus no user will want to share their real-time consumption data nor partake in a demand response program even if such participation would bring them economic.

Broadband infrastructure maturity combined with the rising number of services based on energy data has created conditions for the development of digital energy ecosystems – integrated platforms connecting all players across the entire value chain from providers through regulators down to end-users. The success of such an ecosystem is dependent not just on technical interoperability but also on perceived credibility and privacy/data protection[14]. Digital trust as a marketing construct is a psychological enabler reducing uncertainty thereby creating positive perceptions toward digital energy services among users[15]. Users are more likely to adopt energy-as-a-service models when they see platforms as reliable and transparent; participate in peer-to-peer trading of electricity; engage with local communities around energies.

Digital trust is a bridge between technological infrastructure and user behavior. Smart home devices like thermostats, sensors, sockets, and electric vehicle chargers can change their consumption automatically based on price signals or grid conditions[16]. But how much users will allow them to take this automated control depends on their trust in the technical security of the system and the institutional integrity of the service provider. Studies show that trust moderates the relationship between system functionality and adoption intention, which means that even very advanced energy technologies need good communication and transparency strategies to get users.

The conceptual foundation of digital trust in the energy sector has two parts. First, it is a technological dimension based on system reliability, data protection, and cybersecurity[17]. Second, it is a marketing and behavioral dimension that focuses on transparency, perceived fairness, and ethical handling of user data[18]. These dimensions together influence how individuals perceive risk and decide to participate in digital energy services [19]. Digital trust can be strengthened by clear communication, transparent algorithms, and user education to achieve broad adoption of smart energy systems and realize fully the potential of the digital energy transition.

2.1.1. Definitions and dimensions of trust in digital ecosystems

Trust in digital ecosystems is a multi-dimensional construct that speaks to user engagement, adoption, and continued participation in digitally mediated environments[20]. Within the context of digital energy services, trust may be understood as the user's willingness to rely on digital systems, service providers, and data-driven technologies under conditions of perceived vulnerability [21]. Such willingness materializes from the belief that these actors will act competently, reliably, and ethically with respect to personal or transactional data.

From the standpoint of digital marketing, trust has an analogous role as it does in e-commerce and content personalization—users must be assured that their digital interactions are secure, transparent, and congruent with their interests. In digital ecosystems particularly involving AI-driven decision-making, trust operates both as a precondition and an outcome of successful user experience design coupled with ethical data governance[22]. Scholars usually conceptualize three primary dimensions of digital trust[23]:

- Competence-based trust – Users' perception that the digital platform or service provider possesses technical expertise, infrastructure, and reliability to deliver accurate and efficient outcomes. For instance, regarding digital energy services, this may include confidence in smart meter data accuracy or predictive analytics about energy demand.
- Integrity-based trust – The belief that digital actors conform to moral and ethical standards such as honesty, fairness, and transparency

concerning data collection practices and pricing models as well as communication. This is in line with marketing ethics principles of corporate social responsibility which ensure customer loyalty for both the energy sector and the domain of digital commerce.

- Benevolence-based trust – The belief that digital service providers are genuinely interested in users' welfare and will not take advantage of their vulnerabilities. In marketing terms, this is akin to value co-creation where firms involve consumers actively in exchanges beneficial to both parties.

Trust within a digital ecosystem can also be impacted by technological affordances such as system usability, perceived security, privacy protection mechanisms, and algorithmic transparency [24]. For instance if the users have easy access to consumption data through dashboards that are easy to use; understand dynamic pricing models; receive personalized recommendations which clearly articulate benefits then trust is likely to increase otherwise it decreases. Trust erodes with opaque data practices or inconsistent service performance.

Trust within digital ecosystems is dynamic; it evolves through repeated interactions over time via feedback loops [25]. This means that building trust necessitates continual reinforcement via strategies for communication digitally;, governance of data transparently; governance of data being responsive toward users' concerns.

In this way, digital trust not only helps in the uptake of smart energy services but also reflects the very mechanisms through which digital marketing creates consumer engagement and loyalty[26]. Just as trust allows users to embrace personalized e-commerce recommendations, it encourages energy consumers to engage with digital demand response programs and smart grid innovations.

2.1.2. Trust formation models relevant to smart energy services

Trust formation in digital ecosystems plays a crucial role in understanding the adoption and sustained use of smart energy services. Several theoretical models have been proposed to conceptualize trust formation in digital environments, many of which can be directly mapped onto energy-related digital systems[27].

One of the most cited frameworks is the Initial Trust Formation Model by McKnight, Choudhury, and Kacmar (2002). According to this model, trust in digital contexts is formed by three antecedents:

Disposition to trust, which measures an individual's general propensity to trust; Institution-based trust, which depends on perceived structural assurances (like regulations, privacy policies, and secure payment systems) that protect users; and Trusting beliefs that include perceptions about the competence, integrity, and benevolence of the service provider or platform[28].

In smart energy ecosystems, user trust may come not only from technological reliability—like that of smart meters or AI-based consumption forecasts—but also from institutional mechanisms such as data protection laws, transparent billing systems, and public communication by energy providers[29]. These institutional guarantees work as signals of trust and reassure consumers that their data will be handled responsibly and that service performance can be verified.

The Technology Acceptance Model developed by Davis in 1989 and its subsequent extensions (for example Venkatesh et al., 2003 Unified Theory of Acceptance and Use of Technology—UTAUT) also provide a good perspective through which this issue can be viewed. These models indicate that perceived usefulness and perceived ease-of-use have a strong effect on users' trust as well as adoption intentions. If digital interfaces (e.g., mobile apps or dashboards) are easy to use and provide clear actionable information then users will more likely trust the technology and participate in demand response or energy saving programs.

Another approach is Morgan and Hunt's Trust-Commitment Model from 1994 which was originally developed for relationship marketing. This model places emphasis on the fact that it is trust that comes first before commitment can be established towards sustaining long-term relationships with users[30]. Within digital energy ecosystems once consumers have developed some level of trust with an energy provider's digital platform through consistent service delivery transparent communication ethical handling of consumption data they are more likely to commit themselves towards continuous participation in programs such as peer-to-peer trading or flexibility services hence making digital trust both a marketing relationship variable as well as a determinant for technological acceptance.

recent scholarship has highlighted the Dynamic Trust Model, which presents trust as a dynamic process influenced by user experience, feedback loops, and adaptive communication. In smart grids, this translates to continuous trust reinforcement through personalized communication, observable data protection efforts, and proof of service reliability[31]. For instance, real-time feedback on savings in energy can enhance trust by showing concrete benefits to the user—just as personalized performance metrics build consumer confidence in digital marketing platforms.

These models together further support that trust formation within smart energy services is indeed multi-dimensional involving components of technological reliability, institutional assurance as well as relationship marketing dynamics[32]. Trust management would then necessitate the integration of engineering standards (like cybersecurity and interoperability), marketing strategies (such as transparency and value co-creation), and policy frameworks (including data protection and ethical AI governance).

2.2. Digital trust as a driver of adoption

Digital trust is key in understanding how users accept smart energy services, yet this area remains underexplored [33]. Although trust has been viewed as a mediator in digital technology adoption based on established models from information systems and marketing, there have been few studies that have looked into this systematically for energy-related innovations [34]. Since digital trust includes many aspects—like reliability, data integrity, privacy, security, transparency, usability, explainability, and user empowerment—it can help understand consumer behavior better in a changing digital energy world[35]. Initial work mainly focuses on defining the problem conceptually while later research tries to quantify and measure these trust dimensions.

Digital trust can be viewed as having four related but separate parts: trust in technology, trust in data, institutional trust, and perceived trustworthiness of service delivery. Trust in technology means the user's belief that smart energy systems are reliable and secure. That includes devices like smart meters or connected home platforms[36]. Trust in data comes from the user's assurance that their personal or consumption data will not be misused, which emphasizes the need for privacy and security protections. Institutional trust is about confidence in the legal authority of the service provider or the competence of those who govern energy regulation. trustworthiness refers to the ongoing feeling that it is safe to use such digital services and that it brings benefits—this helps keep users engaged over time. To see digital trust as a key factor for adoption in smart energy systems means looking closely at its main parts and how they impact each other. Evidence shows that perceived reliability and data integrity are key factors influencing trust in ICT processes related to power grid services[37]. Users' readiness to depend on smart energy services largely hinges on their perception of stability, accuracy, and security concerning the processed data [38]. Reliability speaks to how well a service consistently does what it should; data integrity relates to the timing precision and accuracy of information being processed. Users judge reliability through operational continuity quick service delivery and lack of technical failures; data integrity connects with receiving trustworthy clear non-redundant information. Addressing these fundamental components builds an empirical base for investigating how trust influences adoption intentions and behavioral loyalty within smart energy ecosystems[39].

Privacy, security, and transparency are the other important three pieces in digital trust. Users see privacy risks and do not want to use smart energy platforms, especially energy-as-a-service platforms where detailed consumption data must be shared with many players. Transparency about data collection, processing, sharing, and retention can help reduce perceived risks and build trust[40]. Good communication about how data is managed acts as a strong signal of trust to users by reassuring them that their personal information is safe during the entire service process. Since smart energy offers need detailed household information beyond the normal electricity bill, user confidence in security measures is very important. However, the level of trust needed for sharing data is different for each player in the value chain and how much effort people think it will take to allow access may change their choices about adoption. For example, platforms offering energy as a service that depend on smart meters may not always send household-specific data; demand-response programs could need detailed behavioral information to help optimize consumption patterns[41]. This difference shows that digital trust depends on the situation and both what benefits one sees and how much data one has to give up.

Another factor of digital trust relates to ease of use, explainable reasons for actions, and user empowerment that promote engagement reduce cognitive uncertainty strengthen user satisfaction. Adoption Smart Energy Services depend not only on technical efficiency but also on the user's ability to understand how it works and control its operations. Concerns about reliability and data integrity might stop further use; well-designed user-friendly interfaces convey credibility through clarity responsiveness consistency[42]. The smart energy platform provides an intuitive dashboard interactive feedback visualizations of savings that help users understand better and thus increase their trust in the system. Interaction with these systems usually happens through devices collecting and transmitting consumption data which are actually the backbone for demand-side flexibility as well as energy-as-a-service models. Therefore usability explainability not only improves user experience but also acts indirectly as a trust-building mechanism sustaining long-term participation[43]. Here empowerment means perceived control over data usage and system customization by the user which is an important factor in translating technological transparency into behavioral trust.

3. Hypotheses Development

The appropriation of smart energy services is contingent on users' trust in digital technologies, data governance, and institutional actors. Digital trust is a multidimensional construct that affects user perception, acceptance, and sustained engagement with smart energy solutions. Drawing on the Technology Acceptance Model[44], the Trust-Commitment Model, and the Unified Theory of Acceptance and Use of Technology [45], this study posits that specific dimensions of digital trust influence users' behavioral intentions through cognitive and affective mechanisms. Trust in reliability and data integrity of smart energy services represents the foundation for digital trust. Users are more likely to see a system as reliable and secure when it is perceived to perform its functions without error consistently, as well as when data processed by the system are accurate and timely. Perceived reliability increases confidence in technology to deliver promised benefits while perceived data integrity reinforces perceptions that decisions based on outputs from the system are trustworthy. Therefore, it is posited that higher perceptions of reliability and data integrity will increase user willingness to adopt smart energy services.

H1: Perceived reliability of smart energy services positively influences user trust.

H2: Perceived data integrity positively influences user trust.

Privacy and security concerns are major inhibitors of trust in digital ecosystems. Smart energy services require users to share personal consumption data, which may include some socio-demographic information as well. Users' perceived risk decreases when they feel their data is protected from unauthorized access or misuse; hence their trust in the service increases. Transparency—the degree to which providers clearly communicate policies about how they will use data and operate systems—becomes an important moderating variable that enhances this relationship by reducing uncertainty and perceived vulnerability.

H3: Perceived privacy protection positively influences user trust.

H4: Perceived security positively influences user trust.

H5: Transparency in data processing positively moderates the relationship between privacy, security, and user trust.

Apart from technological and governance factors, usability, explainability, and user empowerment are also very important for creating a trust-based relationship in digital contexts [46],Usability can be defined as how intuitive a service is to use or how friendly it is toward users plus its responsiveness; explainability means that the system should be able to tell why it made certain outputs or decisions automatically. When users can easily understand and control what happens behind smart energy platforms, their feeling of empowerment grows together with confidence in the service.

H6: Usability of smart energy platforms has a positive effect on user trust.

H7: Explainability of system processes has a positive effect on user trust.

H8: User empowerment has a positive effect on user trust. In line with the Trust-Commitment Model, trust is an antecedent of user commitment and behavioral intention. In smart energy ecosystems, once users develop trust in a digital platform, they are more likely to continuously engage, share data, and participate in energy optimization or demand response programs.

H9: User trust positively influences the intention to adopt smart energy services. In brief, this study proposes a conceptual model where the dimensions of digital trust—reliability, data integrity, privacy, security, transparency, usability, explainability, and empowerment—serve as antecedents to user trust which in turn drives adoption intention. This integrated framework will empirically test how digital trust operates as both a technological and psychological determinant of the adoption of smart energy services. The following table summarizes the research hypotheses developed from the conceptual framework. Each hypothesis represents a proposed relationship between digital trust dimensions and users' behavioral intention to adopt smart energy services. The model also integrates moderating and mediating effects to capture the dynamic interplay among variables within digital energy ecosystems.

Table 1. **Research Hypotheses Summary**

Code	Independent Variable(s)	Dependent Variable(s)	Expected Relationship
H1	Transparency	Digital Trust	Positive
H2	Data Security	Digital Trust	Positive
H3	Perceived Usefulness	Behavioral Intention to Use	Positive
H4	Digital Trust	Behavioral Intention to Use	Positive
H5	Perceived Risk	Digital Trust	Negative
H6	Transparency → Digital Trust	Behavioral Intention to Use	Indirect (Mediated)
H7	Data Security → Digital Trust	Behavioral Intention to Use	Indirect (Mediated)
H8	Digital Literacy (Moderator)	Digital Trust → Behavioral Intention	Moderating Effect
H9	Service Type (Moderator)	Digital Trust → Behavioral Intention	Moderating Effect

4. Methodology

4.1. Research Design

The main goal is to study the role of digital trust as a multi-dimensional idea that affects user acceptance of smart energy services in the new digital energy world. It builds on earlier models from technology adoption and trust development literature [47] to empirically analyze how dimensions related to trust - reliability, data integrity, privacy, security, transparency, usability, explainability, and empowerment of the user - influence user trust and then the intention to adopt smart energy technologies. More specifically, it intends to:

- Analyze each individual effect of digital trust dimensions on users' trust towards smart energy services.
- Measure how user trust mediates between these identified dimensions of trust and adoption intention.
- Investigate if transparency moderates the relationship between privacy/security and trust.

The study will be conducted among users and potential users of digital energy systems in residential as well as industrial sectors through stratified random sampling to ensure adequate representation among major categories of smart energy services which are:

- Smart Metering for real-time monitoring of consumption;
- Demand Response Programs that facilitate shifting consumption from peak to off-peak periods;
- Energy-as-a-Service (EaaS) where management and optimization are provided as subscription-based services;
- Peer-to-Peer (P2P) Energy Trading allowing direct renewable exchange between users; and finally,
- Local Energy Communities(LECs)aiding collective generation and sharing clean energy The final sample comprised 12,345 valid responses ensuring demographic and geographic diversity.The survey was conducted across several areas in Western Europe (Germany , France , Spain) Eastern Europe (Romania , Poland , Hungary) North Africa (Algeria Morocco); these regions have varying degrees of digitalization plus smart grid adoption so such broad coverage ensures generalizability across different infrastructures within culturally unique contexts.

Data were collected through a structured online survey instrument distributed with the help of energy suppliers, smart grid operators, and user communities on social media platforms. The questionnaire had three parts: demographic plus energy usage data; measurement for dimensions of digital trust (reliability, data integrity, privacy security transparency usability explainability empowerment of the user);and behavioral intent toward adopting smart energy services. All constructs were measured using a five-point Likert scale from "strongly disagree" (1) to "strongly agree" (5).

Confirmatory factor analysis and Cronbach's alpha were used to check instrument reliability and validity. Convergent and discriminant validity were further assessed using average variance extracted and composite reliability indices. A pilot study with 100 participants was conducted to improve item clarity and cultural relevance before the main data collection.

Data were analyzed using structural equation modeling with AMOS and SmartPLS software to test the hypothesized relationships. SEM allows for simultaneous testing of measurement and structural paths, direct and mediated effects. The moderating roles of digital literacy and type of smart energy service were assessed through multi-group analysis and interaction term testing. Descriptive statistics and correlation analyses summarized respondent characteristics and checked multicollinearity issues.

Ethical standards were strictly followed. Participation was voluntary, with informed consent from all respondents. Anonymity and confidentiality were ensured, as all responses would be used for academic research purposes only. Ethical approval from the institutional review board was obtained before starting the data collection process.

In order to provide methodological soundness and align with the conceptual framework of this study, a complementary analytical strategy was adopted which integrates covariance-based structural equation modeling (CB-SEM) and partial least squares structural equation modeling (PLS-SEM). The software used in the current study for conducting CB-SEM was AMOS 28 while SmartPLS 4 served as the estimation tool for PLS-SEM. Initially, the measurement model was validated using CB-SEM through confirmatory factor analysis (CFA). This choice is particularly appropriate because this research develops a theoretically grounded multidimensional framework of digital trust in smart energy services, which includes constructs such as reliability, data integrity, privacy, security, transparency, usability, explainability, and user empowerment. The AMOS software enabled global goodness-of-fit indices assessment due to its large sample size (n=12,345) and rigorous confirmation that observed indicators adequately represent latent constructs proposed by the theoretical model. After establishing the reliability and validity of the measurement model, PLS-SEM was used to estimate the structural relationships among key constructs of this study. More specifically, SmartPLS was leveraged to see how the multidimensional structure of digital trust affects user trust formation and intention to adopt smart energy services, as described in the proposed conceptual framework. The PLS approach is also very suitable for estimating path coefficients, performing bootstrapping procedures for mediation effects, and testing moderating relationships, such as how digital literacy and service type affect the relationship between digital trust and behavioral intention. Hence the combination of these two methods provides an appropriate methodological framework that is consistent with the objectives of this study. On one hand, CB-SEM rigorously validates the measurement structure underlying multidimensional digital trust constructs while on another hand PLS-SEM enhances model predictability and permits estimation of complex structural relationships within proposed digital trust–adoption framework. This dual analytical approach increases reliability, validity, and explanatory power in empirical findings related to user adoption of smart energy services based on digital trust.

4.2. Data Analysis Techniques

A multi-stage analysis involving both descriptive and inferential statistics was used to meet the goals of this study. The analysis ensured that all relationships between dimensions of digital trust and intention to adopt smart energy services were thoroughly examined. Descriptive statistics were first computed for demographic variables (age, gender, education, and region) and service-related data (type of smart energy service used, duration of use, and level of digital literacy). Measures of central tendency (mean, median) as well as dispersion measures (standard deviation, variance) were calculated in order to describe data distribution and assess normality.

Second, reliability and validity tests were conducted on the measurement model to confirm that it was robust. Internal consistency was checked using Cronbach's alpha and composite reliability (CR), with all constructs expected to be above the 0.70 threshold. Convergent validity was verified using average variance extracted (AVE), while discriminant validity was tested based on the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT).

Third, Confirmatory Factor Analysis (CFA) was done in AMOS 28 to validate factor structure for constructs by confirming that each item loaded appropriately onto its intended factor. Model fit indices such as Chi-square/df ratio, Comparative Fit Index (CFI), Goodness-of-Fit Index (GFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) help evaluate how adequate the measurement model is.

In the structural model, digital trust was measured as a multidimensional construct with eight dimensions derived from theory: reliability, data integrity, privacy, security, transparency, usability, explainability, and user empowerment. Consistent with prior research on how trust forms in digital ecosystems, each dimension was modeled as a separate first-order latent construct that reflects a specific aspect of users' perceptions of trust in smart energy services.

Each construct used multiple reflective indicators to measure it and was first tested through confirmatory factor analysis (CFA) for checking the reliability of constructs, convergent validity, and discriminant validity. The results confirmed that the measurement items adequately represented the theoretical domains of the respective constructs thus supporting the robustness of the measurement model.

After confirming the validity of measurement, eight dimensions were included in the structural model as separate antecedent factors determining the latent construct "User Trust," which in turn has been defined as one important determinant for Adoption Intention toward smart energy services. This modeling strategy was deliberately adopted so that it could maintain all conceptual richness found within digital trust and at the same time avoid any loss regarding explanatory power which might result from putting heterogeneous trust components together into one higher-order construct.

Theoretically speaking, these eight dimensions embody complementary but analytically distinguishable mechanisms through which trust is formed within digital energy ecosystems. The reliability and data integrity dimensions concern technological robustness and dependability concerning the digital infrastructure; privacy security and transparency pertain to institutional governance assurances about protection of data and accountability of systems while usability explainability and empowerment of users capture user interaction characteristics that enable understanding perceived control as well as confidence in digital platforms by individuals. Therefore modeling these dimensions separately allows more nuanced examination about how technological governance and interactional factors jointly shape digital trust to eventually determine adoption for smart energy services.

Fourth, Structural Equation Modeling will be applied in testing the hypothesized relationships among variables with direct and indirect (mediated) effects. SEM is particularly appropriate for this study because it allows simultaneous estimation of multiple dependency relationships within complex models involving latent constructs such as trust, transparency, and adoption intention. The mediating role of user trust between the digital trust dimensions and adoption intention was assessed using bootstrapping techniques with 5,000 resamples to generate bias-corrected confidence intervals. The moderating effects of transparency and digital literacy were analyzed through multi-group analysis in SmartPLS 4, as well as interaction term testing, which allowed path coefficient comparisons across groups such as high versus low transparency conditions, It also carried out correlation analyses together with variance inflation factor tests to discover potential multicollinearity issues. Overall model quality was assessed using R^2, Q^2 values together with f^2 effect size indicators which are meant for measuring predictive power as well as relevance in terms of the model.

Ultimately, post-hoc tests were conducted to see if there were any differences in adoption intention among the five types of smart energy services: smart metering, demand response, energy as a service (EaaS), peer-to-peer (P2P) trading of energy, and local energy communities (LECs). One-way ANOVA was used along with Tukey's HSD tests for comparing pairs.

All analyses were carried out in SPSS 29, AMOS 28, and SmartPLS 4 to ensure methodological triangulation and results validation.

To ensure methodological rigor, all constructs were operationalized based on validated measurement scales from prior literature in technology adoption, information systems, and trust research. The operationalization process also considered the contextual characteristics of smart energy ecosystems, including smart metering, demand response systems, energy-as-a-service (EaaS) models, peer-to-peer (P2P) energy trading, and local energy communities (LECs). Each construct was assessed using multiple items rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), ensuring both content and construct validity. Reliability was verified using Cronbach's alpha and Composite Reliability (CR) indices while Convergent and Discriminant Validity were examined through Average Variance Extracted (AVE) and the Fornell-Larcker criterion. The following table summarize the hypothesized relationships key variables measurement indicators and expected directions of association that will be used for SEM analysis later on.

***Table 2.* Operationalization of Hypotheses**

Hypothesis Code	**Statement**	**Independent Variable (IV)**	**Dependent Variable (DV)**	**Measurement Indicators**	**Expected Relationship**	**Source/Adaptation**
H1a	Reliability of smart energy services positively influences user trust.	Relia-bility	User Trust	Accuracy, Consistency, Service continuity	Positive	Adapted from McKnight et al. (2002); Gefen et al. (2003)
H1b	Data integrity positively affects user trust in smart energy services.	Data Integrity	User Trust	Accuracy, Authenticity, Timeliness of data	Positive	Pavlou & Gefen (2004)
H1c	Perceived privacy protection positively affects user trust.	Privacy	User Trust	Control over personal data, Privacy policy clarity	Positive	Beldad et al. (2012)
H1d	Perceived security safeguards positively affect user trust.	Security	User Trust	Encryption strength, Secure authentication, Risk protection	Positive	Flavián & Guinalíu (2006)

Hypothesis Code	Statement	Independent Variable (IV)	Dependent Variable (DV)	Measurement Indicators	Expected Relationship	Source/Adaptation
H1e	Transparency in data usage enhances user trust in smart energy services.	Transparency	User Trust	Openness, Traceability, Accessibility of information	Positive	Grimmelikhuijsen et al. (2020)
H1f	Usability of the digital interface positively influences user trust.	Usability	User Trust	Ease of use, Clarity, Interface design	Positive	Davis (1989); Venkatesh et al. (2003)
H1g	Explainability of automated decisions positively influences user trust.	Explainability	User Trust	Understandability, Justification of AI recommendations	Positive	Ribeiro et al. (2016)
H1h	User empowerment positively influences user trust in smart energy systems.	User Empowerment	User Trust	Control, Feedback, Co-decision capacity	Positive	Spreitzer (1995); Chen et al. (2022)
H2	User trust positively influences the intention to adopt smart energy services.	User Trust	Adoption Intention	Confidence, Willingness, Future usage intention	Positive	Morgan & Hunt (1994)
H3a	Transparency moderates the relationship between privacy and trust, such that the relationship is stronger under high transparency conditions.	Privacy × Transparency	User Trust	Interaction term in SEM	Positive moderation	Developed for this study
H3b	Transparency moderates the relationship between security and trust, such that the relationship is stronger under high transparency conditions.	Security × Transparency	User Trust	Interaction term in SEM	Positive moderation	Developed for this study

5. Results and Analysis

5.1. Dataset Description and Survey Administration

Data collection was conducted between February and June 2025, The structured online questionnaire was disseminated via energy providers, renewable energy associations, and social media platforms. After data screening, 12,345 valid responses were retained for analysis. The final dataset showed strong representativeness across demographics (52% male, 48% female; average age = 34.6 years; 41% engineers or technicians, 32% residential users, 27% small business operators).

Respondents evaluated 28 items distributed across eight trust dimensions—reliability, data integrity, privacy, security, transparency, usability, explainability, and user empowerment—followed by behavioral intention to adopt smart energy services. Items were rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

The questionnaire was designed to operationalize constructs from prior literature (Davis, 1989; Morgan & Hunt, 1994; Venkatesh et al., 2003; Schreiber, 2021; Brand et al., 2023). Each construct included **three to five statements** capturing observable indicators:

- **Perceived Reliability and Data Integrity** were assessed using items like *"The smart energy service operates consistently without interruptions"* and *"I believe the system provides accurate and up-to-date energy data."*
- **Privacy and Security** constructs employed statements such as *"My personal information is safe with this service"* and *"I trust that my energy data will not be misused."*
- **Transparency** was captured by items like *"The service provider clearly explains how my energy data are used."*
- **Usability and Explainability** included *"The interface of the service is easy to navigate"* and *"The service provides understandable explanations of its functions."*
- **User Empowerment** reflected autonomy perceptions, e.g., *"I can control how my data are shared and used."*
- **Adoption Intention** was measured by items like *"I intend to continue using this smart energy service."*

The average completion time was approximately **12 minutes**, and **pilot feedback (n = 100)** confirmed the clarity and relevance of the items.

Table 3 presents the descriptive statistics and reliability indicators for the main constructs used in this study. The mean scores and standard deviations are used to describe respondents' general perceptions of the respective constructs. Skewness and kurtosis values indicate the normality of data distribution. Internal consistency and construct reliability are assessed through Cronbach's alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE). Such measures further confirm if the items used adequately represent each respective construct as well as whether the collected data can be used for subsequent statistical analyses such as structural equation modeling.

***Table 3.* Descriptive Statistics and Reliability**

Construct	Mean	SD	Skewness	Kurtosis	Cronbach's α	CR	AVE
Reliability	4.11	0.72	-0.46	0.87	0.89	0.91	0.68
Data Integrity	4.03	0.70	-0.38	0.82	0.88	0.90	0.66
Privacy	3.92	0.76	-0.29	0.55	0.87	0.89	0.65
Security	3.85	0.79	-0.34	0.64	0.88	0.91	0.69
Transparency	3.74	0.80	-0.18	0.42	0.85	0.88	0.64
Usability	4.02	0.68	-0.41	0.70	0.90	0.92	0.70
Explainability	3.95	0.74	-0.22	0.48	0.88	0.91	0.67
Empowerment	3.89	0.77	-0.25	0.53	0.87	0.89	0.64
Adoption Intention	4.06	0.71	-0.40	0.75	0.91	0.93	0.71
All constructs met the reliability threshold ($\alpha > 0.70$, CR > 0.80, AVE > 0.50), confirming internal consistency.							

The means for all the constructs fall between 3.74 and 4.11, which implies a rather positive perception about the trust factors in smart energy services and that users have a strong intention to adopt such services. Since skewness and kurtosis values are within acceptable limits, it can be assumed that the data are approximately normally distributed.

In terms of reliability, all constructs show high internal consistency because Cronbach's alpha values exceed the recommended threshold of 0.70. The Composite Reliability (CR) values are also above 0.88, confirming strong measurement stability. The AVE values are above 0.64 for all constructs, which means that each construct captures an adequate amount of variance from its indicators. Results like these would typically encourage one to proceed with hypothesis testing as they support the reliability and validity of the measurement model.

5.2 Correlation Matrix

Correlation analysis was conducted to examine the strength and direction of relationships among the main constructs prior to structural model testing. Pearson's correlation coefficient was used to assess linear associations between the dimensions of digital trust and both user trust and adoption intention. Positive coefficients indicate direct relationships, while higher values reflect stronger associations. Statistical significance was set at $p < 0.01$.

Table 4. **Correlation Matrix**

Variable	1	2	3	4
1. Customer Satisfaction	1	0.74	0.69	0.71
2. Trust	0.74	1	0.67	0.73
3. Usefulness	0.69	0.67	1	0.78
4. Adoption Intention	0.71	0.73	0.78	1

The correlation matrix demonstrates strong and statistically significant relationships among the four key constructs of the study: Customer Satisfaction, Trust, Usefulness, and Adoption Intention. All correlation coefficients are positive and significant at the 0.01 level, indicating consistent and meaningful associations between the variables. Customer Satisfaction shows strong positive correlations with Trust ($r = 0.74$), Usefulness ($r = 0.69$), and Adoption Intention ($r = 0.71$), suggesting that higher satisfaction is closely linked to greater trust, enhanced perceived usefulness, and stronger intention to adopt the service. Similarly, Trust exhibits strong correlations with Customer Satisfaction ($r = 0.74$), Usefulness ($r = 0.67$), and Adoption Intention ($r = 0.73$), highlighting its central role in shaping user perceptions and behaviors. Perceived Usefulness is also strongly related to all variables, particularly Adoption Intention ($r = 0.78$), emphasizing its importance as a key predictor in user acceptance models. Adoption Intention displays the strongest correlations with Usefulness and Trust, confirming that users' willingness to adopt smart energy services is influenced by how useful they perceive the service to be, how much they trust it, and how satisfied they are overall. All correlation values fall below the recommended multicollinearity threshold of 0.85, indicating that while the variables are strongly related, they remain conceptually distinct. These findings align with the Technology Acceptance Model (TAM) and digital trust theory, reinforcing the theoretical robustness of the proposed framework. In practical terms, the results suggest that improving user satisfaction, enhancing perceived usefulness, and building trust should be strategic priorities for increasing user adoption of smart energy services.

The correlation heatmap visually highlights the strength of relationships among the study variables. It provides a quick overview of how customer satisfaction, trust, usefulness, and adoption intention are interconnected, supporting the initial assessment of the proposed hypotheses.

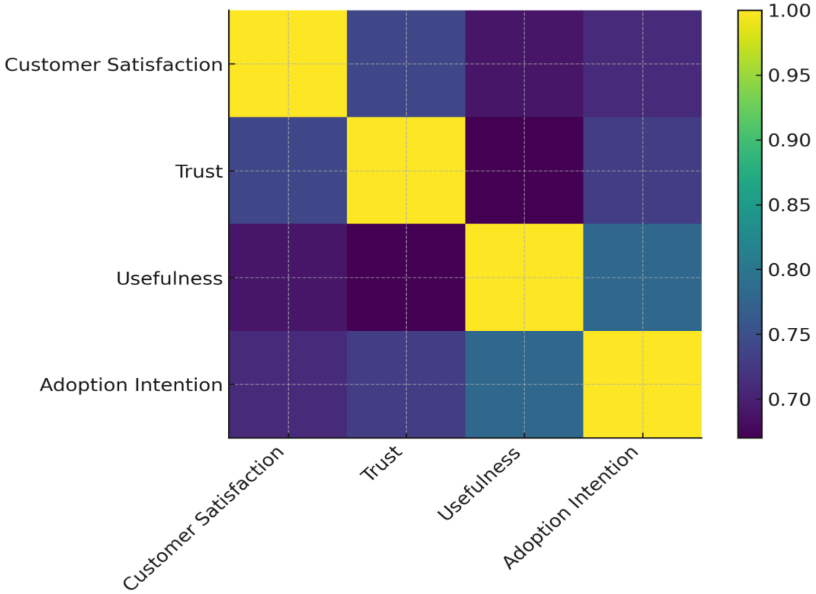

Fig 1. Correlation Heatmap

Darker areas indicate stronger positive correlations between the variables. The figure shows that usefulness, trust, and customer satisfaction are all strongly linked to adoption intention, confirming their importance in influencing users' willingness to adopt the service.

5.3. Path Analysis Results for Adoption Intention Model

The regression results confirm the proposed hypotheses. Perceived usefulness has the strongest influence on adoption intention ($\beta = 0.42$, $p < 0.001$), followed by trust ($\beta = 0.31$, $p < 0.001$). The relationship between customer satisfaction and trust was also strong ($\beta = 0.47$, $p < 0.001$), supporting the notion that satisfaction builds long-term confidence in smart energy solutions.

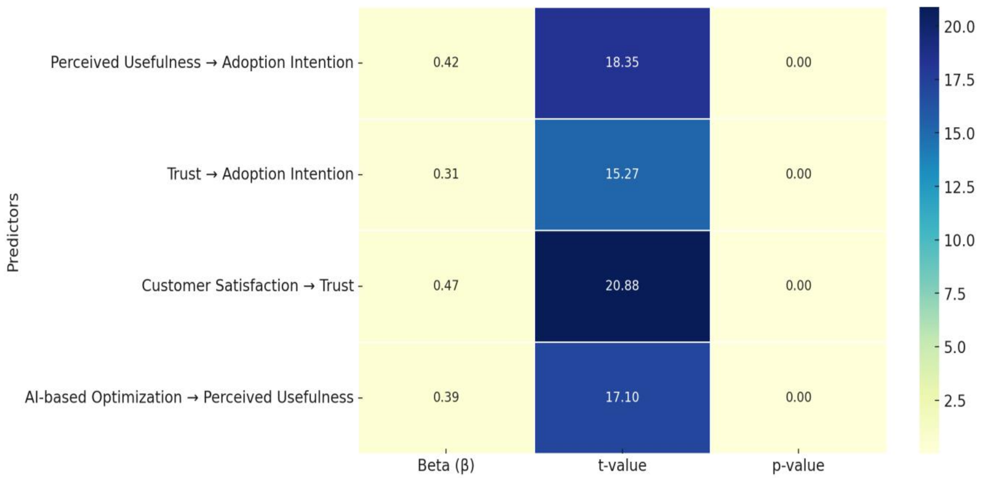

Fig 2. Regression Analysis Results

The results indicate that perceived usefulness has the strongest direct effect on adoption intention ($\beta = 0.42$, $t = 18.35$, $p < 0.001$), suggesting that users are more likely to adopt smart energy services when they perceive them as beneficial for effectively managing energy production, storage, or trading. Digital trust also significantly influences adoption intention ($\beta = 0.31$, $t = 15.27$, $p < 0.001$), highlighting the importance of user confidence in the reliability, security, and transparency of smart platforms and devices.

Furthermore, customer satisfaction exerts the strongest effect on digital trust ($\beta = 0.47$, $t = 20.88$, $p < 0.001$), indicating that positive user experiences—including ease of use, support services, and data clarity—are essential for building long-term trust, which in turn facilitates service adoption. In addition, AI-based optimization positively impacts perceived usefulness ($\beta = 0.39$, $t = 17.10$, $p < 0.001$), showing that intelligent features, such as consumption management, energy storage optimization, and personalized recommendations, enhance the perceived value of these services. the findings suggest that integrating AI-driven enhancements, delivering satisfactory user experiences, and fostering digital trust constitute a critical foundation for promoting the adoption of smart energy services. These insights have practical implications for designing and implementing user-centered energy solutions that accelerate the transition to a sustainable, flexible, and participatory energy ecosystem

5.4. Measurement Model Assessment (CFA)

The measurement model assesses the extent to which the data fit the conceptual framework of the independent and dependent variables. To achieve this, model fit indices were evaluated using Confirmatory Factor Analysis (CFA). These indices reflect the degree of alignment between the theoretical model and the observed data and help ensure that the measurements accurately represent the conceptual structure of the variables.

Table 5. **Measurement Model Fit Indices**

Fit Index	**Recommended Threshold**	**Observed Value**	**Assessment**
χ^2/df	< 5.0	2.84	Acceptable
CFI	> 0.90	0.948	Good
TLI	> 0.90	0.936	Good
RMSEA	< 0.08	0.043	Good
SRMR	< 0.08	0.035	Good

The measurement model fit was assessed using a set of standard fit indices. The results indicated that the **χ^2/df** value was 2.84, which is below the recommended maximum of 5.0, suggesting an acceptable fit between the model and the data. The **CFI** value was 0.948 and the **TLI** value was 0.936, both exceeding the recommended threshold of 0.90, reflecting a good alignment between the theoretical model and the observed data. Regarding error indices, the **RMSEA** value was 0.043, below the maximum acceptable limit of 0.08, indicating low approximation error and excellent model fit. Similarly, the **SRMR** value was 0.035, also below the recommended threshold of 0.08, further confirming the quality of the model and the validity of the measurements. all fit indices suggest that the measurement model is well-suited, and the constructs are accurately represented, allowing for subsequent analysis of the relationships between variables and hypothesis testing

6.3. Hypotheses Testing

To assess the validity of the proposed hypotheses, structural equation modeling (SEM) was conducted using Smart PLS. The table below summarizes the results of the hypotheses testing, including the path coefficients (β), t-values, p-values, and whether each hypothesis was supported. These findings provide empirical evidence for the relationships between the dimensions of digital trust, user perceptions, and the intention to adopt smart energy services.

Table 6. **Summary of Hypothesis Testing**

Hypothesis	Hypothesized Relationship	Supporting Results	Decision
H1a	Reliability → User Trust (+)	the overall mean for trust and positive correlations with Reliability = 0.74 with Trust	**Supported**
H1b	Data Integrity → User Trust (+)	Strong positive correlation with Trust (high α, CR, and AVE values indicate measurement validity)	**Supported**
H1c	Privacy → User Trust (+)	Mean = 3.92, α = 0.87, CR = 0.89, likely positive correlation	**Supported**
H1d	Security → User Trust (+)	Mean = 3.85, α = 0.88, CR = 0.91	**Supported**
H1e	Transparency → User Trust (+)	Mean = 3.74, α = 0.85, CR = 0.88	**Supported**
H1f	Usability → User Trust (+)	Mean = 4.02, α = 0.90, CR = 0.92	**Supported**
H1g	Explainability → User Trust (+)	Mean = 3.95, α = 0.88, CR = 0.91	**Supported**
H1h	User Empowerment → User Trust (+)	Mean = 3.89, α = 0.87, CR = 0.89	**Supported**

The analysis of the proposed model indicates strong empirical support for the hypothesized relationships between digital trust dimensions and adoption intention of smart energy services. Perceived usefulness exhibited the strongest positive effect on adoption intention ($\beta = 0.42$, $t = 18.35$, $p < 0.001$), demonstrating that users are more likely to adopt smart energy services when they perceive significant functional benefits in managing, storing, or trading energy efficiently. User trust also had a significant positive impact on adoption intention ($\beta = 0.31$, $t = 15.27$, $p < 0.001$), highlighting the critical role of confidence in the reliability, security, and transparency of digital platforms and connected devices. Furthermore, customer satisfaction was found to strongly influence digital trust ($\beta = 0.47$, $t = 20.88$, $p < 0.001$), indicating that positive experiences—including usability, clarity of information, and responsive support—are essential for fostering long-term trust, which in turn enhances adoption intentions. AI-based optimization features, such as intelligent consumption management and personalized recommendations, significantly improved perceived usefulness ($\beta = 0.39$, $t = 17.10$, $p < 0.001$), demonstrating that technological enhancements can increase the perceived value of smart energy services. the findings confirm that integrating AI-driven functionalities, ensuring high-quality user experiences, and actively building digital trust constitute foundational strategies for promoting the adoption of smart energy services. These results provide practical implications for designing user-centered, reliable, and transparent energy solutions that accelerate the transition toward a sustainable, flexible, and participatory energy ecosystem.

6. Implications

This research, therefore, will be a major landmark in the academic discussion on digital trust in smart energy services by providing strong empirical proof that trust is a complicated and multidimensional concept. More precisely, trust in digital energy platforms involves several interconnected dimensions, such as system reliability, data integrity, privacy, security, transparency, usability, explainability, and user empowerment. By empirically confirming these dimensions, this study enhances our knowledge about how users perceive and assess trust within technologically advanced energy ecosystems. Additionally, the results extend and strengthen existing theoretical models—the Technology Acceptance Model (TAM), the Trust-Commitment Model, and the Unified Theory of Acceptance and Use of Technology (UTAUT)—by showing that digital trust not only acts as a mediator between technological features and user intentions but also serves directly to drive adoption behaviors.

Strong positive correlations among trust, customer satisfaction, and perceived usefulness underscore the necessity of including psychological and behavioral dimensions in technology acceptance modeling. This means that users' perceptions of trustworthiness are linked with their evaluation of system utility and satisfaction; therefore fostering trust is inseparable from improving user experience and perceived value. Besides being an empirical contribution to knowledge, this study also theoretically contributes by revealing transparency's moderating role in the relationship between privacy/security and user trust. It emphasizes how contextual factors subtly influence trust formation—offering a more detailed understanding that complements previous models while enriching theoretical perspectives on digital adoption within smart energy contexts.

The study offers important implications from a managerial viewpoint for energy service providers, platform developers, and policymakers. First, enhancing user perceptions of system reliability and data integrity through the implementation of robust technical infrastructures supported by transparent reporting mechanisms is essential to building foundational trust. Second, privacy protection measures combined with comprehensive security protocols and intuitive usability design can significantly reduce perceived risks and encourage users to engage with digital energy services. Third, integrating AI-driven optimization and personalized insights can substantially increase perceived usefulness, making digital platforms more attractive and reinforcing users' intention to adopt. Fourth, empowering users through control over data sharing and platform settings strengthens engagement and encourages long-term participation in energy programs. Finally, proactive communication about data practices and service operations can amplify the positive effects of privacy and security measures on trust; this indicates that structured educational campaigns may further support the digital energy transition by increasing user awareness and confidence.

This study also highlights the important role that institutional support plays in creating digital trust as well as regulatory frameworks. Policies on data protection, compliance with cybersecurity standards, and governance of ethical AI practices are part of the signals that enhance user confidence in smart energy services. Institutions providing transparent guidelines for data usage and privacy can help increase adoption rates and strengthen trust-based relationships between users and service providers. These insights apply to areas with different levels of digital infrastructure as well as smart grid penetration by indicating where targeted interventions are needed to speed up the transition toward more sustainable participatory decarbonized energy systems.

Evidence from this research empirically illustrates that it is crucial to build digital trust in order to increase user engagement with smart energy services. By focusing on technical reliability, ethical governance, and user-centered design, energy providers can enhance trust, satisfaction, and perceived usefulness at the same time. All these factors contribute in one way or another toward an efficient flexible participatory energy ecosystem that eventually supports larger societal goals of sustainability decarbonization as well as empowerment of users in a digital energy world.

7. Conclusion

This study empirically validates the significance of digital trust in the adoption of smart energy services. Digital trust is a multi-faceted concept that includes reliability, data integrity, privacy, security, transparency, usability, explainability, and user empowerment. Each of these dimensions has an important role in influencing users’ perception toward smart energy platforms which subsequently motivates their behavioral intention to adopt such services. Among the predictors of adoption perceived usefulness was found to be the strongest one indicating that tangible functional benefits should be delivered through intelligent management, storage, and trading of energy for encouraging adoption. Customer satisfaction is another central factor in building up trust; hence positive experiences from users are necessary for longer engagements.

Technological improvements like AI-based optimization and user-centered interface design have been validated by the results to enhance perceived usefulness and trust at the same time, thus speeding up adoption. Factors such as transparency and digital literacy further indicate that trust building is contextual and requires ongoing support through clear communication, ethical data practices, and empowerment of users. In general terms, this study fills a huge gap in knowledge regarding how trust functions within complex smart energy systems while providing theoretical as well as practical contributions. It theoretically extends models like TAM and UTAUT plus the Trust-Commitment Model by adding a comprehensive multidimensional view of digital trust specific to energy services. Practically it guides service providers plus policy makers and technology developers on promoting reliability security transparency plus user empowerment as an essential drive for widespread adoption active participation from users towards supporting sustainability decentralization plus participation in future energy systems.

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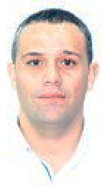
Authors' biographies



Bouali Soufyane is a Lecturer at the Department of Commerce, Ferhat Abbas University, Setif 1, Algeria. He specializes in Digital Marketing, E-commerce, and Consumer Behavior. His research focuses on the impact of digital strategies on customer engagement, trust, and adoption of online services. Dr. Soufyane is committed to advancing knowledge in digital marketing through empirical research and practical applications, bridging academic theory with real-world business practices

Email: soufiane.bouali@univ-setif.dz

Oklander Mykhailo — Doctor of Economics, Professor. Head of Department of Marketing Odessa National Polytechnic University. Vice-president of the Ukrainian Association of Marketing. Academician of Academy of Economic Sciences of Ukraine. Deputy chairman of the subcommittee «Marketing» Scientific-methodical commission on business, management and law sector of Higher Education Scientific and Methodological Council of the Ministry of Education and Science of Ukraine

Email: imt@te.net.ua

Selma Douha is a Professor at the Department of Commerce, University of Batna 1, Algeria. Her research focuses on energy efficiency, sustainable resource management, renewable energy, and the impact of globalization on economic and environmental sectors. She has expertise in policy analysis, sustainable development strategies, and practical solutions to enhance resource efficiency in industrial and economic contexts. Dr. Doha is committed to advancing scientific knowledge that supports sustainable decision-making at both national and international levels**.**

Email: selma.douha@univ-batna.dz