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IoT-Enabled Digital Nudge Architecture for Sustainable Energy Behavior: An SEM-PLS Approach

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Abstract

The growing need for sustainable energy practices necessitates technology-driven interventions that can effectively bridge the disparity between consumer intentions and actual behavior. This paper formulates and empirically substantiates an IoT-enabled digital nudge architecture designed to promote sustainable energy behavior. The architecture provides goal-setting, social comparison, feedback, and informational nudges across multiple digital channels, utilizing linked devices, data processing layers, and a rule-based nudge engine. An 815-responder survey was analyzed using structural equation modeling with partial least squares (SEM-PLS) to identify the drivers of sustainable energy behavior and explore technology readiness as a moderating factor. The results show that nudges utilizing the Internet of Things (IoT) significantly enhance the alignment between intention and behavior. Goal-setting and feedback mechanisms have the highest effects. The findings also demonstrate that being ready for new technology improves nudge response, highlighting the importance of user-centered system design. This paper presents a scalable infrastructure for integrating IoT into sustainability projects, as well as theoretical contributions to technology adoption and behavioral intervention research. The study enhances the dialogue on environmental technology by illustrating the implementation of digital nudges through IoT infrastructures to expedite progress toward the Sustainable Development Goals (SDGs).

Keywords: IoT-enabled nudges; sustainable energy behavior; green behavioral intention; technology readiness; responsible consumption (SDG 12); SEM-PLS

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1. Introduction

Sustainable consumption practices have gained significance in tackling global environmental issues, including climate change, resource depletion, and carbon [1,2]. As one of many technologies, the Internet of Things (IoT) allows smart, real-time modifications to promote energy-conscious lives. Smart meters and plugs are examples of devices that provide customers with direct data on their energy usage, which can help them adjust their habits accordingly. Smart thermostats can suggest settings that are both comfortable and energy-efficient. IoT platforms that work with apps can provide users with individualized feedback, compare their progress with others, and help them set goals that encourage them to live more sustainably. In this study, IoT-enabled gadgets act as digital nudging mechanisms to promote sustainable consumption [2,3]. IoT-driven nudges, including personalized feedback, social comparison, gamification, and goal setting, have been recognized as effective tools for promoting sustainable decision-making [4,5]. These systems affect Energy Awareness, Green Behavioral Intention (GBI), and Perceived Behavioral

Control. Technology Readiness is also very important because it indicates how confident people are in using digital tools to change their behavior in ways that are beneficial for the environment [6,7].

Even while digital nudging is gaining more attention, research gaps still exist. Numerous studies prioritize behavioral intention yet fail to investigate actual sustainable activities thoroughly, or they neglect mediating elements such as Energy Awareness and Perceived Behavioral Control (PBC). The moderating influence of Technology Readiness is also not examined [8,9]. To create more effective interventions that extend beyond just raising awareness and intention to get real, long-term results, these gaps need to be filled.

The present research addresses the need to examine the influence of IoT-enabled nudges on sustainable energy practices, specifically on the use of energy-efficient equipment. It explores how Energy Awareness mediates Green Behavioral Intention and Actual Behaviour towards Sustainability, and how Perceived Behavioral Control acts on intention. The study also compares the effects of Personalized Feedback, Social Comparison, gamification and rewards, and goal-setting and commitment on energy outcomes. It also analyzes how Technology Readiness affects the strength of these interactions.

The novelty of this study lies in proposing and empirically validating an IoT-enabled digital nudge architecture, grounded in an integrated framework that combines the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM) [10], and Nudge Theory [11]. This dual-theoretical approach examines cognitive, technological, and behavioral variables related to sustainability adoption, which have been previously neglected. The paper fills this gap by providing a holistic understanding and practical architecture for how IoT devices might give sustainable consumption nudges.

Beyond academic contributions, our research enables IoT device designers and developers to determine which nudging strategies—such as social comparison, goal setting, or personalized feedback—drive real-world behavior change. It also helps policymakers and corporations create targeted interventions, marketing campaigns, and incentive programs to promote sustainability and the adoption of green technology. The study supports SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action) by directly engaging human behavior through IoT infrastructures.

This research contributes to the body of knowledge in behavioral and managerial studies, as well as in Information and Communication Technologies and Environmental Technologies, which are essential to today's global and technological challenges. The study employs an IoT-enabled digital nudge architecture to illustrate how real-world systems can influence sustainable energy practices. An interdisciplinary strategy that enhances theoretical understanding and technical implementation integrates cognitive aspects (Energy Awareness and PBC), technological readiness, and IoT-driven treatments. The study provides practical insights for engineers, system designers, and policymakers seeking to operationalize sustainability through connected technologies, aligning with the UN's Sustainable Development Goals. Additionally, the study is built on earlier research by presenting a cohesive IoT-enabled digital nudge architecture that amalgamates goal-setting, tailored feedback, social comparison, and gamification into a singular behavioral framework. This approach integrates TPB, TAM, and Nudge Theory to relate technical design with behavioral dynamics, unlike previous studies that focused on nudge types or intention-based results. The study provides a novel and comprehensive perspective on how IoT systems can bridge the intention–behavior gap in sustainable energy use by examining both intention and actual sustainable behavior and using Energy Awareness, Perceived Behavioral Control, and Technology Readiness as mediators and moderators.

To guide this research, the research is driven by the following central question:

RQ1: How do IoT-driven behavioral nudges, Energy Awareness, Perceived Behavioral Control, and Technology Readiness influence Green Behavioral Intention and Actual Behavior Towards Sustainability?

2. Literature Review

This study examines the impact of IoT-driven behavioral nudges on sustainable energy consumption and associated patterns. The conceptual framework proposes four forms of nudges from IoT devices that may have a potential effect on individual behavior: personalized feedback, social comparison, goal-setting and commitment, and gamification with rewards. The Nudge Theory suggests that these nudges could gently encourage energy-saving behavior without limiting choice. These nudges modify users' awareness of their energy consumption and its environmental impact, as well as their perception of their energy usage management and confidence in their ability to reduce it. The Theory of Planned Behavior (TPB) proposes that these two psychological factors function as mediators, illustrating how IoT interventions lead to intentions to conserve energy and, ultimately, to actual energy-saving activities.

The conceptual framework (as shown in Figure 1) illustrates the individual behavioural pattern in context to IoT nudge technology readiness—the degree of familiarity with the new technology—may influence the result. Technologically savvy individuals are more likely to respond to IoT nudges, leading to increased energy savings. The theoretical framework illustrates how IoT nudges influence awareness, control, intention, and behavior, depending on the level of technological readiness. This integrative method uses behavioral economics, psychology, and technology adoption theories to examine how IoT could help consumers utilize energy responsibly.

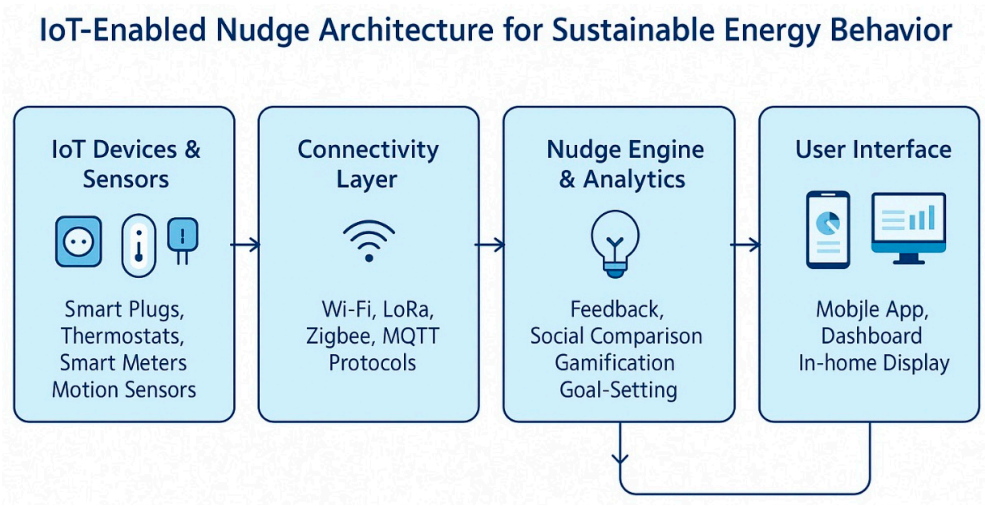

Figure 1. IoT-Enabled Nudge Architecture for Sustainable Energy Behavior.

System Architecture and Nudge Logic

Figure 1 illustrates a conceptual IoT-based Digital Nudge Delivery Architecture, which demonstrates the technology underlying our study. Connected devices, cloud data flows, and nudge delivery are integrated:

IoT Data Capture—Smart meters, plugs, and sensors collect real-time energy consumption data and transmit it via secure protocols (e.g., MQTT, HTTP) to a cloud server.
Data Processing Layer—Consumption logs are analyzed to identify baseline usage patterns and trigger thresholds.
Nudge Logic Engine—Based on defined rules (goal attainment, peer comparison gaps, or overconsumption alerts), the system selects the most contextually relevant nudge.

Delivery Channels—Nudges are communicated through mobile apps, SMS notifications, or in-home displays.
Feedback Loop—User responses and consumption changes are fed back into the system to refine personalization continuously.

Figure 1 here: IoT-enabled architecture diagram (Devices → Data Processing → Nudge Engine → Delivery Channels → Feedback Loop).

2.1. Framework of the Study

The study addresses sustainable behavior aspects using TPB, TAM, and Nudge Theory. Cognitive and motivational factors of behavior include attitudes, intentions, and perceived behavioral control [12,13]. TAM contributes to TPB by examining technological adoption, utility, simplicity of use, and preparedness. The Nudge Theory explains the behavioral interventions that influence users to make sustainable decisions with the help of subtle stimuli, such as individual feedback, social comparison, goal-setting, and gamification [11]. The above three frameworks collectively provide a comprehensive overview of the psychological and technical factors that drive behavior, which is essential for achieving SDG 7, SDG 11, and SDG 12 [14,15].

2.2. IoT-Driven Nudge

2.2.1. Personalized Feedback Nudges

Personalized feedback nudges are designed to help individuals achieve their goals while also providing them with the option to choose. Based on behavioral economics and psychology [16]. They tailor information to the person's situation, making it clearer, more useful, and easier to act upon. Nudges improve awareness, motivation, and perceived control in healthcare, energy conservation, and education [17,18]. Nevertheless, privacy issues, along with complicated designs, are still significant issues [19,20].

In healthcare, personalized diabetes feedback coupled with training has demonstrated significant efficacy [21]. Personalized feedback enhanced motivation and self-management over time [22,23]. In the Theory of Planned Behavior, these results show how perceived behavioral control affects intentions. In sustainability, feedback systems that provide real-time energy data make people more aware of their environmental impact and increase trust in responsible energy management [24,25].

Personalized nudges also affect what consumers purchase. Recommendations for e-commerce made consumers more likely to buy [26,27], nutritional feedback encouraged people to choose healthier foods [28], and framing green items as both good for the environment and personally beneficial increased adoption [29,30]. Eco-friendly conversational agents have an impact on online buying; however, consumer trust is crucial [31,32]. Eco-packaging and framing strategies help bridge the "green gap" between how people think and how they act [33].

However, efficacy is influenced by defaults, societal norms, and personality qualities such as nonconformity [34]. Stressful situations also lessen the effect of nudges [35,36]. When nudges appear to be manipulative, ethical concerns arise [37]. Thus, effective nudges must be transparent, flexible, and autonomous. They may help people stay motivated in the short term, but to have a lasting effect, there needs to be supportive structures, such as affordable green products and infrastructure, that make it easier for them to use. Personalized feedback nudges help people make decisions that benefit the environment, supporting SDG 7, SDG 12, SDG 13, and SDG 4.

2.2.2. Social Comparison Nudges

Social comparison nudges, which capitalize on people's tendency to compare themselves to others, are highly effective in altering individuals' intentions to purchase green products, their willingness to pay (WTP), and their sustainable consumption habits. Upward comparisons can pose risks but motivate pro-environmental behavior, while downward comparisons can inspire pride and lead to sustainable choices. Self-monitoring affects how well they work because people who are good at self-monitoring respond more strongly [38–40].

Peer-based nudges are most effective for individuals who are already concerned about climate change or who hold an individualistic or hierarchical worldview [41]. Additionally, they can elevate WTP when consumers discover that peers are spending more on eco-labeled products, demonstrating conformity [42,43]. Strong descriptive norms can, however, encourage green buying, even when baseline norms are not very strong [44]. However, nudges alone are not always effective; when used in conjunction with moral or climate appeals, they are more effective [45,46].

Social norms and social pressures [47,48], cognitive dissonance [38,39], emotional triggers like guilt, pride [49,50], empathy, or satisfaction [51–53], moral identity, and behavioral transfer within networks [54,55] are all factors that can cause this to occur. But utilizing too many negative emotions can make things more challenging and lower participation [56,57]. Cultural and contextual disparities are essential. Some areas use nudges well [58,59], but not so well in others, such as green fashion e-commerce [60]. Several nudges may either strengthen one another or reduce their efficacy [61,62].

In practice, policymakers and marketers can incorporate peer comparisons into campaigns, associate nudges with social identity [63], and employ emotional framing to enhance effectiveness. To achieve lasting behavior change, nudges must be tailored to the situation, ethically constructed, and accompanied by moral appeals to prevent unintended consequences and optimize long-term sustainability results.

2.2.3. Gamification & Reward Nudges

Gamification integrates game components, such as points, badges, and leaderboards, into non-gaming environments to enhance participation in education, business, and healthcare [64,65]. Nudges, based on behavioral economics, help people make informed decisions without compromising their freedom [66]. Nudges help consumers make smarter, greener decisions in public policy, healthcare, and sustainability, and are increasingly incorporated into digital platforms and IoT systems. However, their success is contingent upon design quality and ethical utilization [67–69].

Gamification and reward nudges hold substantial potential for influencing green purchase intentions and fostering sustainable behaviors by enhancing satisfaction, perceived utility, and engagement through mechanisms such as competition, achievement, and social interaction [70,71]. Gamification does more than just make things entertaining; it also helps consumers build their own and their social identity. Social engagement is often more effective than competition at promoting environmental consciousness. Rewards like points, medals, and tangible goods encourage loyalty and eco-friendly behavior, such as proper waste disposal. These interventions enhance hedonic, utilitarian, and social value, thereby strengthening environmental concern and purchase intentions [53]. They also enhance psychological incentives, such as awareness, health consciousness, and perceived control [72–74]. Gamification closes the gap between intention and action by boosting self-efficacy [75] and encouraging people to take responsibility for making environmentally responsible choices [76]. While autonomy, visible progress, and meaningful rewards are crucial to success, poor system design can lead to short-term involvement without lasting change.

Reward nudges also promote low-carbon travel by enhancing satisfaction [77,78] and augmenting the willingness to pay (WTP) for sustainable products, such as eco-labeled items and sustainable fashion [64,65]. They work for online defaults and in-store food selections, but results differ [79–81]. Cultural environment is important: urban customers usually respond well [82,83], but success depends on careful execution [63]. Uncertain goals might lower trust, and poorly designed rewards can enhance WTP for unsustainable options like non-vegetarian items [84,85]. So, gamification and incentive nudges are powerful tools, but they must be tailored to the specific situation, transparent in their ethics, and compatible with technology to have the greatest long-term impact on sustainability.

2.2.4. Goal-Setting & Commitment Nudges

Goal-setting and commitment nudges are behaviourally informed interventions that change the choice environment to increase follow-through on intended actions. A nudge is any choice architecture intervention that predictably changes behavior without forbidding options or significantly altering economic incentives, and commitment devices are self-created or designed arrangements that bind future behavior to help fulfill plans that would otherwise fail due to self-control problems [86,87]. Goal-setting and commitment nudges effectively influence pro-environmental customer behavior by providing guidance, accountability, and incentives. Goal-setting nudges help customers establish clear, quantifiable objectives that direct their behavior, with evidence indicating their capacity to modify or reinforce sustainable practices [69,88]. Commitment nudges, through public or private vows, enhance adherence by eliciting feelings such as pride and remorse, reinforced by social norms [89]. Goal framing theory demonstrates how hedonic, normative, and gain frames influence eco-friendly attitudes, particularly when purchasing online [90]. When integrated with social cues, forecasts lead to increased purchases of green products [91]. These nudges increase self-efficacy and motivation, making consumers more inclined to make purchases [92,93]. However, consumers must decide between price and green features [33,94]. "Moral licensing" may make people less inclined to act sustainably in the future [95], and poorly designed nudges can lead people to choose unsustainable options, such as livestock [96]. Behavioral ability, infrastructure support, and cultural variations can affect [97,98]. Goal-setting and commitment nudges are effective in the short term. Still, they must be carefully planned, aligned with policy frameworks, and tailored to bridge the gap between intention and behavior.

Hence, the following hypotheses are proposed:

H1. *IoT-driven behavioral nudges have a positive effect on Green Behavioral Intention.*

H2. *IoT-driven behavioral nudges have a positive effect on Actual Behavior towards Sustainability.*

H3. *IoT-driven behavioral nudges positively influence Green Behavioral Intention through Energy Awareness.*

H4. *IoT-driven behavioral nudges positively influence Perceived Behavioral Control through Energy Awareness.*

H5. *IoT-driven behavioral nudges positively influence Green Behavioral Intention through Perceived.*

2.3. Energy Awareness

The intention to buy eco-friendly products indicates that people are willing to modify their habits to be more environmentally friendly. Environmentally informed individuals trust green products, perceive a lower risk, and value quality, which increases their

purchasing intention [99]. However, purpose does not always manifest in actions. The intention–behavior gap persists due to societal norms, behavioral skills, and institutional constraints [100,101]. Barriers such as high costs and poor infrastructure make choices more difficult, but psychological factors, including awareness of the environment and health consciousness, increase the likelihood that people will consume sustainably [102]. By focusing on the long-term benefits of sustainability, awareness efforts, and supportive laws can help close these gaps [103]. Models like the Motivation–Intention–Context–Behavior model emphasize that for meaningful change to happen, motivation, enabling conditions, and supporting settings must all work together [104,105].

Technologies such as the Internet of Things (IoT) address this issue by employing real-time data, automation, and feedback loops to facilitate sustainable consumption [106]. IoB analytics and IoT-driven nudges can frame choices, provide personalized reminders, and underline social norms to guide decisions [77,107,108]. However, ethical dangers persist: dark nudges—ambiguous or manipulative designs—may compromise autonomy and privacy [109,110].

Through smart buildings, waste reduction, and real-time monitoring, IoT promotes sustainability [111,112]. Effectiveness depends on how well technology fits culture and infrastructure, and technostress and digital fatigue must be addressed. IoT nudges support the achievement of SDGs 12 (Responsible Consumption and Production), 13 (Climate Action), 11 (Sustainable Cities and Communities), and 9 (Industry, Innovation, and Infrastructure). However, different levels of technology readiness and high expenses make it challenging for individuals to adopt it. To achieve long-lasting results, you need clear designs, consider the situation, and focus on the user. Sustainable outcomes require transparent, context-sensitive, and user-centered designs, combined with policies that lower barriers and build trust.

2.4. Perceived Behavioural Control

Digital nudging, powered by the Internet of Things (IoT), may significantly enhance perceived behavioral control (PBC), a crucial factor in bridging the intention-behavior gap for environmentally beneficial actions. PBC refers to an individual's confidence in their ability to perform a specific task, and IoT interventions, such as smart meters that provide consumers with real-time feedback on their energy use, offer them useful information that facilitates more sustainable decisions and enhances their self-efficacy [4,113]. Design components that encourage reflective behavior, such as prompts or "design friction," improve awareness of the consequences of actions, hence reinforcing perceived behavioral control (PBC) and promoting consistent, sustainable behavior [114,115]. IoT nudges assist in closing the gap between pro-environmental intentions and actual behavior by improving PBC. This directly supports SDG 7 (Affordable and Clean Energy) and SDG 12 (Responsible Consumption and Production) through energy-efficient activities and conscious resource usage. Nonetheless, this impact can be mitigated by technostress, information overload, and cognitive load, which may obstruct the conversion of perceived control into tangible action [5]. Ethical design is also important to ensure that nudges give people autonomy instead of controlling them, thereby protecting their freedom while also encouraging sustainability [116,117]. In this way, IoT nudges enhance PBC and contribute to achieving SDG-related goals. However, they only work if they are designed with care and focus on the user, taking into account information, usability, and ethical responsibility.

2.5. Green Behavioral Intention and Actual Behaviour Towards Sustainability

A person's green purchase intention is their expressed willingness to buy eco-friendly items. A person's green purchasing behavior refers to the actual act of buying environmentally friendly products. The Theory of Planned Behavior (TPB) [12] says that three things determine intention: attitudes ("are green products good?"), perceived social pressure,

and perceived control over the conduct. Long-term research repeatedly demonstrates that positive attitudes, norms, and perceived behavioral control enhance intentions for green consumption [118,119]. However, in reality, intentions do not always lead to purchases, which is a well-known gap between intentions and action [120].

However, established gaps exist when green solutions are more expensive, difficult to find, or perceived as performing poorly, forcing customers to choose between price, quality, and convenience [121,122]. Second, context and friction are important: restricted availability, ambiguous eco-labels, and choice fatigue make it more difficult to transition from intention to action. Third, habit and status quo bias are the most significant factors in routine categories; even customers who care about the environment tend to choose products that are not environmentally friendly [123]. Fourth, moral licensing and rebound effects can impede progress—performing one environmentally friendly action might, ironically, permit less sustainable decisions subsequently, or savings from efficiency may be used in carbon-intensive ways [124]. These obstacles elucidate the phenomenon of intention frequently over-predicting behavior in meta-analyses [125].

A growing body of research identifies key levers that can close the gap. Enhancing perceived behavioral control (providing clear information on how, where, and at what cost to purchase green products; facilitating simple returns; and ensuring trustworthy certifications) enhances the transition from intention to action [12,126]. Social norms and identification signals, such as informing people about what others like or allowing them to make public commitments, help both intentions and behaviors last longer. Choice architecture is also helpful: defaults, simpler comparisons, and trustworthy labeling make it easier to make a decision [121]. It is essential to recognize that intrinsic motivators, such as values, identity, and competence, tend to persist longer than extrinsic benefits, like discounts, which can eventually diminish or overshadow inherent motivation [124].

From a critical perspective, two conceptual explanations are essential. First, "green intention" is not uniform; intentions to attempt, switch, pay a premium, and repurchase indicate increasing complexity and may possess distinct predictors [127]. Considering intention as a singular entity may exaggerate its predictive capacity. Second, several studies depend on self-reports obtained in low-stakes environments; social desirability biases exaggerate both intentions and recalled behaviors [128]. High-indexed journals are increasingly demanding behavioral field metrics (e.g., transaction data, telemetry from smart meters) to validate laboratory and survey findings [129].

Real-time feedback, default settings, and personalized reminders can enhance perceived control and salience at the moment of decision-making, thereby increasing the likelihood of intention realization (in accordance with SDG 12 on Responsible Consumption and SDG 13 on Climate Action). However, technology is not a universal remedy; its efficacy depends on trust, privacy protection, and user-friendliness; otherwise, techno-stress and reactance undermine progress [121]. The most promising evidence combines a message that aligns with the person's identity, low-friction design, and trustworthy certification, rather than relying solely on nudges or discounts [124,129].

The study emphasizes the determinants that affect individuals' propensity to act on their sustainable goals. The construct "Actual Behaviour Towards Sustainability" represents real-world behaviors like minimizing energy use, buying eco-friendly items, and adopting low-impact behaviors in this study.

2.6. Technology Readiness as a Moderator in Green Purchase Behavior

Technology Readiness (TR) indicates an individual's willingness to adopt and proficiently utilize emerging technologies, such as IoT-enabled systems that promote sustainable consumption [130]. In relation to green behavioral intention and actual conduct, TR serves

as a moderating factor, affecting the degree to which intentions are converted into tangible actions. A high TR individual is more likely to employ smart energy meters, automated recycling reminders, or IoT-enabled sustainable product platforms to close the intention-to-action gap. A low TR may weaken the relationship because people may struggle with technology or not trust digital nudges, making it less likely that they will act on their environmental objectives.

Several studies focus on the direct impacts of awareness, perceived behavioral control, and nudges on green behavior. However, without considering TR as a moderator, the adoption dynamics remain unclear. Technology readiness not only promotes adoption but also engages with perceived behavioral control and IoT nudges to improve self-efficacy, decrease cognitive load, and streamline sustainable initiatives [6,131]. For instance, input from IoT devices on energy use is effective if the user knows how to utilize the gadget; TR makes sure that people can interact with technical cues in a meaningful way.

Integrating TR as a moderator supports SDG 7 (Affordable and Clean Energy) by encouraging energy-efficient technologies, SDG 12 (Responsible Consumption and Production) by equipping consumers to act on their sustainable intentions, and SDG 13 (Climate Action) by reducing energy waste and carbon emissions through smart systems. Thus, TR is a behavioral facilitator that may improve sustainability activities when mediated by IoT nudges, awareness, and behavioral control.

TR emphasizes equality and accessibility. Failing to consider the needs of individuals with lower technological skills or limited access to IoT devices may exacerbate the digital divide in sustainable practices [6,130]. User-friendly interfaces, guided lessons, and adaptive nudges that cater to varied readiness levels can make sustainability adoption more inclusive and successful. Future studies should explore these treatments.

H6. *Technology Readiness positively moderates the relationship between Green Behavioral Intention and Actual Behaviour towards Sustainability, such that the relationship is stronger when Technology Readiness is high.*

The proposed conceptual model as shown in Figure 2 was formulated subsequent to an extensive review of prior research concerning IoT-driven behavioral nudges, sustainable energy practices, and pertinent theories, including the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), and Nudge Theory. The model's primary variables and relationships were identified from these studies. So, the model shows how the hypotheses were made based on evidence from previous studies, illustrating how IoT technologies and behavioral factors integrate to affect sustainable energy behaviors.

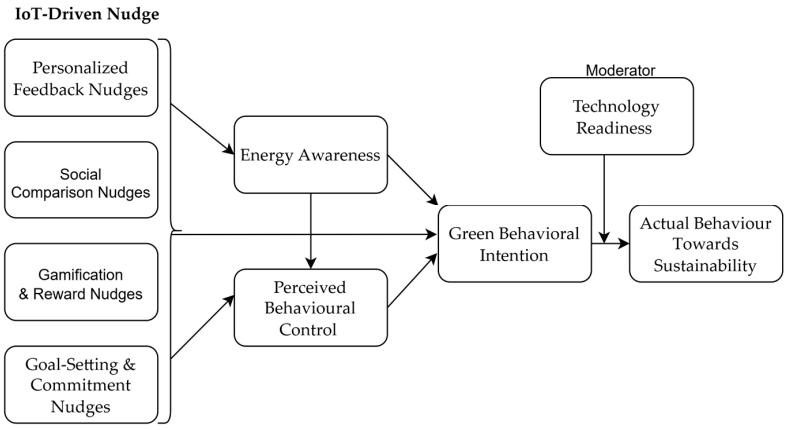

Figure 2. Framework of the Study.

2.7. Nudge Logic and Implementation Parameters

Table 1 transforms theoretical nudging categories into IoT-enabled infrastructure-implementable guidelines. Using IoT, it shows how the four nudge families were operationalized. Different nudges have different triggers, delivery mechanisms, and timings.

Table 1. IoT-Enabled Nudge Logic and Delivery Framework.

Nudge Type	Trigger Condition	Delivery Mechanism	Frequency/Cadence
Goal-Setting Nudges	User-defined energy reduction target not yet achieved	Mobile app notification	Weekly progress reminders
Social Comparison Nudges	Household usage exceeds the neighborhood average by >15%	Dashboard + push alert	Monthly benchmarking
Feedback Nudges	Daily consumption exceeds the prior 7-day average by >10%	In-home display alert	Daily real-time feedback
Information Nudges	Policy updates or sustainability tips become available	Email + app alert	Monthly or event-triggered

3. Methods

This study embraces both formative and reflective constructions, contingent upon the definitions of each variable. In a reflective framework, the primary idea or concept shapes the responses to the questions. This means all the questions reflect the same belief or attitude. Since they reflect people's energy-saving beliefs and intentions, Energy Awareness, Green Behavioral Intention, and Perceived Behavioral Control were treated as reflective. A formative approach, on the other hand, suggests that the concerns work together to develop or form the idea. We modeled IoT-Driven Nudges as formative because it has several different components, such as goal setting, personalized feedback, social comparison, gamification, and rewards, that all work together to make up the overall nudge structure. We assessed the reliability and consistency of the reflective variables and the overlap between items, and the relevance of each aspect of the formative construct [132]. In this study, a disjoint two-stage approach was employed as a crucial method of analysis. The higher-order constructs (HOCs) are widely recommended in PLS-SEM when the research deals with multidimensional constructs, as they help in providing a clear estimation of both lower-order components (LOCs) and their contribution to the higher-order construct. To proceed with the formal analysis, we assessed all lower–order constructs individually to ensure their validity and reliability. In the second stage, the latent variable scores of these LOCs were used as indicators for the higher-order construct [49,133].

3.1. Research Design

This study employs a quantitative, cross-sectional research approach to investigate how IoT-driven behavioral nudges, energy awareness, perceived behavioral control, and technological readiness influence individuals' intentions and behaviors related to sustainability. A cross-sectional approach was used, as it enables the acquisition of extensive data at a single time point, thereby permitting a comprehensive statistical examination of the interactions across constructs [134].

3.2. Framework

The study integrates the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), and Nudge Theory to comprehensively capture the drivers of sustainable behavior.

3.3. Population and Sampling

The study focused on adults who use IoT-enabled energy-efficient gadgets. To ensure diversity in age, gender, and technical skill, stratified random sampling was employed. Although the stratified random sampling approach improved demographic representation, online recruitment may still involve a degree of self-selection bias, as participation required respondents to have prior experience with IoT devices and internet access. IoT users provided efficient and systematic replies via an online survey. The final dataset comprised 815 valid responses after screening, providing SEM-PLS with sufficient statistical power [132]. The demographic analysis, referred to in Appendix G, reveals a balanced distribution across gender, age, and education, with a predominant representation of professionals and employees. Most participants indicated that they had moderate to high expertise in IoT. This means that the sample is a good representation of digitally active consumers in Saudi Arabia. This variety enhances the study's reliability and applicability to other situations.

3.4. Variables and Measures

The study assessed essential elements affecting sustainable behavior using 31 items. A dozen items measured IoT-driven behavioral nudges. Three questions each were used from Personalized Feedback, Social Comparison, Gamification & Reward, and Goal-Setting & Commitment. Energy Awareness, Perceived Behavioral Control (PBC), Green Behavioral Intention (GBI), Technology Readiness, and Actual Behavior Towards Sustainability were measured with four items each. This revealed the cognitive, behavioral, and technical aspects that influence the adoption of sustainability (for details, refer to Appendix F).

3.5. Data Analysis Strategy

SEM-PLS was used to examine the data. This method performs well with complex models that have mediating and moderating factors, and does not need normally distributed data [132,135]. The analysis initially evaluated the measurement model for reliability (Cronbach's alpha and composite reliability) and validity (convergent and discriminant validity). Then, the structural model was evaluated using path coefficients, R^2, f^2, and significance levels. The total and specific indirect effects demonstrated how Energy Awareness and Perceived Behavioral Control served as mediators. We also examined how Technology Readiness influences the relationship between behavioral intention and actual behavior. Lastly, model fit indices (SRMR, d_ULS, d_G, Chi-square, NFI) indicated that the framework was strong. The detailed output generated from the analysis can be accessed and downloaded from the Supplementary File, which is provided via the link mentioned in the Supplementary File section.

3.6. Ethical Considerations

All participants gave their informed consent, and their privacy and identity were protected. Participants may choose whether or not to participate, and the study adhered to ethical guidelines for social research.

Justification for Methodology.

The integration of TPB, TAM, and Nudge Theory with SEM-PLS analysis guarantees that the study encompasses cognitive, technical, and behavioral aspects of sustainable adoption. This empirical approach yields strong and accurate insights into the efficacy of IoT-driven methods in fostering sustainable behaviors within everyday settings.

To align with applied technology and emphasis on reproducibility, the following materials are provided as electronic supplements:

1. Survey Instrument and Codebook—Full questionnaire, item wordings, and coding schema.

2. SmartPLS4 Project File and Output—Including bootstrapping settings with 5000, model fit indices, and latent variable scores.
3. R/R(version number R 4.4.2)/Python(Version-3.12.6) Analysis Scripts—Scripts used for data preprocessing, reliability/validity checks, and structural model estimation.
4. Dataset—An anonymized and resampled dataset allowing replication of analyses without violating privacy.
5. Nudge Scheduler Pseudocode—Rule-based logic for delivering nudges (conditions, triggers, cadence).
6. Architecture Diagram (Figure 1)—High-resolution version of the IoT-based system framework.

4. Data Analysis & Interpretation

4.1. Measurement Model

The measurement methodology verifies that all constructs in this investigation are both reliable and valid. Strong construct representation was shown by indicator loadings above 0.7. The results for Cronbach's Alpha and Composite Reliability were both above 0.7, indicating that the tests were consistent. The AVE values above 0.5 indicated that convergent validity was established, while the HTMT ratios and Fornell–Larcker criterion demonstrated discriminant validity (Refer Table 2 and Appendix J). The VIF values were less than 3 (refer to Appendix A), which means that multicollinearity does not indicate any issue. Using Q^2 predict, RMSE, and MAE, as indicated in Appendix H, indicates how well the model can make predictions. All constructions have positive Q^2 values, which means they are effective at predicting outcomes. Green Behavioral Intention is the most accurate, while Perceived Behavioral Control is moderately accurate but still acceptable. All indicators reveal that the loadings are appropriate (0.26–0.45) (refer to Appendix I), which means that each one adds something important to its build. Goal-setting, Gamification, and Feedback Nudges have the greatest impact, while Technology Readiness and Behavior have a moderate role. Overall, the results show that there is a reliable and well-defined way to measure IoT-enabled nudging behavior.

These results suggest that the model is accurate and robust, providing a solid platform for assessing the proposed framework's structural linkages.

Table 2 shows that the measurement model is reliable and convergent across all constructs. Both Cronbach's alpha and composite reliability (rho_a and rho_c) are above 0.7, indicating consistent construct responses. For all constructs, the Average Variance Extracted (AVE) surpasses 0.50, indicating that each construct explains a significant percentage of indicator variance [136]. These results demonstrate that the survey items effectively capture the targeted constructions, laying the groundwork for a structural analysis. The HTMT (Heterotrait-Monotrait) values in the correlation matrix indicate that the constructs are valid. The HTMT correlations are all below the commonly suggested cutoff of 0.85. This means that each construct, such as Energy Awareness, Green Behavioral Intention, Perceived Behavioral Control, and various IoT-driven nudges, is separate and measures a distinct part of the research model. The low values for the interaction term (Technology Readiness $\times$ Green Behavioral Intention) further support the idea that the moderating influence does not have much in common with the major dimensions. The HTMT analysis shows that the measurement model is discriminant valid, which means that the constructs may accurately represent their intended dimensions without any problems with multicollinearity, as shown in Table 2.

Table 2. Convergent Validity & Discriminant Validity.

Constructs	Cronbach's α	rho_a	rho_c	AVE	AB	EA	GN	GS	GBI	PBC	PFN	SCN	TR	TR × GBI
Actual Behaviour (AB)	0.870	0.873	0.911	0.720	–	0.580	0.390	0.368	0.637	0.536	0.438	0.462	0.338	0.062
Energy Awareness (EA)	0.747	0.750	0.840	0.568	0.580	–	0.344	0.412	0.568	0.424	0.392	0.431	0.232	0.077
Gamification Nudges (GN)	0.786	0.789	0.875	0.700	0.390	0.344	–	0.249	0.462	0.310	0.217	0.249	0.165	0.031
Goal-Setting Nudges (GS)	0.805	0.805	0.885	0.720	0.368	0.412	0.249	–	0.373	0.315	0.250	0.233	0.236	0.049
Green Behavioral Intention (GBI)	0.801	0.804	0.883	0.716	0.637	0.568	0.462	0.373	–	0.528	0.440	0.433	0.344	0.028
Perceived Behavioral Control (PBC)	0.773	0.779	0.854	0.594	0.536	0.424	0.310	0.315	0.528	–	0.396	0.384	0.197	0.035
Personalized Feedback Nudges (PFN)	0.791	0.801	0.877	0.705	0.438	0.392	0.217	0.250	0.440	0.396	–	0.245	0.248	0.020
Social Comparison Nudges (SCN)	0.783	0.793	0.873	0.696	0.462	0.431	0.249	0.233	0.433	0.384	0.245	–	0.223	0.021
Technology Readiness (TR)	0.826	0.827	0.885	0.657	0.338	0.232	0.165	0.236	0.344	0.197	0.248	0.223	–	0.005
TR × GBI	–	–	–	–	0.062	0.077	0.031	0.049	0.028	0.035	0.020	0.021	0.005	–

4.2. Structural Model

We used 5000 subsamples and two-tailed tests at a 95% confidence level in SmartPLS 4 to check the statistical significance of path coefficients, mediation, and moderation effects. This method complies with [132] PLS-SEM analysis requirements and has stable standard errors. The structural model in Figure 3 and Table 3 indicates that the proposed framework adequately explains essential components associated with sustainable behavior. The R^2 value for Actual Behaviour Towards Sustainability is 0.311, whereas the R^2 values for Green Behavioral Intention, Energy Awareness, and Perceived Behavioural Control are 0.365, 0.239, and 0.213, respectively. This means that these values have moderate explanatory power. The model fit indices, including SRMR (0.077), d_ULS (3.558), d_G (0.225), Chi-square (1079.030), and NFI (0.847), suggest that the model fits the data reasonably well. Overall, the model fit indices were good. The SRMR score (0.085) falls within the marginally acceptable range ($\leq$0.10), indicating the model accurately describes the data. While the NFI value (0.868) falls below the optimal criterion ($\geq$0.90), it is still suitable for complicated PLS-SEM models with various mediators and moderators [132] (Hair et al., 2022). NFI's small divergence may be due to model complexity, not misspecification. Since all reliability and validity criteria were met, the model was preserved as theoretically and empirically robust without respecification.

Harman's single-factor test and the comprehensive collinearity methodology [137] were used to check for possible common method bias. The unrotated factor analysis showed that the first component explained 34.2% of the variance, below 50%. Also, all of the collinearity VIF values were less than 3.3, which shows that there was no significant common method variance. Common technique bias is unlikely to alter construct relationships.

The data in Table 4 and Figure 4 reveal that IoT-based behavioral nudges have a clear and steady effect on sustainability outcomes. Nudges not only enhance individuals' green intentions (H1) but also affect their Actual Behaviour towards Sustainability (H2), with both effects being highly significant ($p < 0.000$). This suggests that IoT nudges are not only changing people's perceptions but also influencing their behavior, which is an acknowledged issue in research on sustainability. The indirect effects also support this idea. Nudges increase awareness of energy, which makes individuals more likely to follow through on their plans (H3). They also make people feel like they have more control over their behavior (H4), which makes them more likely to act in a way that is good for the environment. Despite perceived control mediating intention (H5), the

impact holds, demonstrating that nudges empower users. Technology readiness also helps turn intention into action (H6), although its effect is minimal (f^2 = 0.007). The moderation effect of Technology Readiness (f^2 = 0.007) is statistically small; however, its practical relevance persists in growing digital ecosystems like Saudi Arabia. Small effects can matter in large populations or complicated behavioral systems [138,139]. In this context, even little improvements in technological readiness might help people turn their good intentions into real actions, especially when digital literacy and IoT use are still growing. Readiness appears to be a supportive enabler rather than a primary determinant, emphasizing the need for training, awareness campaigns, and user-friendly IoT interfaces to improve behavioral results. So, even though the number is not large, it shows that it is a really important step toward making technology use more sustainable and reaching SDGs 9 and 12 through digital participation that includes everyone. The f^2 results demonstrate the relative effects of various factors. Green Behavioral Intention significantly influenced actual sustainable behavior (f^2 = 0.326, indicating a moderate to strong effect), being the primary driver. Energy Awareness was moderately impacted by IoT-driven behavioral nudges (0.315), while intention (0.135) and perceived control (0.136) were less. Energy awareness (0.048) and perceived control (0.047) alone were insufficient to drive change without additional support, such as rewards or system structures. Energy Awareness had a small effect on perceived behavioral control (0.020). In contrast, Technology Readiness had a small effect on actual sustainability behavior (0.030) with negligible moderating impact (Technology Readiness × Green Behavioral Intention = 0.007) (see Appendix E).

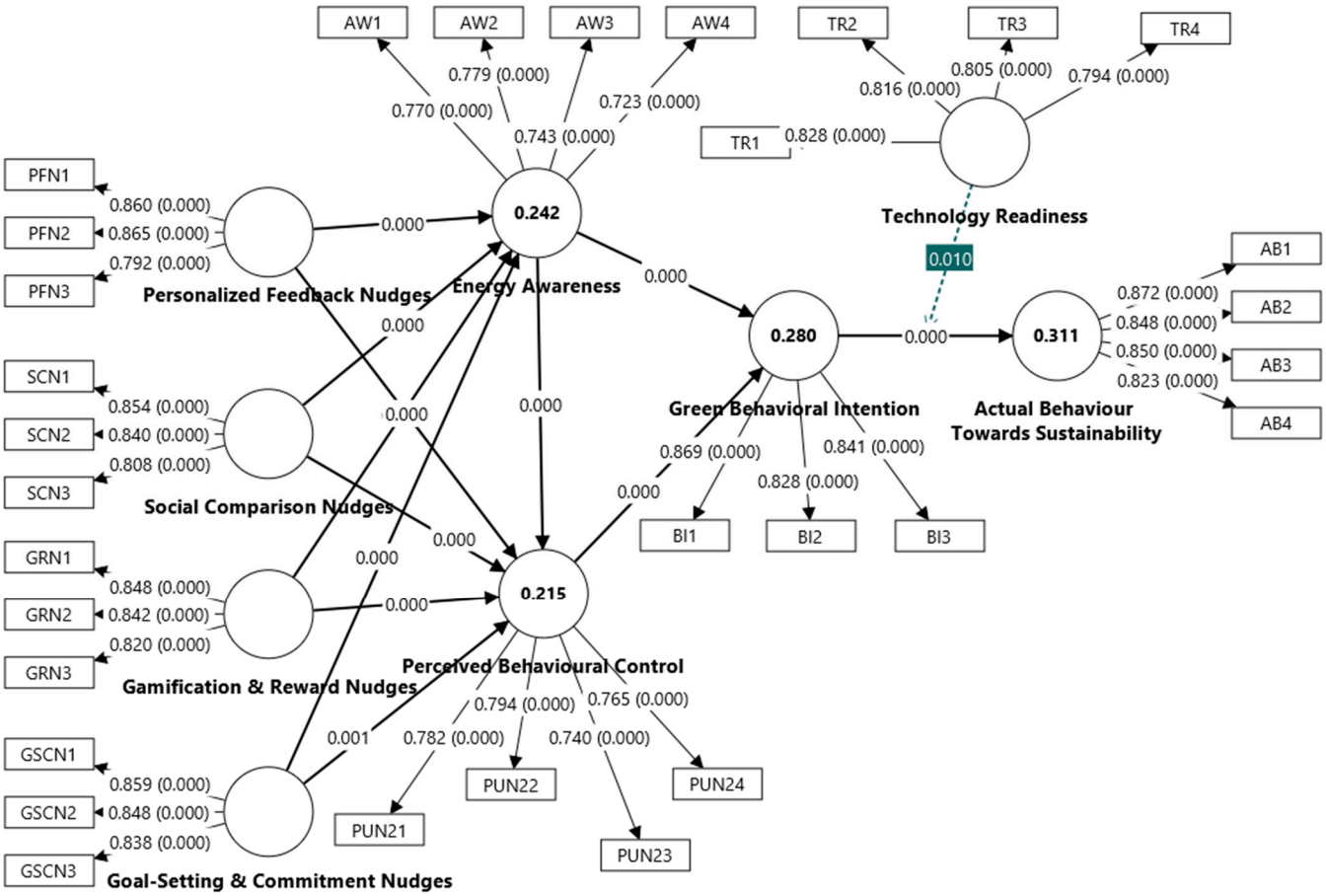

Figure 3. Measurement & Structural Model—Reflective.

Table 3. Model Fit Assessment Result.

Construct/Fit Index	R^2	R^2 Adjusted	Saturated Model	Estimated Model	Threshold/Rule of Thumb	Interpretation
Actual Behaviour Towards Sustainability	0.311	0.308	-	-	Moderate (0.26–0.50)	Moderate explanatory power
Energy Awareness	0.239	0.238	-	-	Weak to Moderate (0.19–0.25)	Weak–moderate explanatory power
Green Behavioral Intention	0.365	0.363	-	-	Moderate (0.26–0.50)	Moderate explanatory power
Perceived Behavioural Control	0.213	0.212	-	-	Weak to Moderate (0.19–0.25)	Weak–moderate explanatory power
SRMR	-	-	0.045	0.077	≤0.08 (good), ≤0.10 (acceptable)	Excellent (saturated); marginally acceptable (estimated)
d_ULS	-	-	0.557	1.621	Lower is better; no strict cutoff	Acceptable
d_G	-	-	0.183	0.225	Lower is better; no strict cutoff	Reasonable
Chi-square	-	-	937.380	1079.030	Lower is better; *p*-value considered	Reasonable
NFI	-	-	0.868	0.847	≥0.90 (good), ≥0.80 (acceptable)	Acceptable

Table 4. Hypothesis Testing and Effect Size.

Hypothesis	Path	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics	*p* Values	Remarks	f^2 Effect Size (Target Constructs)
H1	IoT-Driven Behavioural Nudge -> Green Behavioral Intention	0.185	0.186	0.021	8.95	0.000	Supported	f^2 = 0.135 Weak–Moderate
H2	IoT-Driven Behavioural Nudge -> Actual Behaviour Towards Sustainability	0.268	0.270	0.021	12.542	0.000	Supported	f^2 = 0.136 Weak–Moderate
H3	IoT-Driven Behavioural Nudge -> Energy Awareness -> Green Behavioral Intention	0.099	0.099	0.017	5.784	0.000	Supported	-
H4	IoT-Driven Behavioural Nudge -> Energy Awareness -> Perceived Behavioural Control	0.070	0.070	0.017	4.16	0.000	Supported	-
H5	Perceived Behavioural Control -> Green Behavioral Intention	0.073	0.073	0.014	5.237	0.000	Supported	f^2 = 0.047 Weak
H6	Technology Readiness × Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.071	0.071	0.027	2.572	0.010	Supported	f^2 = 0.007 Very Weak

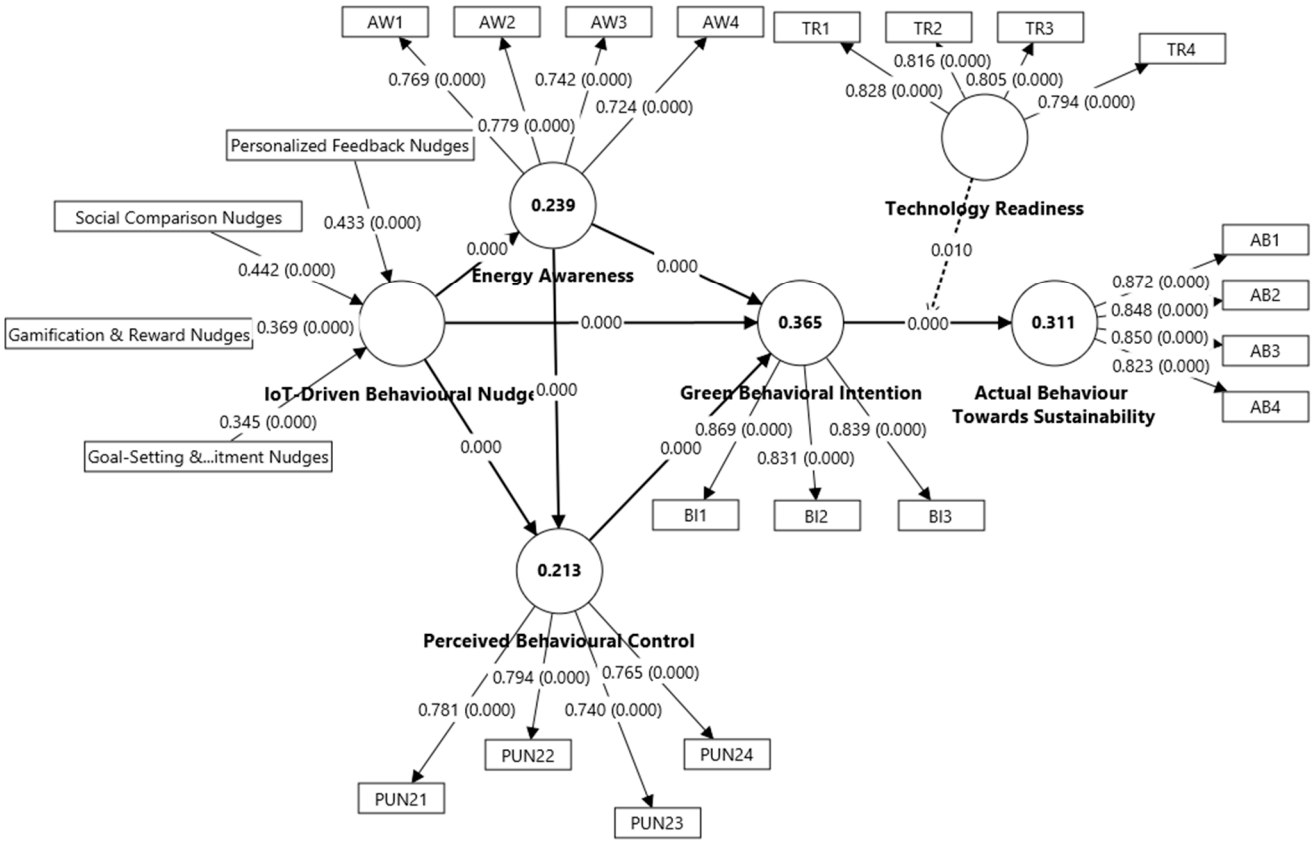

Figure 4. Structural Model—Formative—Reflective.

$EA = 0.257N + \varepsilon_1$
$\partial EA/\partial N = 0.257$
$PBC = 0.272EA + \varepsilon_2$
$\partial PBC/\partial EA = 0.272$
$GBI = 0.185N + 0.385EA + 0.308PBC + \varepsilon_3$
$\partial GBI/\partial N = 0.185$, $\partial GBI/\partial EA = 0.385$, $\partial GBI/\partial PBC = 0.308$
$AB = 0.268N + 0.494GBI + 0.152PBC + 0.190EA + 0.071(TR \times GBI) + \varepsilon_4$
$\partial AB/\partial N = 0.268$, $\partial AB/\partial GBI = 0.494 + 0.071TR$, $\partial AB/\partial PBC = 0.152$, $\partial AB/\partial EA = 0.190$
$SO = \omega \cdot AB + \varepsilon_5$
$\partial SO/\partial AB = \omega$
Refer to Appendix I for the abbreviation.

In general, the results demonstrate that nudges based on the Internet of Things (IoT) improve awareness, planning, and control. However, intention is the most effective way to predict long-term behavior. Technology readiness plays a role in this process, but motivation and structural supports are more important. This study shows how a multilayered IoT nudge architecture, from sensors to apps, can lead to observable changes in behavior. This is important for SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action).

The moderation analysis (Figure 5) indicates that Technology Readiness enhances the correlation between Green Behavioral Intention and Actual Behaviour towards Sustainability ($\beta = 0.071$, $p = 0.01$), although the effect is very minor. A straightforward slope analysis demonstrates that persons with higher readiness display a more significant intention–behavior trajectory, signifying a greater likelihood of acting upon their sustainable objectives. On the other hand, people who are not ready show a flatter slope, which means that having strong intentions alone may not lead to conduct without the right digital

skills. These results highlight that, although technical readiness enhances the efficacy of IoT-enabled nudges, it is not the exclusive factor influencing sustainable behavior. To reduce the gap between intention and behavior, we still need bigger changes to motivation and structure. This fits with the technology concentration on ICT applications that help achieve sustainability goals, which directly support SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action).

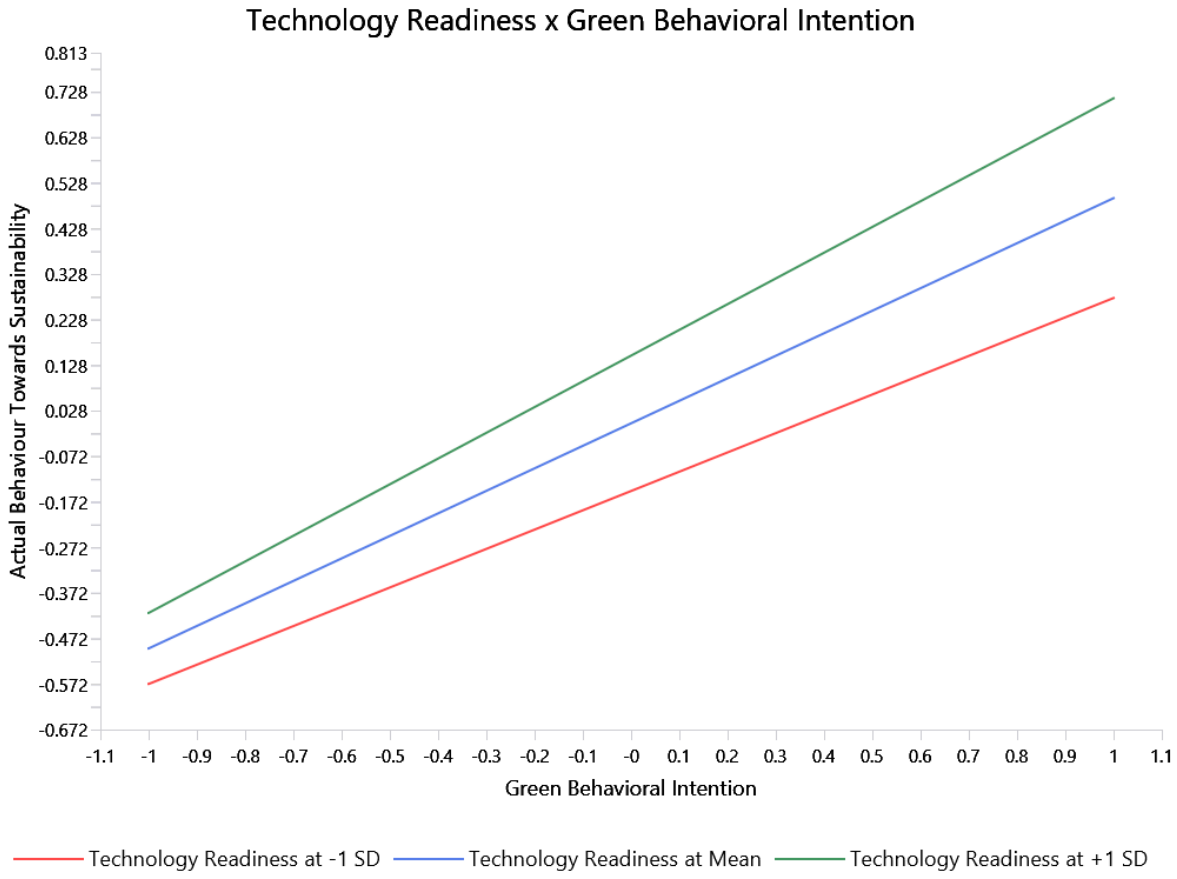

Figure 5. Slope Analysis for Moderator.

Importance Performance Map Analysis

Importance-Performance Map Analysis (IPMA) in SEM-PLS is an advanced approach that enhances the approach of coefficient analysis by investigating both the importance (the overall impacts of predictors on a target construct) and the performance (the average scores of the latent variables) [93,140,141] (see Appendix D).

The IPMA results in Table 5 show that Green Behavioral Intention (GBI) is the most important component in encouraging people to act sustainably, both in terms of importance (0.494) and performance (49.877). This implies that nudging intention is more important than increasing awareness or control. The impacts of IoT-driven nudges (0.268; 49.76) and Energy Awareness (0.114; 49.561) are secondary to intention, even though they are helpful. Perceived Behavioral Control (PBC) and Technology Readiness exhibit comparatively diminished relevance, suggesting that although confidence and readiness promote adoption, they are not the primary behavioral catalysts for adoption. This implies developers should create IoT systems that improve intention through individualized, engaging nudges, and politicians should support these efforts with awareness campaigns and supportive infrastructure to sustain impact, as shown in Figure 6.

Table 5. IPMA.

Constructs	Performance	Green Behavioral Intention	Actual Behaviour Towards Sustainability
Energy Awareness	49.561	0.23	0.114
Green Behavioral Intention	49.877	0.543	0.494
IoT-Driven Behavioural Nudge	49.744	0.195	0.268
Perceived Behavioural Control	49.323	-	0.096
Technology Readiness	49.115	-	0.149

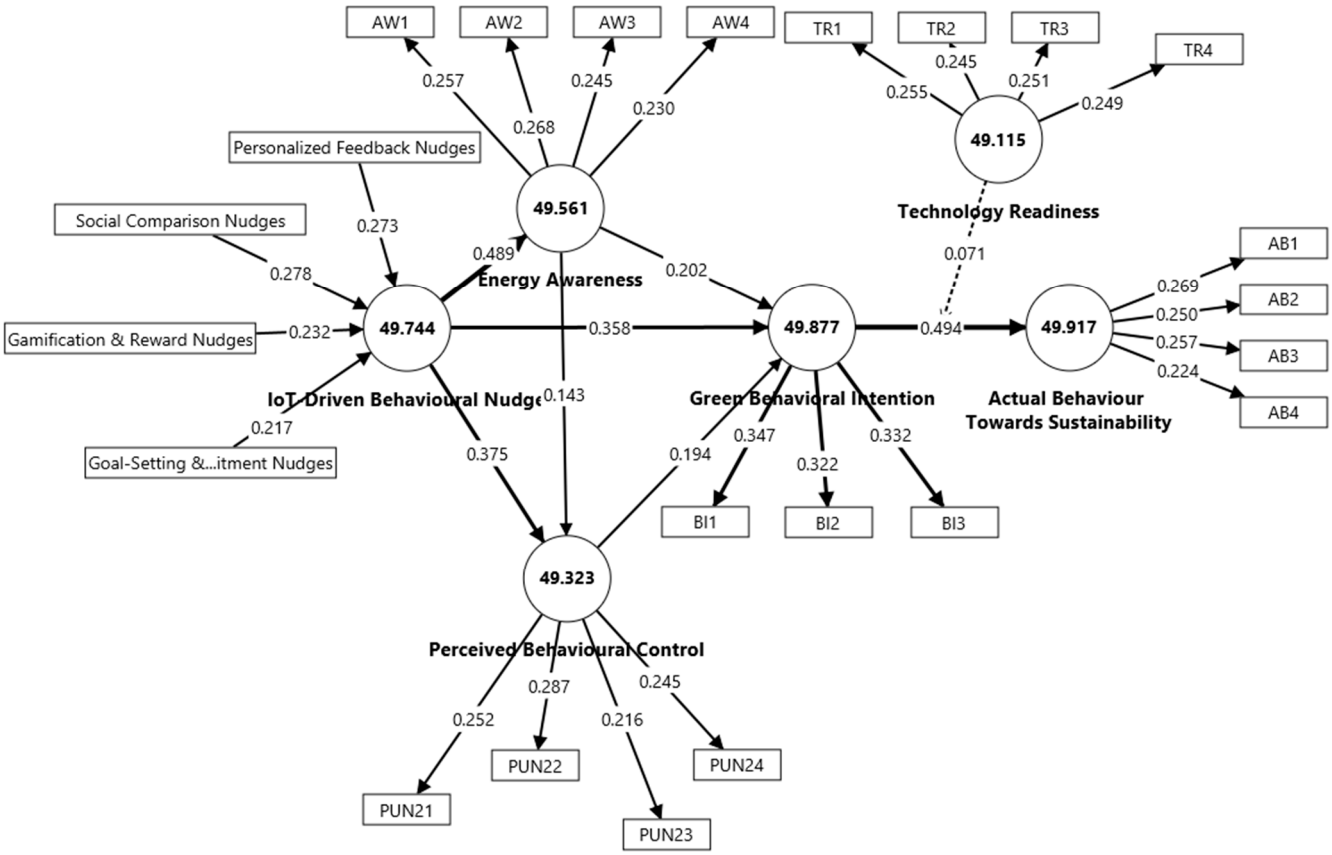

Figure 6. IPMA (Graphical).

5. Discussion

This study advances understanding of how IoT-driven behavioral nudges shape sustainable consumption by combining the Theory of Planned Behavior (TPB) [12], the Technology Acceptance Model (TAM), and Nudge Theory into an integrated framework. The results demonstrated that the measurement model had strong reliability and validity. In contrast, the structural model explained a moderate but meaningful variance in behavioral outcomes (R^2 = 0.215–0.311), consistent with standards for technology adoption and behavioral research [136]. This confirms the suitability of applying behavioral and technology-focused models in the context of IoT-enabled sustainability interventions.

A key finding is that Energy Awareness strongly predicts Green Behavioral Intention (GBI) (β = 0.385) and moderately affects Actual Behavior (β = 0.190). These results reinforce the idea that awareness is necessary for sustainable choices, but not sufficient on its own,

echoing prior work that shows knowledge must be coupled with enabling contexts to influence behavior [8,103,142]. GBI remains the most important driver of sustainable behavior (β = 0.494), in line with TPB's emphasis on intention as a primary antecedent of action [143]. Similarly, Perceived Behavioral Control (PBC) influences both intention (β = 0.308) and actual behavior (β = 0.152), supporting earlier studies that highlight competence and self-efficacy as critical to bridging the intention–behavior gap [114,144,145].

The analysis also revealed that Social Comparison and Goal setting & Commitment nudges were the most effective at strengthening awareness and control. This aligns with recent evidence showing that peer-based comparisons and goal-oriented feedback drive pro-environmental behavior more consistently than extrinsic rewards alone [41,45]. In contrast, personalized feedback had only a small effect, suggesting that bundling nudges may be more effective than deploying them in isolation [5,146]. These findings align with SDG 4 (Quality Education) by emphasizing the significance of awareness and empowerment in fostering long-term sustainable decision-making.

The study demonstrates that IoT-enabled nudges enhance awareness and control through both direct and indirect channels. The indirect benefits were less strong, though, which means that infrastructure, affordability, and cultural support must all work together to create enduring changes in behavior. This is a drawback that [9] also pointed out. Tech Readiness had a small direct effect (β = 0.149) and a positive moderating role (β = 0.071), suggesting that individuals fluent in IoT technologies are more likely to act on their intentions (see Appendixes B and C for details). This corroborates previous research connecting digital readiness to sustainable adoption [6] and is consistent with SDG 9 (Industry, Innovation & Infrastructure) and SDG 13 (Climate Action). However, the results show that Technology Readiness has only a small moderate effect, indicating that while it influences the relationship, its overall impact is less. This suggests that individual readiness for technology enhances adoption behavior to some extent, but it is not a dominant determinant in the model, which can further open avenues for future research. Future studies can also examine Technology Readiness across different user segments or cultural settings to better understand its evolving role in technology adoption dynamics. Refer to Table 6 for details.

Table 6. Linkage of Constructs to SDG Contribution.

Construct	Role in Study	Relevant SDG(s)	SDG Contribution
Energy Awareness	Mediator between IoT Nudges and Intention/Behavior	SDG 12 (Responsible Consumption & Production) SDG 13 (Climate Action)	Enhances consumer knowledge about energy use, encouraging responsible choices and reducing carbon impact.
Green Behavioral Intention (GBI)	Strongest predictor of Actual Behaviour towards Sustainability	SDG 12 (Responsible Consumption & Production)	Drives willingness to adopt eco-friendly products, practices, and consumption patterns.
Actual Behavior Towards Sustainability (ABS)	Outcome of the model (dependent variable)	SDG 11 (Sustainable Cities & Communities) SDG 13 (Climate Action)	Reflects the measurable adoption of sustainable practices, such as energy conservation, recycling, and environmentally friendly purchasing.

Table 6. *Cont.*

Construct	Role in Study	Relevant SDG(s)	SDG Contribution
Perceived Behavioral Control (PBC)	Influences both Intention and Actual Behavior	SDG 12 (Responsible Consumption & Production)	Increases confidence and ability of individuals to engage in sustainable behaviors.
IoT-Driven Behavioral Nudges	Independent variables: personalized feedback, social comparison, gamification, goal-setting	SDG 7 (Affordable & Clean Energy) SDG 12 (Responsible Consumption & Production)	Provide real-time feedback and motivation, encouraging users to adopt energy-efficient and sustainable choices.
Technology Readiness	Moderator between Intention and Actual Behavior	SDG 9 (Industry, Innovation & Infrastructure) SDG 12 (Responsible Consumption & Production)	Ensures users' confidence and capability to adopt IoT solutions, bridging the gap between intention and action.

Even with these contributions, there are still problems. Knowledge did not always affect behavior, and nudges varied in effectiveness. Barriers, including high costs, restricted access to IoT infrastructure, and cultural differences, made it challenging to achieve the desired results [147–149]. To close these gaps, we need to take action on multiple levels, combining IoT-driven nudges with effective legislation, regulations, and community education. This way, IoT may reach its full potential to help with SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 12 (Responsible Consumption and Production).

6. Conclusions

The present study developed and evaluated an IoT-enabled digital nudge framework to promote sustainable energy practices. It demonstrates that integrating nudging techniques—such as tailored feedback, social comparison, gamification, and goal-setting—within IoT systems effectively narrows the disparity between individuals' intentions and their actual sustainable behaviors. SEM-PLS investigation of 815 participants indicated that goal-setting and feedback nudges most strongly influence Green Behavioral Intention and Actual Sustainable Behavior. The study also indicated that Technology Readiness is crucial. People who are more comfortable and knowledgeable with digital technologies are more likely to respond to IoT-based interventions. This means that future designs should take into account how ready people are to use technology.

This paper provides a scalable framework for integrating IoT solutions into sustainability programs beyond its theoretical advantages. Encouraging energy efficiency and lowering carbon emissions, it helps many UN Sustainable Development Goals (SDGs): SDG 7 (Clean Energy), SDG 11 (Sustainable Cities), SDG 12 (Responsible Consumption), and SDG 13 (Climate Action). This research demonstrates the collaborative potential of IoT and behavioral science to foster significant, technology-driven sustainable behavior.

While this study makes important contributions, several gaps remain that create opportunities for future research. This study uses self-reported survey data, a limited number of nudging methods, and a conceptual IoT architecture. Secondly, the present study used stratified random sampling to ensure diversity. Online recruitment may still have introduced some self-selection bias, since participation depended on individuals who already use IoT technologies and have internet access. As a result, the findings mainly represent digitally active households. Future research could employ mixed or offline

sampling methods to include a broader range of participants and enhance external validity. Bridging these gaps can enhance technology-enabled behavior change theory and the design of sustainable IoT systems. Table 7 illustrates the study's implications, while Table 8 lists the significant gaps, offers further study, and discusses the implications for scholars, practitioners, and policymakers.

Table 7. Implications of the Study.

Type of Implication	Description	Practical/Scholarly Impact
Theoretical	Integrates TPB, TAM, and Nudge Theory into a single IoT-enabled framework, highlighting Energy Awareness and PBC as mediators, and confirms the moderating role of Technology Readiness.	Extends behavioral theories into the digital technology domain, guiding future studies on technology-behavior interactions.
Social	IoT-enabled nudges help reduce the gap between awareness and actual sustainable actions at the household and community levels.	Supports climate change mitigation, resource efficiency, and everyday adoption of sustainable lifestyles.
Managerial & Policy	Identifies which nudges (goal-setting and feedback are strongest; social comparison and gamification are supportive) are most effective in IoT contexts.	Provides evidence-based guidance for businesses, policymakers, and program designers to implement scalable sustainability initiatives aligned with SDGs (7, 11, 12, 13).
Technological	Proposes a scalable IoT digital nudge architecture that can be applied beyond energy to domains such as water, waste management, and transportation.	Offers a blueprint for system developers, emphasizing privacy-by-design, adaptive logic, and the potential for IoT personalization.

Table 8. Future Avenues of Research and Its Implications.

Identified Gap in Current Study	Proposed Future Research Direction	Implication of Addressing This Gap
Reliance on self-reported survey data for behavior measurement	Conduct field experiments or IoT pilot studies with real device usage logs	Enhances the reliability and external validity of findings, ensuring that IoT systems can demonstrate a measurable impact in real-world contexts.
Focused only on four types of nudges (feedback, social comparison, gamification, goal-setting)	Explore advanced digital nudges, including IoT personalization and adaptive nudges.	Helps designers create more personalized and effective IoT interventions, improving user engagement and energy savings.
Examined only the moderating effect of Technology Readiness	Investigate other moderators like digital literacy, culture, or trust in IoT systems	Provides richer insights into user diversity, supporting inclusive system design across populations.
Limited to SEM-PLS quantitative analysis	Use mixed methods (interviews, longitudinal tracking, usability studies)	Provides a deeper understanding of user experience and adoption barriers, enhancing the design of future IoT-enabled nudges.

Table 8. *Cont.*

Identified Gap in Current Study	Proposed Future Research Direction	Implication of Addressing This Gap
Proposed IoT-based architecture conceptually, but not tested as a live prototype	Build and evaluate a working prototype with real-time feedback and privacy safeguards.	Demonstrates technical feasibility and scalability, supporting adoption by industry and policymakers.
Focused only on individual-level adoption	Extend to organizational or community-level applications (smart cities, workplaces)	Broadens impact, enabling system-wide sustainability programs and collective energy efficiency gains.
Applied to the energy efficiency domain only	Extend the IoT nudge framework to water conservation, waste reduction, sustainable transport, and health.	Enhances cross-sectoral relevance, showing that IoT nudges can tackle multiple sustainability challenges beyond energy.

Supplementary Materials: Supplementary Materials are available at: https://drive.google.com/drive/folders/1J4De4kGexczDtKfo1ZQ4CJ_RYLIcEy2C?usp=drive_link, (accessed on 20 October 2025).

Author Contributions: S.M.F.A.K.: Conceptualization, Methodology, Formal Analysis, Writing—Original Draft. T.H.: Methodology, Data Curation, Validation, Investigation, Writing—Review and Editing. F.H.M.: Investigation, Data Curation, Supervision, Project Administration, Funding Acquisition, Writing—Review and Editing. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Ethical approval was obtained from the Deanship of Scientific Research, Jazan University, which serves as the Institutional Review Board (IRB), under Project Number JU202503267-DGSSR-RP-2025, approved on 27 May 2025.

Informed Consent Statement: All participants in this study were informed about the research objectives, procedures, and their rights before participation. Participation was voluntary, and respondents provided their consent before completing the survey. Confidentiality and anonymity were ensured, with no personally identifiable information collected or disclosed. Participants were assured that the data would be used solely for academic and research purposes.

Data Availability Statement: Data could be downloaded from the following link: https://drive.google.com/drive/folders/1J4De4kGexczDtKfo1ZQ4CJ_RYLIcEy2C?usp=drive_link (accessed on 20 October 2025).

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

IoT	Internet of Things
N	IoT-Driven Nudges
EA	Energy Awareness
PBC	Perceived Behavioral Control
GBI	Green Behavioral Intention
AB	Actual Behaviour Towards Sustainability

TR	Technology Readiness
SO	Sustainability Outcome
SDG	Sustainable Development Goal
SEM-PLS	Structural Equation Modeling—Partial Least Squares
AVE	Average Variance Extracted
CR	Composite Reliability
HTMT	Heterotrait–Monotrait Ratio
VIF	Variance Inflation Factor
SRMR	Standardized Root Mean Square Residual
d_ULS	Squared Euclidean Distance (Unweighted Least Squares)
d_G	Geodesic Distance
NFI	Normed Fit Index
f^2	Effect Size
R^2	Coefficient of Determination

Appendix A. VIF

Factors	**VIF**
AB1	2.309
AB2	2.089
AB3	2.092
AB4	1.960
AW1	1.452
AW2	1.458
AW3	1.403
AW4	1.375
BI1	1.862
BI2	1.675
BI3	1.672
GRN1	1.687
GRN2	1.627
GRN3	1.618
GSCN1	1.839
GSCN2	1.757
GSCN3	1.656
PFN1	1.761
PFN2	1.773
PFN3	1.535
PUN21	1.532
PUN22	1.490
PUN23	1.473

PUN24	1.481
SCN1	1.598
SCN2	1.710
SCN3	1.593
TR1	1.833
TR2	1.798
TR3	1.714
TR4	1.639
Technology Readiness × Green Behavioral Intention	1.000

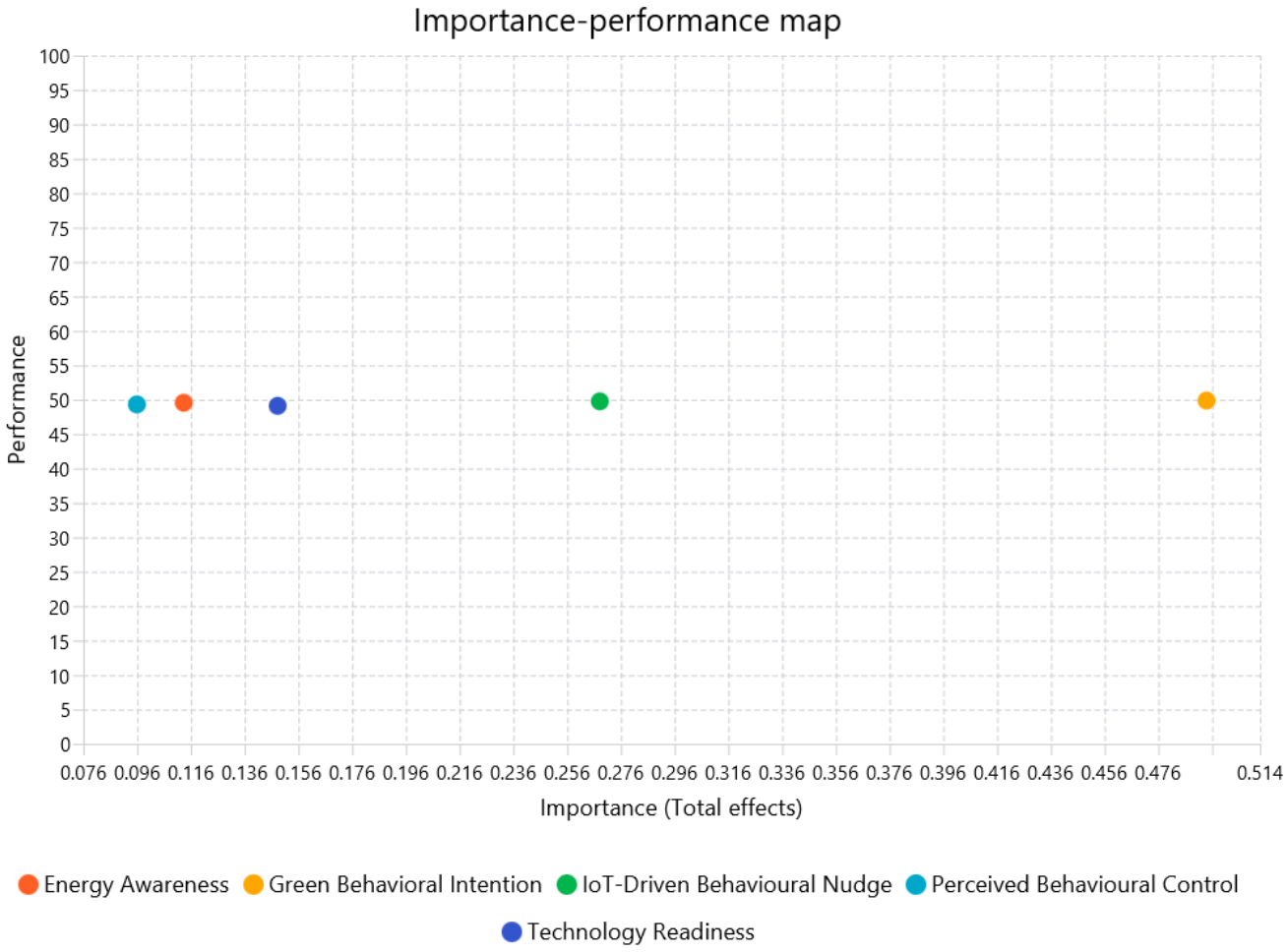
Appendix B. Total Direct Effect (Reflective)

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	*p* Values
IoT-Driven Behavioural Nudge -> Actual Behaviour Towards Sustainability	0.268	0.270	0.021	12.542	0.000
IoT-Driven Behavioural Nudge -> Energy Awareness	0.490	0.491	0.025	19.547	0.000
IoT-Driven Behavioural Nudge -> Green Behavioral Intention	0.543	0.545	0.024	22.948	0.000
IoT-Driven Behavioural Nudge -> Perceived Behavioural Control	0.444	0.445	0.028	16.030	0.000
Energy Awareness -> Actual Behaviour Towards Sustainability	0.114	0.114	0.018	6.352	0.000
Energy Awareness -> Green Behavioral Intention	0.230	0.230	0.033	7.065	0.000
Energy Awareness -> Perceived Behavioural Control	0.143	0.143	0.033	4.348	0.000
Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.494	0.495	0.026	19.015	0.000
Perceived Behavioural Control -> Actual Behaviour Towards Sustainability	0.096	0.096	0.017	5.786	0.000
Perceived Behavioural Control -> Green Behavioral Intention	0.195	0.194	0.031	6.282	0.000
Technology Readiness -> Actual Behaviour Towards Sustainability	0.149	0.150	0.030	4.882	0.000
Technology Readiness × Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.071	0.071	0.027	2.572	0.010

Appendix C. Specific Indirect Effect (Reflective)

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	*p* Values
IoT-Driven Behavioural Nudge -> Energy Awareness -> Green Behavioral Intention	0.099	0.099	0.017	5.784	0.000
Energy Awareness -> Perceived Behavioural Control -> Green Behavioral Intention	0.028	0.028	0.008	3.585	0.000
IoT-Driven Behavioural Nudge -> Energy Awareness -> Perceived Behavioural Control	0.070	0.070	0.017	4.160	0.000
Perceived Behavioural Control -> Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.096	0.096	0.017	5.786	0.000
IoT-Driven Behavioural Nudge -> Energy Awareness -> Perceived Behavioural Control -> Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.007	0.007	0.002	3.350	0.001
IoT-Driven Behavioural Nudge -> Energy Awareness -> Perceived Behavioural Control -> Green Behavioral Intention	0.014	0.014	0.004	3.469	0.001
IoT-Driven Behavioural Nudge -> Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.177	0.178	0.019	9.182	0.000
IoT-Driven Behavioural Nudge -> Perceived Behavioural Control -> Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.036	0.036	0.007	4.855	0.000
IoT-Driven Behavioural Nudge -> Perceived Behavioural Control -> Green Behavioral Intention	0.073	0.073	0.014	5.237	0.000
Energy Awareness -> Perceived Behavioural Control -> Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.014	0.014	0.004	3.479	0.001
IoT-Driven Behavioural Nudge -> Energy Awareness -> Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.049	0.049	0.009	5.273	0.000
Energy Awareness -> Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.100	0.100	0.017	5.706	0.000

Appendix D. IPMA



Appendix E. Total Effect (Formative)

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	*p* Values
Energy Awareness -> Actual Behaviour Towards Sustainability	0.190	0.191	0.020	9.644	0.000
Energy Awareness -> Green Behavioral Intention	0.385	0.385	0.030	12.782	0.000
Energy Awareness -> Perceived Behavioural Control	0.143	0.142	0.033	4.323	0.000
Gamification & Reward Nudges -> Actual Behaviour Towards Sustainability	0.046	0.046	0.009	5.308	0.000
Gamification & Reward Nudges -> Energy Awareness	0.145	0.145	0.030	4.805	0.000
Gamification & Reward Nudges -> Green Behavioral Intention	0.092	0.093	0.016	5.729	0.000
Gamification & Reward Nudges -> Perceived Behavioural Control	0.139	0.141	0.031	4.443	0.000
Goal-Setting & Commitment Nudges -> Actual Behaviour Towards Sustainability	0.057	0.057	0.009	6.192	0.000

Goal-Setting & Commitment Nudges -> Energy Awareness	0.211	0.211	0.032	6.623	0.000
Goal-Setting & Commitment Nudges -> Green Behavioral Intention	0.115	0.115	0.016	6.957	0.000
Goal-Setting & Commitment Nudges -> Perceived Behavioural Control	0.139	0.139	0.032	4.343	0.000
Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.494	0.495	0.026	19.020	0.000
Perceived Behavioural Control -> Actual Behaviour Towards Sustainability	0.152	0.153	0.019	8.235	0.000
Perceived Behavioural Control -> Green Behavioral Intention	0.308	0.309	0.031	9.905	0.000
Personalized Feedback Nudges -> Actual Behaviour Towards Sustainability	0.066	0.067	0.010	6.757	0.000
Personalized Feedback Nudges -> Energy Awareness	0.194	0.195	0.031	6.355	0.000
Personalized Feedback Nudges -> Green Behavioral Intention	0.134	0.135	0.017	7.874	0.000
Personalized Feedback Nudges -> Perceived Behavioural Control	0.219	0.220	0.031	7.059	0.000
Social Comparison Nudges -> Actual Behaviour Towards Sustainability	0.070	0.071	0.010	6.860	0.000
Social Comparison Nudges -> Energy Awareness	0.229	0.230	0.031	7.393	0.000
Social Comparison Nudges -> Green Behavioral Intention	0.142	0.143	0.018	8.032	0.000
Social Comparison Nudges -> Perceived Behavioural Control	0.206	0.207	0.033	6.334	0.000
Technology Readiness -> Actual Behaviour Towards Sustainability	0.149	0.150	0.030	4.882	0.000
Technology Readiness × Green Behavioral Intention -> Actual Behaviour Towards Sustainability	0.071	0.071	0.027	2.573	0.010

Appendix F. Items

Construct	Measurement Items (5-Point Likert: 1 = Strongly Disagree . . . 5 = Strongly Agree)	Reference
Personalized Feedback Nudges (IV)	1. I receive real-time feedback on my energy consumption from IoT devices. 2. The personalized energy-saving tips provided by IoT devices are helpful. 3. IoT devices offer tailored suggestions to reduce my energy usage.	[150]
Social Comparison Nudges (IV)	1. I am shown how my energy usage compares to similar households through IoT devices. 2. Seeing my energy consumption relative to others motivates me to reduce usage. 3. IoT devices provide benchmarks that help me understand my energy consumption.	[151]
Goal-Setting & Commitment Nudges (IV)	1. IoT devices allow me to set specific energy-saving goals. 2. I receive reminders from IoT devices to stay committed to my energy-saving targets. 3. Setting energy-saving goals through IoT devices has improved my energy conservation habits.	[152]

Gamification & Reward Nudges (IV)	1. I earn rewards for reducing my energy consumption through IoT devices. 2. The gamified features of IoT devices make energy saving more engaging. 3. Competing with others via IoT platforms motivates me to save energy.	[153]
Energy Awareness (MV)	1. I am aware of how much energy my household consumes daily. 2. IoT devices have increased my awareness of my energy usage patterns. 3. I understand the environmental impact of my energy consumption. 4. I actively monitor my energy consumption to reduce unnecessary usage.	[151]
Perceived Behavioral Control (MV)	1. I feel confident in my ability to reduce my energy consumption. 2. I have the resources needed to save energy in my household. 3. I can control my energy usage with the help of IoT devices. 4. I am capable of maintaining energy-saving habits even without external reminders.	[154]
Technology Readiness (ModV)	1. I am eager to try new IoT technologies for energy management. 2. I feel comfortable using IoT devices to monitor my energy consumption. 3. I believe IoT technologies can improve my energy-saving efforts. 4. I am confident in my ability to learn and adapt to new IoT technologies for energy management.	[155]
Green Behavioural Intention (DV)	1. I intend to reduce my energy consumption in the coming months. 2. I plan to implement energy-saving practices in my household. 3. I am committed to achieving my energy-saving goals.	[156]
Actual Behaviour Towards Sustainability (DV)	1. I regularly turn off lights and appliances when not in use. 2. I have reduced my energy consumption by adjusting thermostat settings. 3. I actively monitor and manage my household's energy usage.	[157]

Appendix G. Demographic Representation

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	430	52.8
	Female	385	47.2
Age Group	18–25 years	210	25.8
	26–35 years	260	31.9
	36–45 years	190	23.3
	46 years and above	155	19
Education Level	High School or less	100	12.3
	Undergraduate	310	38
	Postgraduate	280	34.4
	Doctorate/Other	125	15.3
Occupation	Student	170	20.9
	Professional/Employee	420	51.5
	Entrepreneur	135	16.6
	Other	90	11
Experience with IoT	Low (<2 years)	250	30.7
	Moderate (2–5 years)	320	39.3
	High (>5 years)	245	30
Monthly Income (SAR)	<5000	185	22.7
	5000–9999	310	38
	10,000–14,999	200	24.5
	15,000 and above	120	14.8

Appendix H. Model Predictive Relevance and Out-of-Sample Accuracy

Constructs	Q^2predict	RMSE	MAE
Actual Behaviour Towards Sustainability	0.265	0.859	0.738
Energy Awareness	0.236	0.876	0.72
Green Behavioral Intention	0.292	0.843	0.697
Perceived Behavioural Control	0.194	0.9	0.74

Appendix I. Outer Weights of the Construct

	Actual Behaviour Towards Sustainability	Energy Awareness	Gamification & Reward Nudges	Goal-Setting & Commitment Nudges	Green Behavioral Intention	Perceived Behavioural Control	Personalized Feedback Nudges	Social Comparison Nudges	Technology Readiness	Technology Readiness × Green Behavioral Intention
AB1	0.313									
AB2	0.296									
AB3	0.302									
AB4	0.267									
AW1		0.342								
AW2		0.355								
AW3		0.323								
AW4		0.304								
BI1					0.410					
BI2					0.372					
BI3					0.399					
GRN1			0.408							
GRN2			0.415							
GRN3			0.371							
GSCN1				0.391						
GSCN2				0.390						
GSCN3				0.397						
PFN1							0.417			
PFN2							0.425			
PFN3							0.346			
PUN21						0.328				
PUN22						0.369				
PUN23						0.278				

PUN24	0.320				
SCN1		0.453			
SCN2		0.384			
SCN3		0.360			
TR1			0.317		
TR2			0.299		
TR3			0.308		
TR4			0.310		
Technology Readiness × Green Behavioral Intention					1.000

Appendix J. Discriminant Validity—Fornell–Larcker Criterion

Constructs	Actual Behaviour Towards Sustainability	Energy Awareness	Gamification & Reward Nudges	Goal-Setting & Commitment Nudges	Green Behavioral Intention	Perceived Behavioural Control	Personalized Feedback Nudges	Social Comparison Nudges	Technology Readiness
Actual Behaviour Towards Sustainability	0.849								
Energy Awareness	0.470	0.754							
Gamification & Reward Nudges	0.324	0.265	0.837						
Goal-Setting & Commitment Nudges	0.308	0.321	0.200	0.848					
Green Behavioral Intention	0.534	0.441	0.368	0.299	0.846				
Perceived Behavioural Control	0.442	0.326	0.245	0.249	0.419	0.771			
Personalized Feedback Nudges	0.365	0.306	0.170	0.200	0.349	0.311	0.840		
Social Comparison Nudges	0.383	0.335	0.196	0.186	0.346	0.303	0.196	0.834	
Technology Readiness	0.287	0.182	0.133	0.193	0.280	0.158	0.199	0.182	0.811

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