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Study on Consumers' Perceived Benefits and Risks of Smart Energy System

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ABSTRACT

This study explores consumer perceptions of smart energy systems, delving into both the perceived benefits and risks associated with their adoption and usage. This study addresses a crucial gap in understanding the consumer side of smart energy system implementation. Through ordinal logistic regression analysis, the study examines the relationship between various independent variables and an ordinal dependent variable represented on a Likert scale. The findings highlight a significant consumer emphasis on "Safe Energy System Construction" and "Economic Benefits," including "Home Energy Saving" and "New Profit Creation." However, the perceived benefits and risks are influenced by these factors and individual propensities, such as sensitivity to environmental destruction and acceptance of new technology. The study uncovers new areas of concern, exceptionally high energy consumption and the "Uncertainty of Electricity Rates," which have not been extensively addressed in previous research. The conclusions drawn from this study suggest a need for balanced policy-making that fosters technological advancement while addressing consumer apprehensions about energy consumption, rate volatility, and privacy. This study contributes to the broader discourse on technology acceptance and the sustainable implementation of smart energy solutions by providing a nuanced understanding of consumer perceptions in the evolving landscape of smart energy systems.

Keywords: Smart Energy Systems, Consumer Perceptions, Ordinal Logistic Regression, Technology Acceptance, Digitalization in Energy Sector
JEL Classifications: D10, D12, O33

1. INTRODUCTION

Smart technology, defined as a system that augments operational efficiency in various environments by identifying and responding to environmental cues (Worden et al., 2003; Bagio and Budidharmanto, 2023), requires digitization, recording, networking, and rapid analysis of physical asset data. Implementation involves leveraging digital technologies such as the Internet of Things (IoT), big data, and artificial intelligence (AI) (Dey et al., 2018). IoT, which facilitates the interconnection of devices and individuals via the Internet, enables real-time data exchange, processing, and analysis through AI-applied big data analytics (Park and Jeong, 2018; Raja and Saraswathi, 2023). Recent advancements in machine learning, particularly deep learning techniques, have further enhanced the capabilities of smart energy systems (Sharma and Yadav, 2023).

Smart technology finds application in managing household energy consumption (Baig et al., 2013; Dincer and Acar, 2017; Razghandi et al., 2024) within the smart home energy management market. This application encompasses the installation and operation of systems designed to regulate various home appliances, enabling consumers to manage energy production and storage efficiently, ultimately allowing them to become energy prosumers. Smart technology optimizes information flow to prosumers, facilitating energy trade in markets or between individuals.

Smart consumer energy systems, leveraging fourth industrial revolution technologies like IoT, big data, and AI, optimizes energy supply and demand. The systems, relying on digitalization and sensor networks, processe vast amounts of data to contribute to an efficient, environmentally friendly, stable, and safe energy system.

The progression of technology plays a pivotal role for the widespread adoption of innovative technologies like smart energy systems, but consumer acceptance is equally significant. Consumer perception significantly influences the acceptance of products or services, as evidenced in the works of Sheth and Stellner (1979) and Rogers (1983). Consequently, research on consumer awareness aims to identify factors enhancing acceptance of smart energy systems, particularly focusing on consumer perceptions of smart grids (Park et al., 2014; Bigerna et al., 2016; Park et al., 2017; Shaukat et al., 2018; Acakpovi et al., 2019; Veloso et al., 2023; Satrya et al., 2023; Dragomir et al., 2023). Various consumer perception surveys cover smart home technologies (Wilson et al., 2017), home energy management systems through IoTs (Park et al., 2018), IoT-based demand response business models (Radenković et al., 2020; Luo, 2022), edge computing for IoT-Enabled smart grids (Minh et al., 2022).

As smart energy systems continue to evolve in tandem with advancements in information and communications technologies (ICTs), discussions focus on leveraging machine intelligence with vast data. Smart energy services combine networks, sensors, data, analytics, and visualization technologies, necessitating an integrated perspective when analyzing consumer perceptions. While examining perceptions of specific technologies and services provides direct insights, a comprehensive understanding of digital technologies in the energy sector allows for more generalized consumer perceptions of smart energy systems.

This study endeavors to address a critical lacuna in existing research by offering a comprehensive analysis of both the benefits and risks associated with smart energy systems, a topic that has received limited attention in existing literature. Our approach offers novel insights into factors that could significantly enhance system acceptance. Perceived benefits and risks influence product or service acceptance (Abramova and Böhme, 2016; Wilson et al., 2017; Park et al., 2018; Khan and Abideen, 2023). Recognizing the system's benefits and addressing consumer concerns, such as security threats and privacy invasion, is crucial, as higher risk perception hampers acceptance (Park et al., 2014; Park et al., 2018; Samanthula and Patel, 2023). A unique contribution of our study is the exploration of under-researched areas such as the implications of becoming energy prosumers, the impact of the digital divide, and the uncertainty of electricity rates. These aspects have been largely overlooked in previous research, making our findings particularly valuable. It also considers consumer perceptions of the smart energy system and individual propensities, examining factors influencing overall perceived benefits and risks.

The structure of this study is organized as follows: Section 2 presents a literature review, Section 3 outlines the methodology employed, Section 4 provides an analysis of the results, Section 5 discusses the results, and Section 6 concludes the study.

2. LITERATURE REVIEW

2.1. Types of Perceived Benefits of the Smart Energy System

The application of digital technologies in energy systems engenders novel value propositions in terms of economics, supply stability, environmental impact, and safety. Economically, consumers benefit by producing and consuming energy efficiently, storing surplus energy in energy storage systems, and participating in energy trading (Park and Heo, 2020). Consumers anticipate the ability to monitor real-time rates, manage energy consumption, and consequently achieve savings in energy expenditures (Smart Energy GB, 2016; Shi et al., 2022). Additionally, they have the potential to realize economic gains by selling excess energy through the smart energy system (Abdmouleh et al., 2018).

In relation to supply stability, enhanced energy demand management and forecasting through digital technologies facilitate the optimized storage and management of produced energy (Miah et al., 2023). This advancement in digital technology renders energy consumption more flexible, improving the stability and reliability of energy supply systems. Smart energy systems and power grids, exchanging real-time data on energy demand, are expected to stably supply power even during peak periods and swiftly deliver stored energy in emergencies, such as power outages (Yutian et al., 2016; Sharma et al., 2023).

Environmentally, the adaptation of smart energy systems to the variable output of renewable energy sources aids in increasing renewable energy generation (Sharma and Yadav, 2023). This capability of smart energy systems contributes to the decarbonization of energy by reducing reliance on fossil fuel-based power generation (Global e-Sustainability Initiative, 2018). Furthermore, the analysis of energy supply and demand-related data facilitates the efficient utilization of energy resources, ultimately benefiting the global environment (Stadler et al., 2018; Saleem et al., 2023).

Concerning safety, the use of digital technologies in smart energy systems enables early detection and response to issues in energy supply infrastructures (Saleem et al., 2023). These systems collect extensive real-time data from energy supply facilities through IoT and analyze them using AI technology. This approach of utilizing real-time data and AI in smart energy systems enables timely identification of the need for facility maintenance in response to asset aging and ensures the safe operation of mechanical devices and related assets (Park and Heo, 2020; Qiu et al., 2022).

2.2. Types of Perceived Risks of the Smart Energy System

The smart energy system, while offering numerous advantages, also presents several risk factors encompassing economic, privacy, environmental, security, performance, digital divide, and electromagnetic radiation concerns. Economically, the initial and ongoing costs associated with purchasing and updating the smart energy system may outweigh the benefits of its utilization. This perception of disproportionate costs compared to energy savings poses a barrier to consumer adoption of the technology (Kaur and Singh, 2015; Khouzestani et al., 2023; Harbott, 2016; Liu et al., 2023). Additionally, the expenses related to system customization and the frequent need to update system options, coupled with the potential bankruptcy or service cessation of system suppliers, present significant financial risks (Processmate, 2018).

In terms of energy pricing, there exists a risk of increased price volatility due to time-variant pricing, potentially leading to higher costs during periods of peak energy demand (Park and Jeong, 2018; Meng et al., 2022). Privacy concerns arise as users' personal and energy usage information may be exposed or misused by third parties without consent, increasing the risk of crimes such as voice phishing (Taylor et al., 2014; Abdalzaher et al., 2022; Alsuwian et al., 2022). There is also apprehension that energy suppliers may access and monitor smart meter information, and the interconnectedness of home devices through IoTs could lead to data breaches and privacy violations (Balta-Ozkan et al., 2013; Abdalzaher et al., 2022; Deloitte, 2019).

From an environmental perspective, the energy consumption of the smart energy system itself may exceed the energy savings it facilitates, potentially exacerbating overall energy consumption and environmental strain (WBGU, 2019; Morley et al., 2018). Furthermore, efficient energy management leading to reduced energy prices might paradoxically encourage increased energy consumption (Vivanco et al., 2016; Peng et al., 2023).

Security issues are prominent, with risks that hacking of the smart energy system could allow remote control of connected home appliances by unauthorized individuals (Bronk and Tikk-Ringas, 2013; Hellgren and Andersson, 2023). Additionally, cyberattacks on digitalized energy supply facilities could disrupt energy supply and lead to physical damage (Von Solms and Van Niekerk, 2013; Campbell, 2018).

Performance issues are also of concern. The energy storage system requires regular charging and discharging to maintain optimal conditions, and improper control, especially in fluctuating weather, could damage batteries and diminish energy savings (Regen, 2017). Network errors might also impair system functionality, with concerns about smart meter malfunctions being particularly significant (Balta-Ozkan et al., 2013; Banerjee et al., 2022; Park et al., 2014).

The digital divide presents another challenge, as individuals lacking understanding or physical access to the system may be excluded from its benefits. This concern extends to those unfamiliar with related technologies or lacking the technical skills for effective system utilization (Norris, 2001; Luan et al., 2023; Steele, 2018). In-depth interviews with UK consumers revealed apprehensions that the elderly and those with limited technical proficiency may not fully benefit from the system (Buchanan et al., 2016).

Finally, concerns about electromagnetic radiation arise from the potential health effects of waves emitted during the system's wireless communication processes. Regardless of the actual harm, consumer apprehension about electromagnetic radiation is a recognized issue associated with the smart energy system (Park et al., 2014; Hess and Coley, 2014; Milchram et al., 2018).

2.3. Individual Propensity and Technical Characteristics Perception

Factors influencing the perception of benefits and risks associated with the smart energy system encompass specific judgments about the technology and individual propensities. Park et al. (2018) posited that individual propensities, including sensitivity to changes in electricity prices, concerns about environmental destruction, and receptiveness to new technologies, play a pivotal role in the acceptance of such technologies. Both economic and environmental considerations have been identified as critical determinants in the adoption of energy-related products and services (Park et al., 2018). Moreover, given the innovative nature of the smart energy system, the sensitivity to economic and environmental factors, along with individual innovativeness, significantly influences the perception of this technology (Bhatti, 2007). A propensity for innovation, characterized by a readiness to embrace change and experiment with new concepts, tends to reduce risk perception and enhance the willingness to adopt new technologies (Aldás-Manzano et al., 2009; Park et al., 2018; Kliuchnikava, 2022).

Additionally, the consumer's aspiration to directly manage energy production and consumption can also influence their perception of the benefits and risks associated with the smart energy system (Zhang et al., 2022). The system's ability to facilitate direct management of energy production and consumption means that a stronger desire for such control correlates with higher perceived benefits and lower perceived risks. The concept of perceived controllability, which relates to a user's ability and sense of control over the technology, has been found to positively impact the acceptance of IoTs (Gao and Bail, 2014; Zhang et al., 2022).

3. METHODOLOGY

3.1. Data and Variables

This study aims to empirically examine the determinants of perceived benefits and risks among current and potential users of smart energy systems in South Korea, in the context of the global trend towards digitalization in the energy sector. The research surveyed adults aged 19 and above, focusing on their perceptions of the benefits and risks associated with smart energy systems (Appendix). The methodology adopted for this survey involved presenting respondents with detailed information about these benefits and risks prior to collecting their responses.

The sample for this study was randomly selected to ensure proportional representation across various demographics, including gender, age, and region. This sampling was based on the resident registration population data as of September 2019. The total sample size comprised 1020 individuals, with a sampling error of ±3.1% at a 95% confidence level. The survey was conducted by Korea Research, a professional polling firm, from September 27 to October 7, 2019.

In our research model, the independent variables are composed of five benefit factors and seven risk factors pertaining to smart energy systems. The dependent variables in this study are the overall perceived benefits and risks, quantified through respondents' reactions to each factor. Specifically, the benefit factors are "Home Energy Saving," "New Profit Creation," "Stable Energy Supply," "Eco-friendly Energy System Construction," and "Safe Energy System Construction." Conversely, the risk factors include

"Electromagnetic Radiation Risk," "High Energy Consumption," "Performance Risk," "Privacy Invasion Risk," "Digital Divide Deepening," "Cybersecurity Threat," "Financial Risk," and "Uncertainty of Electricity Rates."

Both sets of independent and dependent variables were measured using a 7-point Likert scale across four questions. Exploratory factor analysis was employed to refine these variables, with items exhibiting a factor loading below 0.5 being excluded. Following this analysis, all factor loadings exceeded 0.5, and these items were subsequently integrated into meaningful variables.

Furthermore, this study incorporated "Sensitivity to Electricity Price Changes," "Sensitivity to Environmental Destruction," "Sensitivity to New Technology Acceptance," and "Direct Control Desire" as additional independent variables representing individual propensities, each assessed on a 7-point scale.

Demographic factors, including Age, Gender, Income, and Education, were also evaluated as potential influencers on the perceived benefits and risks and were thus included in the study as variables.

Table 1 below presents the basic statistics of these variables. Given that the independent and dependent variables are based on a 7-point Likert scale, the average of the four questions was computed to represent each variable in the basic statistical analysis.

In the survey analysis, the variables, each encompassing four questions, underwent consolidation through factor analysis. The dependent variables, namely "perceived benefits" and "perceived risks," were categorized into three tiers for analysis: "Low-level perception," "medium-level perception," and "high-level perception." These categories were treated as ordinal variables to facilitate a more straightforward interpretation of the results. Consequently, the original 7-point scale used for these dependent variables was restructured into these three distinct levels for analytical clarity and precision.

3.2. Statistical Model

This study utilized ordinal logistic regression analysis to investigate the relationship between independent variables and a dependent variable, which is represented by an ordinal Likert scale (Liao, 1994). The ordinal logistic model, predicated on the assumption that the random error term follows a logistic distribution, is an extension of the binary logistic model. This model is designed to assess the association between the independent variables and the ordinal dependent variable. It operates under certain key assumptions, including the absence of multicollinearity, which is akin to the basic regression model, and adheres to the proportional odds assumption (Harrell, 2005).

The fundamental formula for the ordinal logistic model is expressed as follows:

$$\log\left[\frac{P\left(y \le j|x\right)}{1-P\left(y \le j|x\right)}\right] = \mu_j - \sum_{K=1}^{K} \beta_K x_K \quad (1)$$

Where "y" denotes the ordinal dependent variable, "j" specifies each ordered category of the dependent variable, "x" represents the set of independent variables, "β_K" are the coefficients indicating the effect of each independent variable K, and "μ_j" are the threshold parameters for each category level. This approach allows us to understand how changes in the independent variables influence the log odds of the response variable being at or below a certain ordinal level, thereby offering insights into the factors that drive consumer perceptions of smart energy systems in terms of benefits and risks.

In the context of ordinal logistic regression, the odds ratio is utilized to indicate the alteration in the probability ratio for an individual's likelihood of belonging to a specific category, contingent upon a one-unit increase in the independent variable. This cumulative odds approach facilitates the examination of shifts in the probability ratio across n-ordered categories when there is a change in the independent variable. For example, in the case of a four-category dependent variable, this method assesses changes in the probability ratio between the first, second, third, and fourth categories or between the combined first, second, and third categories and the separate fourth category.

The present study incorporates six distinct models, which include three models each for the perception of benefits and risks, employing the ordinal logistic regression framework. The independent variables consist of five factors related to the perception of benefits and seven factors pertaining to the perception of risks. Additionally, this study analyzes the influence of four individual propensity variables and four demographic variables on the users' perceived benefits and risks.

To effectively manage multicollinearity and explore the factors influencing perceptions of benefits and risks, a basic model was established (Model 1 for benefits and Model 4 for risks). Models 2 and 5 were then developed to augment the analysis by incorporating consumers' propensity variables, specifically "Sensitivity to Electricity Price Changes," "Sensitivity to Environmental Destruction," "Sensitivity to New Technology Acceptance," and "Direct Control Desire." Finally, Models 3 and 6 were introduced to include demographic variables such as age, gender, income, and education, thereby offering a comprehensive view of the factors influencing benefit and risk perception in the context of smart energy systems.

4. RESULTS

This study was conducted with the objective of identifying independent variables that influence the overall perception of benefits and risks associated with the smart energy system and evaluating the impact of each independent variable on the dependent variables.

During the exploratory factor analysis for the perception of benefits, one questionnaire item pertaining to the "Stable Energy Supply" variable was excluded due to its factor loading falling below 0.5. The subsequent analysis led to the integration of questionnaire items as meaningful variables, with each item demonstrating a factor loading of 0.5 or higher. All factor loadings for the dependent variables related to perceived benefits registered at 0.863 or higher.

Table 1: Descriptive statistics of variables

Categories	Variables	Description	Mean	Min.	Max.	Std. dev
Dependent variables	Overall perceived benefit	The degree of perceived benefits of current and potential users of the smart energy system	5.30	1	7	1.05
	Overall perceived risk	The degree of perceived risks of current and potential users of the smart energy system	3.79	1	7	1.27
Perceived benefits - ındependent variables	Home energy saving	The degree of usefulness of the smart energy system for home energy saving	5.15	1	7	1.01
	New profit creation	The degree of usefulness of the smart energy system for new profit creation	4.84	1	7	1.07
	Stable energy supply	The degree of usefulness of the smart energy system for stable energy supply	4.98	1	7	1.04
	Eco-friendly energy system construction	The degree of usefulness of the smart energy system for eco-friendly energy system construction	5.25	1	7	1
	Safe energy system construction	The degree of usefulness of the smart energy system for safe energy system construction	5.05	1	7	1.01
Perceived risks-ındependent variables	Electromagnetic radiation risk	The degree of perceived risk on the electromagnetic waves emitted from the smart energy system	4.99	1	7	1.07
	High energy consumption	The degree of thinking that the smart energy system consumes more energy	4.56	1	7	1.05
	Performance risk	The degree of thinking that the smart energy system has performance risk	4.96	1	7	1.04
	Privacy ınvasion risk	The degree of thinking that the smart energy system has a risk of personal information exposure	5.37	1	7	1.16
	Digital divide deepening	The degree of thinking that the digital divide can be further deepened with the smart energy system	5.49	1	7	0.97
	Cybersecurity threat	The degree of thinking that the smart energy system is a threat to cybersecurity	5.47	1	7	1.06
	Financial risk	The degree of thinking that the smart energy system can be a financial burden	5.30	1	7	0.94
	Uncertainty of electricity rates	The degree of thinking that uncertainty of electricity rates can increase with the smart energy system	5.07	1	7	1.06
Individual propensity ındependent variables	Sensitivity to electricity price changes	The degree of sensitivity of consumers to changes in electricity price	5.15	1	7	1.27
	Sensitivity to environmental destruction	The degree to which consumers are concerned about environmental destruction	5.32	1	7	1.15
	Sensitivity to new technology acceptance	The degree to which consumers willingly accept new technology	5.00	1	7	1.12
	Direct control desire	The degree of survey respondents' desire for direct control	5.03	1	7	1.14
Demographic variables	Gender	0=Female, 1=Male	0.49	0	1	0.50
	Age	Over the age of 19	47.02	19	83	14.61
	Education	The highest level of education they have completed	3.03	1	6	1.21
	Income	The average monthly income of households	4.29	1	7	1.68

*When there are 4 questionnaire questions for a variable, basic statistics are calculated by the average as the representative value of the variable

In the exploratory factor analysis for the perception of risks, the "Performance Risk" variable was removed because its factor loading was below 0.5. Additionally, the "Financial Risk" variable was excluded as all four of its questionnaire items had factor loadings below 0.5 and were highly correlated with the "Uncertainty of Electricity Rates" variable. Following these exclusions, seven factors were finalized for the risk perception model, each with factor loadings above 0.5, all exceeding 0.867.

Post factor analysis, five independent variables for the perceived benefit model and seven for the perceived risk model were identified as final key variables. These were subsequently analyzed through ordinal logistic regression. The analysis was conducted using the "MASS" package in the "R" statistical program, supplemented by the "oglmx" package to derive marginal effects. The model fit was assessed using the "lmtest" package. Prior to the analysis, Variance Inflation Factor (VIF) values were calculated to check for multicollinearity, revealing low VIF values between 1 and 2 points across all variables, indicating minimal multicollinearity.

The log-likelihood ratio test, executed with the "lrtest" function of the "lmtest" package, was applied to all six models. This test determined that Model 3 was the most appropriate for the perceived benefit model and Model 5 for the perceived risk model. Consequently, the study proceeded with analyses based on these models.

In Model 3, presented in Table 2, all five variables—"New Profit Creation," "Safe Energy System Construction," "Home Energy Saving," "Eco-friendly Energy System Construction," and "Stable Energy Supply"—were statistically significant at the 1% level. The Exp(β) values for each variable were 3.269, 6.129, 5.750, 4.822, and 2.552, respectively. These values indicate an odds ratio increase of 226.9%, 512.9%, 475.0%, 482.2%, and 155.2% when each variable increased by one unit. Among these five benefit factors, "Safe Energy System Construction" and "Home Energy Saving" exhibited the most substantial impact on the overall perceived benefits of the smart energy system.

In terms of individual propensity, none of the variables, including "Sensitivity to Electricity Price Changes," "Sensitivity to Environmental Destruction," "Sensitivity to New Technology Acceptance," and "Direct Control Desire," were found to be statistically significant in influencing the perceived benefits.

In the analysis of risk perception, as delineated in Model 5 of Table 3, five variables—"Uncertainty of Electricity Rates," "Privacy Invasion Risk," "Electromagnetic Radiation Risk," "High Energy Consumption," and "Performance Risk"—were found to have statistically significant impacts at the 1% significance level. Conversely, the variables "Digital Divide Deepening" and "Cybersecurity Threat" did not demonstrate statistical significance.

Upon examining the influence of these critical risk perception variables on perceived risk, the Exp(β) values for "Uncertainty of Electricity Rates," "Privacy Invasion Risk," "Electromagnetic Radiation Risk," "High Energy Consumption," and "Performance Risk" were calculated to be 2.054, 1.428, 1.862, 3.005, and 1.736, respectively. These values indicate that the odds ratio of perceived risk increases by 105.4%, 42.8%, 86.2%, 200.5%, and 73.6% for each respective variable when it increases by one unit. Essentially, an elevated user-perceived risk in relation to "Uncertainty of Electricity Rates," "Privacy Invasion Risk," "Electromagnetic Radiation Risk," "High Energy Consumption," and "Performance Risk" corresponds to an increased overall risk perception of the smart energy system. Notably, "High Energy Consumption" and "Uncertainty of Electricity Rates" are observed to have the most profound impact on the overall risk perception among the five statistically significant risk factors.

Regarding variables associated with individual propensity, "Sensitivity to New Technology Acceptance" and "Direct Control Desire" emerged as significant, albeit in a negative direction. This observation suggests that a higher level of acceptance of new technology and a stronger desire for direct control are associated with a reduced overall risk perception.

Tables 4 and 5 delineate the marginal effects of each independent variable on the perceived benefits and risks. These tables highlight

Table 2: Variable impact analysis results on overall benefit perception

Variables	Overall benefit perception					
	Model 1		Model 2		Model 3	
	β	Exp(β)	β	Exp(β)	β	Exp(β)
New profit creation	1.190*** (0.120)	3.290	1.155*** (0.121)	3.175	1.185*** (0.122)	3.269
Safe energy system construction	1.794*** (0.137)	6.016	1.771*** (0.138)	5.878	1.813*** (0.141)	6.129
Home energy saving	1.716*** (0.135)	5.563	1.690*** (0.137)	5.421	1.749*** (0.140)	5.750
Eco-friendly energy system construction	1.56*** (0.128)	4.778	1.532*** (0.130)	4.629	1.573*** (0.132)	4.822
Stable energy supply	0.956*** (0.120)	2.601	0.920*** (0.122)	2.510	0.937*** (0.124)	2.552
Sensitivity to electricity price changes			0.070 (0.107)	1.072	0.077 (0.108)	1.080
Sensitivity to environmental destruction			0.092 (0.108)	1.096	0.183 (0.113)	1.201
Sensitivity to new technology acceptance			0.126 (0.116)	1.134	0.060 (0.119)	1.062
Direct control desire			0.068 (0.114)	1.071	0.073 (0.115)	1.076
Gender					0.354* (0.195)	1.424
Age					−0.238** (0.097)	0.788
Education					0.045 (0.1)	1.046
Income					−0.108 (0.098)	0.898
Number of cases	1020		1020		1020	
Log-likelihood	−389.058		−385.968		−380.288	
AIC	792.115		793.937		790.575	
McFadden's R2	0.509		0.513		0.520	

***: Significance level 0.001, **: Significance level 0.01, *: Significance level 0.05, . : Significance level 0.1. 2) Values in parentheses are standard error

Table 3: Variable impact analysis results on overall risk perception

Variables	Overall risk perception					
	Model 4		Model 5		Model 6	
	β	Exp(β)	β	Exp(β)	β	Exp(β)
Digital divide deepening	−0.165** (0.082)	-0.084	−0.097 (0.084)	0.907	−0.078 (0.085)	0.925
Uncertainty of electricity rates	0.727*** (0.084)	2.070	0.720*** (0.085)	2.054	0.718*** (0.086)	2.050
Privacy ınvasion risk	0.383*** (0.081)	1.467	0.356*** (0.081)	1.428	0.358*** (0.082)	1.430
Electromagnetic radiation risk	0.633*** (0.080)	1.882	0.621*** (0.083)	1.862	0.659*** (0.086)	1.932
High energy consumption	1.080*** (0.090)	2.945	1.100*** (0.092)	3.005	1.097*** (0.093)	2.994
Cybersecurity threat	0.063 (0.090)	1.065	0.090 (0.080)	1.094	0.100 (0.081)	1.105
Performance risk	0.529*** (0.084)	1.697	0.551*** (0.086)	1.736	0.539*** (0.087)	1.715
Sensitivity to electricity price changes			0.055 (0.079)	1.057	0.048 (0.080)	1.050
Sensitivity to environmental destruction			0.113 (0.084)	1.120	0.151 (0.086)	1.164
Sensitivity to new technology acceptance			−0.335*** (0.085)	0.716	−0.357*** (0.087)	0.700
Direct control desire			−0.215** (0.085)	0.807	−0.211** (0.086)	0.810
Gender					0.106 (0.147)	1.112
Age					−0.142* (0.074)	0.867
Education					−0.044 (0.072)	0.956
Income					−0.048 (0.072)	0.953
Number of cases	1020		1020		1020	
Log-likelihood	−738.377		−720.114		−717.508	
AIC	1494.75		1466.299		1469.017	
McFadden's R2	0.207		0.227		0.230	

***: Significance level 0.001, **: Significance level 0.01, *: Significance level 0.05, . : Significance level 0.1. 2) Values in parentheses are standard error

Table 4: Marginal effects (Benefit perception: Model 3)

Variables	Low-level perception	Medium-level perception	High-level perception
New profit creation	−0.0005	−0.2628	0.2633
Safe energy system construction	−0.0008	−0.4022	0.4030
Home energy saving	−0.0008	−0.3880	0.3888
Eco-friendly energy system construction	−0.0007	−0.3490	0.3497
Stable energy supply	−0.0004	−0.2078	0.2082
Sensitivity to electricity price changes	−0.00003	−0.0171	0.0171
Sensitivity to environmental destruction	−0.00008	−0.0407	0.0408
Sensitivity to new technology acceptance	−0.00003	−0.0134	0.0134
Direct control desire	−0.00003	−0.0162	0.0162

Table 5: Marginal effects (risk perception: Model 5)

Variables	Low-level perception	Medium-level perception	High-level perception
Digital divide deepening	0.01306	−0.00573	−0.00733
Uncertainty of electricity rates	−0.09671	0.04242	0.05429
Privacy ınvasion risk	−0.04782	0.02098	0.02685
Electromagnetic radiation risk	−0.08349	0.03662	0.04687
High energy consumption	−0.14781	0.06483	0.08298
Cybersecurity threat	−0.01204	0.00528	0.00676
Performance risk	−0.07407	0.03249	0.04158
Sensitivity to electricity price change	−0.00743	0.00326	0.00417
Sensitivity to environmental destruction	−0.01520	0.00667	0.00853
Sensitivity to new technology acceptance	0.04496	−0.01972	−0.02524
Direct control desire	0.02889	−0.01267	−0.01622

significant effects for specific variables within the domains of perceived benefit and risk.

In the realm of overall benefit perception, it was observed that a 1-unit increase in the perceived benefits associated with "Safe Energy System Construction" leads to a marginal change in the probabilities across different levels of perception. Specifically, there is a 0.08% decrease in the likelihood of selecting "low-level perception," a substantial 40.22% decrease in the likelihood of opting for "medium-level perception," and a corresponding 40.30% increase in the probability of choosing "high-level perception."

Similarly, in the context of overall risk perception, the impact of a 1-unit increase in the perceived risks related to "High Energy Consumption" was analyzed. This increase results in a 14.78% decrease in the probability of selecting "low-level perception," a 6.48% increase in the probability of choosing "medium-level perception," and an 8.29% increase in the probability of selecting "high-level perception."

These findings underscore the significant influence of specific variables on the perceptions of benefits and risks associated with smart energy systems. The marginal effect calculations provide insightful implications for understanding how changes in perceptions of specific factors can significantly shift the overall perception levels among users.

5. DISCUSSION

5.1. Benefit Perception

The findings of this study bring to light the critical importance that consumers attribute to "Safe Energy System Construction" in smart energy systems. This emphasis on safety and reliability is not an isolated trend but echoes broader themes in the existing literature, as noted by Park and Heo (2020). The focus on safety underscores a shift in consumer priorities, where there is an increasing demand not only for energy efficiency but also for the stability and resilience of the system. Particularly in the context of renewable energy, where output can be variable and unpredictable, this finding is significant. Sharma and Yadav's (2023) work on managing the intermittency of renewable energy sources further validates this trend, highlighting the growing need for robust and reliable energy infrastructures that can adapt to and balance these fluctuations.

Moreover, the prioritization of safety may reflect a broader societal shift towards sustainability and resilience in infrastructures. In light of increasing environmental challenges and heightened awareness of climate change, consumers are likely becoming more conscious of the need for sustainable energy practices that are also reliable in emergencies, such as power outages. The insights provided by Yutian et al. (2016) and Sharma et al. (2023) reinforce this view, indicating a consumer preference for energy systems that can withstand and function efficiently during unforeseen circumstances.

Regarding "Economic Benefits," the study reveals nuanced insights into how consumers perceive economic advantages in the realm of smart energy systems. "Home Energy Saving" emerged as a more influential factor than "New Profit Creation," highlighting that immediate, tangible economic benefits are more compelling to consumers than the prospective long-term financial gains. This finding aligns with Park and Heo's (2020) observations on consumer preferences and suggests that the immediate cost-saving aspect of smart energy systems is a predominant driver of consumer interest and adoption. This preference for immediate savings over potential future gains may also indicate a gap in consumer understanding or skepticism about the long-term economic benefits of these systems.

The less pronounced impact of "New Profit Creation" as a benefit suggests that the concept of generating profit through smart energy systems may still be in its nascent stages in the consumer consciousness. As pointed out by Abdmouleh et al. (2018), this area represents a growing field within the smart energy sector, yet one that is perhaps not fully comprehended or valued by the average consumer. This disparity highlights the need for targeted education and communication strategies that clearly articulate the long-term economic benefits and potential revenue-generating aspects of smart energy systems. Such efforts could not only enhance consumer knowledge and acceptance but also drive the adoption of these systems by illustrating their full economic potential.

The findings on benefit perception in smart energy systems reveal a complex interplay of consumer values and preferences, with a current focus on safety and immediate economic benefits. To address the need for greater consumer awareness about the long-term economic and sustainability benefits of these systems, educational initiatives and transparent communication strategies could be instrumental. Implementing such efforts could lead to broader acceptance and integration of smart energy technologies in the consumer market by illuminating their full economic and environmental potential.

5.2. Risk Perception

The identification of high energy consumption as a key risk factor in the adoption of smart energy systems brings to the forefront a significant paradox. While these systems are designed to improve efficiency, the findings suggest they may inadvertently contribute to increased overall energy use, corroborating concerns raised by WBGU (2019) and Morley et al. (2018). This contradiction highlights a crucial aspect of sustainable energy system design: The need to balance efficiency improvements with overall energy consumption. The high energy consumption associated with these systems suggests a potential misalignment with environmental objectives, emphasizing the need for continued advancements in technology that prioritize net energy savings.

The study's findings on the "Uncertainty of Electricity Rates" present a unique challenge, one that has not been extensively addressed in the existing literature on smart energy systems. This uncertainty, likely exacerbated by dynamic pricing models, underscores a gap in consumer understanding and acceptance of time-variant pricing strategies (Park and Jeong, 2018; Meng et al., 2022). The results suggest a need for more transparent and stable electricity pricing models that can mitigate consumer concerns about cost unpredictability. Addressing these apprehensions is crucial for fostering trust and confidence in smart energy systems, particularly as they become more integrated into daily life.

Electromagnetic radiation emerges as a significant risk factor, reflecting longstanding consumer apprehensions about the health impacts of wireless technology (Park et al., 2014; Hess and Coley, 2014; Milchram et al., 2018). Despite the lack of conclusive evidence linking low-level electromagnetic radiation to adverse health effects, the persistence of these concerns underscores the importance of clear and effective communication strategies. Addressing these fears through scientifically grounded information and transparent dialogue can help in demystifying the technology and alleviating unwarranted fears.

The findings also touch upon the issues of the digital divide and cybersecurity threats, although these were not as prominent in the perceived risks. The risk of excluding certain demographics, highlighted by Norris (2001) and Steele (2018), emphasizes the importance of inclusive technology design and accessible educational resources. Additionally, security concerns related to data breaches and system hacking (Bronk and Tikk-Ringas, 2013;

Hellgren and Andersson, 2023; Von Solms and Van Niekerk, 2013; Campbell, 2018) highlight the critical area for ongoing focus and improvement.

5.3. Individual Propensity

The study's findings regarding individual propensities present a nuanced picture of consumer behavior towards smart energy systems. While initial models suggested significant roles for factors like "Sensitivity to Environmental Destruction" and "New Technology Acceptance," subsequent analysis revealed a reduction in their significance. This shift, particularly noted in the transition from Model 2 to Model 3, indicates a complex dynamic where the benefits provided by the system potentially overshadow individual predispositions. This observation, diverging from Park et al. (2018), points towards a multifaceted relationship between individual traits and technology acceptance, suggesting that tangible benefits may have a more pronounced impact on consumer decisions than previously understood.

The study's findings also highlight the influence of economic and environmental sensitivities on the adoption of smart energy systems. Park et al. (2018) and Bhatti (2007) underscore the importance of these factors in shaping consumer attitudes towards new technologies. However, this study indicates that while these sensitivities are crucial, their impact might be moderated by the direct benefits perceived by users. This result suggests that consumers may prioritize immediate and tangible benefits over broader economic or environmental considerations when it comes to adopting smart energy systems.

A propensity for innovation, characterized by a readiness to embrace change and experiment with new concepts, has been traditionally seen as reducing risk perception and enhancing the willingness to adopt new technologies (Aldás-Manzano et al., 2009; Park et al., 2018; Kliuchnikava, 2022). This study corroborates the idea that a propensity for innovation significantly influences consumer attitudes, indicating that innovativeness plays a crucial role in shaping positive perceptions towards smart energy systems. Additionally, the desire for direct control over energy production and consumption, as discussed by Zhang et al. (2022), emerged as a key factor in influencing perceptions. The ability of smart energy systems to enable this control aligns with a growing consumer trend towards greater autonomy and empowerment in energy management.

The concept of perceived controllability, which relates to a user's ability and sense of control over the technology, has been identified as a positive influencer in the acceptance of IoTs (Gao and Bail, 2014; Zhang et al., 2022). Our study extends this understanding to smart energy systems, suggesting that perceived controllability could play a crucial role in enhancing user acceptance and satisfaction. This aspect emphasizes the importance of designing smart energy systems that are user-friendly and provide consumers with a sense of control and mastery over the technology.

6. CONCLUSION

This study significantly enriches the understanding of consumer perceptions in the realm of smart energy systems. By intricately analyzing the nuances of benefit and risk perceptions, and the influence of individual propensities, this study bridges existing knowledge gaps and contributes fresh insights into the evolving landscape of consumer expectations amid rapid digitalization.

From a policy perspective, the findings underscore the need for a balanced and multifaceted approach to promoting and implementing smart energy systems. The strong emphasis consumers place on safety and economic benefits necessitates policies that not only propel technological advancement but also address prevalent consumer apprehensions. Such policy development includes addressing key issues such as energy consumption, the volatility of electricity rates, and privacy concerns associated with smart energy systems. Developing policies that reassure consumers about these aspects while highlighting the potential economic and environmental advantages of smart energy systems is paramount.

Moreover, this study reveals the importance of consumer education and communication strategies in fostering a deeper understanding of the long-term benefits and potential risks associated with smart energy systems. Given the complexities surrounding these technologies, clear and effective communication is crucial in demystifying misconceptions and building trust among potential users.

The focus on enhancing user experience, as highlighted in this study, is critical in an era where technology is increasingly integrated into everyday life. Designing smart energy systems that empower users and provide them with a sense of control can significantly enhance user acceptance and satisfaction.

In conclusion, while corroborating many findings from previous studies, this study also uncovers new dimensions of consumer perception. It highlights the critical impact of environmental concerns and economic uncertainties on the acceptance of smart energy systems. These insights pave the way for future research to delve deeper into the interaction effects between various variables that influence consumer perception. Further exploration of aspects such as perceived ease of use, trustworthiness, and the role of consumer education could provide a more comprehensive understanding of the dynamics involved in adopting smart energy systems.

Future research should also explore the long-term effects of these systems on consumer behavior and the environment. Studies could investigate how perceptions and acceptance of smart energy systems evolve over time as consumers become more familiar with the technology and as the systems the mselves become more advanced and integrated into the energy infrastructure. Understanding these temporal dynamics will be crucial for developing strategies that effectively address the challenges and maximize the benefits of transitioning to smart energy systems.

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APPENDIX

Appendix: Survey questions on benefit and risk perception of the smart energy system

Questions on perceived usefulness (7-point scale questions)

Overall benefit perception

(Overall benefit perception) This section contains questions about the overall usefulness of the [Smart Energy System]. Please indicate your level of agreement with each statement.

- I think the [smart energy system] is useful
- The [smart energy system] contributes to creating new value
- The proliferation of the [smart energy system] is beneficial
- The [smart energy system] has a high level of usability.

Detailed benefit perception

(Home energy saving) The following questions are about how useful the [Smart Energy System] is in saving home energy costs. Please indicate your level of agreement with each statement.

- We can reduce energy consumption using the [smart energy system]
- The [smart energy system] will enable more efficient energy usage
- The [smart energy system] will help lower the cost of energy supply and reduce electricity bills
- The [smart energy system] will allow efficient use of separately stored energy.

(New profit creation) The following questions are about how useful the [smart energy system] is in creating new profits. Please indicate your level of agreement with each statement.

- The [smart energy system] will facilitate individuals to smoothly produce energy directly
- With the [smart energy system], we can be compensated for the surplus energy produced and used
- The [smart energy system] will enable us to consume energy outside high-consumption periods and receive compensation
- The [smart energy system] will allow us to sell separately stored energy.

(Stable energy supply) The following questions are about how useful the [smart energy system] is in providing a stable energy supply. Please indicate your level of agreement with each statement.

- The [smart energy system] will better manage the output variability and uncertainty of renewable energy influenced by weather
- The [smart energy system] will increase the reliability of energy production and delivery systems
- The [smart energy system] will make energy consumption more flexible and improve the stability of the energy system
- The [smart energy system] will ensure continuous energy supply even in the event of power outages.

(Eco-friendly energy system construction) The following questions are about how useful the [Smart Energy System] is in constructing an eco-friendly energy system. Please indicate your level of agreement with each statement.

- The [smart energy system] will facilitate smooth utilization of eco-friendly renewable energy
- The [smart energy system] will reduce carbon emissions by reducing energy consumption
- The [smart energy system] will decrease the use of fossil fuels by efficiently utilizing energy
- The [smart energy system] will advance the technology for using storage devices like electric vehicles and ESS.

(Safe energy system construction) The following questions are about how useful the [smart energy system] is in constructing a safe energy system. Please indicate your level of agreement with each statement.

- The [smart energy system] will quickly identify problems in energy supply facilities and enhance safety
- The [smart energy system] will increase the safety of the energy system through real-time, autonomous responses
- The [smart energy system] can respond more intelligently than manual human responses, making the energy system safer
- The [smart energy system] will enable us to predict safety issues in the energy system in advance.

Questions on risk perception (7-point scale questions)

Overall risk perception

(Overall risk perception) The following questions are about the overall concerns related to the [Smart Energy System]. Please indicate your level of agreement with each statement.

- Using the [smart energy system] is risky
- Using the [smart energy system] makes me anxious
- Using the [smart energy system] is harmful
- I am afraid of the spread of the [smart energy system].

Detailed risk perception

(Electromagnetic radiation risk) The following questions are about the electromagnetic radiation risk associated with the [smart energy system]. Please indicate your level of agreement with each statement.

- The proliferation of the [smart energy system] could increase electromagnetic radiation in the surroundings
- I am concerned about the electromagnetic radiation from the [smart energy system]
- The spread of the [smart energy system] is concerning due to potential health issues
- Using the [smart energy system] might increase electromagnetic radiation in the home.

(High energy consumption risk) The following questions are about the high energy consumption risk associated with the [smart energy system]. Please indicate your level of agreement with each statement.

- The [smart energy system] might consume more energy than it saves
- The energy saved by the [smart energy system] might increase our desire to consume more energy
- Increased energy consumption due to the [smart energy system] could harm the environment
- The [smart energy system] could promote the consumption of more resources.

(Performance risk) The following questions are about the performance risk associated with the [Smart Energy System]. Please indicate your level of agreement with each statement.

- The [smart energy system] might experience operational errors due to communication problems
- The [smart energy system] might not be managed properly
- The [smart energy system] might not control energy effectively, reducing energy-saving effects
- The performance of the [smart energy system] might not meet expectations.

(Privacy invasion risk) The following questions are about the privacy invasion risk associated with the [Smart Energy System]. Please indicate your level of agreement with each statement.

- Using the [smart energy system] might expose personal information
- Personal information exposed through the [smart energy system] could be misused for criminal activities
- Personal information exposed through the [smart energy system] could be used without consent for marketing purposes
- Using the [smart energy system] might expose my family's information.

(Digital divide deepening) The following questions are about the digital divide risk associated with the [Smart Energy System]. Please indicate your level of agreement with each statement.

- The digital divide might cause significant differences in the utilization of the [smart energy system]
- As the [smart energy system] becomes more sophisticated, the issue of information disparity in the energy sector might worsen
- Only those with extensive ICT knowledge might benefit from the [smart energy system]
- People who are not well-informed about the [smart energy system] could be relatively marginalized.

(Cybersecurity threat) The following questions are about the cybersecurity threat associated with the [Smart Energy System]. Please indicate your level of agreement with each statement.

- Cyber hackers could install malicious software and hack the [smart energy system]
- Cyber hackers could unauthorizedly access and disrupt the energy system through the [smart energy system]
- Using the [smart energy system] might not ensure safe authentication between devices
- Cyber hackers could hack the [smart energy system] and collaborate in terrorist activities.

(Financial risk) The following questions are about the financial risk associated with the proliferation of the [smart energy system]. Please indicate your level of agreement with each statement.

- Using the [smart energy system] might lead to financial losses due to carelessness
- Using the [smart energy system] might involve additional costs due to increased service charges
- The cost of replacing devices for the [smart energy system] could be burdensome
- Installing the [smart energy system] without using it could result in financial losses.

(Uncertainty of electricity rates) The following questions are about the uncertainty of electricity rates associated with the proliferation of the [Smart Energy System]. Please indicate your level of agreement with each statement.

- The [smart energy system] could make the rapid fluctuations in energy rates depending on the time of day more inconvenient
- Frequent rate changes due to the [smart energy system] could be confusing
- Using the [smart energy system] makes me anxious about how future energy bills will turn out
- I might not be able to effectively respond to rapid rate changes caused by the [smart energy system].