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Article

Investigating the factors affecting the intention to adopt smart electricity meters in Indian households

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Abstract: Smart electric meters play a pivotal role in making energy systems decarbonized and automating the energy system. Smart electric meters denote huge business opportunities for both public and private companies. Utility players can manage the electricity demand more efficiently whereas customers can monitor and control the electricity bill through the adoption of smart electric meters. The study examines the factors affecting the adoption intention of smart electric meters in Indian households. This study draws a roadmap that how utility providers and customers can improve the smart electric meters adoption. The study has five independent variables (performance expectancy, effort expectancy, social influence, environmentalism, and hedonic motivation) and one dependent variable (adoption intention). The sample size for the study is four hundred and sixty-two respondents from Delhi and the National Capital Region (NCR). The data was analysed using structural equation modelling (SEM). The results of this study have confirmed that performance expectancy, environmentalism, and social influence have a significant impact on the intention of adopting smart electric meters. Therefore, utility providers can improve their strategies to attract more customers to adopt smart electric meters by focusing more on the performance of smart electric meters and by making them environmentally friendly. This research offers meaningful insights to both customers and utility providers to make energy systems decarbonized and control energy consumption.

Keywords: energy; smart electric meters; environmentalism; performance; adoption intention
JEL Classification: M14; M31; M38

1. Introduction

Smart electric meters are Internet of Things (IoT) devices that monitor and transmit data about electricity consumption regularly. These meters are very different from the traditional meters. All companies/suppliers are installing smart electric meters in households as the Government has mandated it across India to upgrade the energy system. Smart electric meters also enable checking the meter reading automatically without manual interferences. Moreover, customers can also view the status of their energy consumption. The main objective behind installing smart electric meters is to save energy costs and have a personalized view of energy consumption behavior. The smart electric meters send the information to both customers and utility providers simultaneously. Utility providers can monitor the electricity unit usage at specific locations and buildings. On the other hand, customers can control the level of energy consumption. Furthermore, the segmentation of the market is based on the nature of the product which includes smart electric meters, smart water meters, and smart gas meters. For end users, the market is further divided into three categories namely: Industrial, Residential, and Commercial. In India, the residential market is expected to dominate the market and will generate maximum revenue as compared to the industrial and commercial segments. Due to improvement in per capita income, industrialization, changes in lifestyle, westernization, urbanization, and attraction towards smart technologies have attracted customers toward smart electric meters' adoption. Keeping in mind the record of the energy market, smart electric meters have garnered maximum market share as compared to smart water meters and smart gas meters. It is predicted that smart electric meters will dominate the market share till 2026. Therefore, companies are interested to know what tempts customers to adopt smart electric meters so that they can increase their market share. Monitoring the electricity consumption through smart meters will make the energy market more attractive for investors because customers cannot hide or avoid the payment of electricity bills. Announcements for the huge investment in the smart electric meters segment are made by both public and private companies. Even, the Government of India has invited various private companies to start the manufacturing of smart electric meters.

The Indian Government encourages customers to install smart electric meters to help them evaluate and control their energy usage and level of energy consumption. Previous studies have projected that customers can save approximately 20% on energy bills (Darby, 2006). In addition to it, Customers can contribute to reducing carbon footprint, protecting the environment, and conserving resources. Furthermore, utility companies can manage the peak demand and low demand by understanding when the consumption of electricity is high and low. Most of the previous studies concentrated on the engineering dimension of smart electric meters (Kaufmann et al., 2013). Recently, a large number of studies have started focusing on the customer aspect of research such as the adoption of smart electric meters, customers' perceptions and attitudes towards smart electric meters, smart water meters, and smart gas meters (Hess, 2013).

Although there has been a lot of research on technology adoption, there is still a lack of understanding about the exact elements influencing the adoption of smart electric meters in Indian households. The importance of various variables such as environmentalism, hedonistic motivation, etc. is acknowledged in the literature, but its influence on the adoption of smart meters in India has not been thoroughly investigated. Moreover, it is necessary to conduct research combining various aspects such as performance expectancy, effort expectancy, and social influence to understand their combined effect on adoption intentions. Moreover, most of the prior research on the propensity to use smart electric meters has been conducted in the European setting, with only a limited number of studies available in the Indian context (Kranz and Picot, 2012; Wunderlich et al., 2019). Hence, this study aims to fill this gap by investigating the factors influencing the intention to adopt smart electric meters in the Indian context.

2. Literature review

Past research studies are mainly influenced by the theory of planned behavior and the sustainable energy technology acceptance model. The above-mentioned models highlight the main factors affecting the customers' adoption intention. Further, extended models of these theories are also studied which incorporated a few additional factors and examined their impact on the adoption intention of smart electric meters. However, the results of all previous studies are not similar. For instance, a study has confirmed that perceived costs and perceived usefulness have a significant impact on the intention to use or purchase smart electric meters (Chen et al., 2017). While, Gumz et al. (2022) found no influence of associated cost on the decision making of adoption of electric meters. On the other hand, perceived privacy risk does not impact the adoption intention of smart electric meters significantly (von Loessl, 2023). Factors affecting the adoption intention of smart technology are not the same across geography, political, and cultural backgrounds (Hori et al., 2013; Wunderlich et al., 2019). Customers' preferences, perceptions, and values which affect the adoption intention of smart electric meters vary from country to country (Chou and Yutami, 2014; Fleiß et al., 2024). Various theories and models have specified the main determinants of the adoption intention of smart electric meters in a given situation.

2.1. Adoption intention

The main construct for the study is the adoption intention. Adoption intention is the decision-making process before purchasing the product. Adoption intention denotes the willingness of the customers to use the smart electric meters. There are numerous factors affecting the adoption intention of smart electric meters such as social influence, performance expectancy, effort expectancy, environmentalism, and hedonic motivation. The intention to adopt smart electricity meters is rooted in theories such as the theory of planned behavior (Ajzen, 1991), the technology acceptance model (Davis, 1989), and the integrated theory of technology acceptance and use (Venkatesh et al., 2003), which emphasize factors such as attitudes, perceived usefulness, and social influences. Cultural context significantly shapes these intentions, with Hofstede's dimensions indicating that high power distance cultures such as India value authority support, while collectivist norms emphasize community benefits (Hofstede, 2016). The adoption intention of the smart electric meter is also influenced by the customers' attitude towards the smart energy technologies. However, previous studies have confirmed that attitude is not only an important determinant of using smart electric meters but also intention to use (Chawla et al., 2019; Idoko et al., 2021; Kranz and Picot, 2012; Naushad, 2018; Wunderlich et al., 2019; Yang et al., 2017).

2.2. Performance expectancy

Performance expectancy (PE) is a key variable in technology adoption, rooted in the unified theory of acceptance and use of technology, which posits that individuals are more likely to adopt a technology if they believe it will enhance their performance (Venkatesh et al., 2003). This concept aligns with the technology acceptance model (Davis, 1989) and the diffusion of innovations theory (Rogers, 2003), both of which emphasize perceived usefulness and relative advantage. Cultural context significantly shapes PE, as represented by Hofstede's dimensions: high power distance cultures, such as India, rely on authority support; collectivist societies emphasize community benefits; and high uncertainty avoidance cultures require clear, proven performance benefits (Hofstede, 2001). Performance expectancy reflects the functional value of a product, specifically its ability to satisfy customer needs (Venkatesh et al., 2003). Customers believe that smart electricity meters can help manage electricity bills more efficiently and accurately, allowing for easier monitoring of meter readings from remote locations (Cioc et al., 2023). Additionally, performance expectancy has been shown to positively and significantly influence adoption intention in contexts such as e-commerce and mobile services (Kranz and Picot, 2012; Wunderlich et al., 2019). In the context of smart electricity meters, performance expectancy significantly influences adoption intention (Gumz and Fettermann, 2022; Kranz and Picot, 2012; Rajaguru et al., 2023). Therefore, it is hypothesized that:

H1: Performance expectancy positively influences the adoption of smart electric meters.

2.3. Effort expectancy

Effort expectancy refers to the degree of ease and comfort experienced by customers when using smart electricity meters, as well as the speed at which they can understand the operation process. Customers prefer products that are easy to use and allow them to maximize the product's capabilities (Venkatesh et al., 2003). It is believed that ease of use significantly influences customers' intentions to adopt smart electricity meters in their homes (Freitas et al., 2021). Customers want the ability to manage and regulate smart meters independently, without dependence on third parties (Kowalska-Pyzalska et al., 2020).

Effort expectancy, an important variable in technology adoption, is based on the Unified Theory of Acceptance and Use of Technology (Naushad and Sulphey, 2020; Venkatesh et al., 2003). It is consistent with the perceived ease of use from the technology acceptance model (Davis, 1989) and the concept of complexity from the diffusion of innovations theory (Rogers, 2003). Cultural context significantly influences effort expectancy: high power distance cultures such as India rely on approval from authority; collectivist cultures value community feedback; and high uncertainty avoidance cultures require explicit support and user-friendly interfaces (Hofstede, 2001). In India, where power distance and collectivism are prevalent, approval from influential bodies and positive community experiences may increase perceptions of ease of use, thereby facilitating adoption of smart meters. Therefore, it is hypothesized that:

H2: Effort expectancy positively influences the adoption of smart electric meters.

2.4. Social influence

Social influence refers to the influence of individuals or groups that are considered important, such as friends, colleagues or the community, on households' decision to adopt smart electricity meters. Social influence is an important variable in predicting the planned behavior, which aligns with the theory of reasoned action (Fishbein and Ajzen, 1977), the theory of planned behavior (Ajzen, 1991) and social cognitive theory (Bandura, 1986). While social influence has been extensively researched in the context of technology adoption (Girod et al., 2017; Gumz et al., 2022; Venkatesh et al., 2012), its specific effect on the adoption of smart electricity meters has been uncleared. Previous studies have suggested that social influence does not significantly affect the intention to adopt smart electricity meters, as consumers do not typically seek advice from others when purchasing these devices (Ahn et al., 2016; Gimpel et al., 2020; Girod et al., 2017). This finding is quite pragmatic and advocates that consumer behavior toward electric smart meters is quite different from other technology's buying behavior. Therefore, it is inferred that:

H3: Social influence positively influences the adoption of smart electric meters.

2.5. Environmentalism

Gradually, customers are becoming more environmentally conscious, preferring to buy products that are environmentally friendly and energy-efficient (Whittle et al., 2020). As a result, Ahn et al. (2016) introduced the concept of environmentalism. Environmentalism is an important variable in technology adoption, which has its theoretical foundation in the value-belief-norm theory (Stern et al., 1999) and the theory of planned behavior (Ajzen, 1991), which emphasize the role of personal norms, values, and beliefs in promoting pro-environmental behavior. Cultural contexts significantly shape environmentalism: high power distance cultures such as India respond well to authority approval, collectivist societies are driven by community norms, and long-term-oriented cultures value sustainable benefits (Hofstede, 2001). Previous studies have confirmed that reducing energy consumption and protecting the environment are important factors influencing the intention to adopt smart electric meters (Balta-Ozkan et al., 2014; Wilson et al., 2017). However, environmentally conscious customers who prefer environmentally friendly products are relatively few. Perri et al. (2020) found that environmental friendliness does not significantly influence the intention to adopt smart electricity meters. This is because marketing strategies for smart meters often emphasize smart homes, home improvement, and convenience rather than resource conservation and environmental protection (Furszyfer Del Rio et al., 2021). Thus, while environmental protection and resource conservation are perceived as secondary benefits, they are not the primary drivers for smart meter adoption (Furszyfer Del Rio et al., 2021). Therefore, it is hypothesized that:

H4: Environmentalism positively influences the adoption of smart electric meters.

2.6. Hedonic motivation

Hedonic motivation is defined as the pleasure that customers have derived after using a product (Venkatesh et al., 2012). Hedonic Motivation is crucial in technology adoption. Various studies suggest that Hedonic Motivation as a determinant of technology use (Venkatesh et al., 2012). Customers prefer some extent of entertainment and fun while using a product which impacts the customers' intention to use an electric smart meter (Venkatesh et al., 2003). The items used in this study measure the degree of pleasure that customers enjoy using electric smart meters. Thus, hedonic motivation is likely to influence the customers' decision to use the electric smart meter. Therefore, it is hypothesized that:

H5: Hedonic motivation positively influences the adoption of smart electric meters.

2.7. Research gap

Despite extensive research on technology adoption, significant gaps remain in understanding the specific factors influencing the adoption of smart electricity meters in Indian households. Environmentalism is recognized as significant, its impact on smart meter adoption in India is understudied, especially given that current marketing strategies do not highlight environmental benefits adequately. The role of hedonic motivation, or the intrinsic enjoyment derived from using smart meters, has also been underexplored in the Indian context. Furthermore, there is a need for research that integrates various factors, such as performance expectancy, effort expectancy, and social influence, to understand their collective impact on adoption intentions. Moreover, most of the previous studies on the adoption intention of smart electric meters are in the European context, and only a few studies are available in the Indian Context (Kranz and Picot, 2012; Wunderlich et al., 2019). Therefore, this study intends to bridge this gap by researching the factors affecting the adoption intention of smart electric meters in Indian context. The proposed model for the research is exhibited in **Figure 1**.

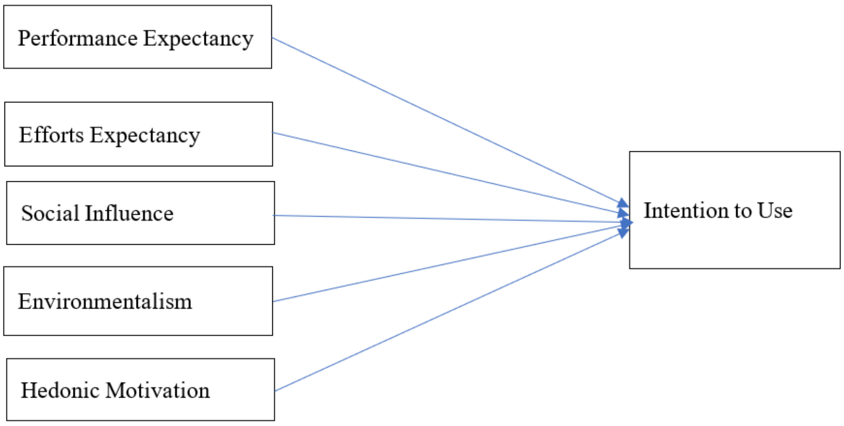

Figure 1. Proposed research model.

2.8. Aims and hypotheses

This study intends to investigate the factors affecting the intention to use smart electric meters. Furthermore, the study aims to examine factors like performance expectancy, effort expectancy, social influence, environmentalism, and hedonic motivation which influence the customers' adoption intention. The study underlines the importance of energy conservation, environment protection, and resource conservation. The study highlights the importance of using products that are environmentally friendly and do not have any negative impact on the environment. The main feature of this research work is to identify the factors affecting the adoption intention of smart electric meters in their households. Based on the above discussion, it is hypothesized that:

- H1: Performance expectancy positively influences the adoption of smart electric meters.
- H2: Effort expectancy positively influences the adoption of smart electric meters.
- H3: Social influence positively influences the adoption of smart electric meters.
- H4: Environmentalism positively influences the adoption of smart electric meters.

- H5: Hedonic motivation positively influences the adoption of smart electric meters.

3. Research methods

Customers' preferences are shifting rapidly towards environment-friendly products that are efficient and have no negative impact on the environment. Electric smart meters are also being preferred by customers in place of traditional smart meters because these meters are more efficient and easier to monitor. Several studies have been published that investigated the important factors affecting the adoption intention of electric smart meters. This study also intends to investigate the main factors affecting the adoption intention of electric smart meters in households. Data for this research work was collected from Delhi and the National Capital Region (NCR). Delhi and National Capital Region (NCR) was intentionally selected for the data collection because here, customers are more educated and are well aware of the advantages and disadvantages of using electric smart meters. Customers in Delhi and the National Capital Region (NCR) reasonably understand the need and importance of purchasing and using electric smart meters in their households. Feedback from these customers is based on their personal experience and observations. The total population of Delhi and the National Capital Region (NCR) is approximately 20 million, out of them, 1.5 million people are young and above 18 years of age. The questionnaire used in this study was carefully designed to ensure comprehensive data collection and analysis. It was divided into two sections to efficiently collect relevant information. The first section focused on demographic details, including age, gender, education, and income, indicating the socio-economic background of the respondents, which is important for contextualizing their answers. The second section collected data on the key constructs of the study: performance expectancy, effort expectancy, social influence, environmentalism, hedonistic motivation, and adoption intention. The constructs for the study were adopted from Chou and Yutami (2014); Große-Kreul (2022); Gumz and Fettermann (2022). These constructs included five independent variables and one dependent variable, with a total of twenty-one items measured on a 5-point Likert scale, ranging from 1 (completely disagree) to 5 (completely agree). The questionnaire items were adapted from scales established in previous research to ensure content validity.

The survey methodology was chosen for its ease of administration and flexibility, allowing it to be conducted via mobile devices, online platforms, email, and social media. Approximately 700 questionnaires were distributed to targeted respondents using both online and offline methods to ensure a large and diverse sample size. Convenience and snowball sampling techniques were used to recruit respondents, leveraging personal networks to reach a wider audience. Data collection took place between October 2023 and December 2023. Despite receiving a large number of completed questionnaires, many were excluded due to being improperly completed. Additionally, data cleaning procedures identified and excluded outliers and answers with missing data, resulting in a final sample size of 462 questionnaires suitable for analysis. Various statistical techniques were used to analyze the collected data, including correlation analysis, regression analysis, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Structural equation modeling (SEM) was also used to examine the relationships between variables. IBM SPSS and IBM AMOS were the primary tools for data analysis, while Microsoft Excel was used for initial data management and demographic analysis. SEM was conducted in two phases: the first phase involved validating the measurement model through CFA to ensure that the constructs were measured reliably, and the second phase validated the structural model, testing the hypothesized relationships between variables. SEM was used to test the causal relationship between interrelated constructs and to examine the strength of the relationships between variables. It provides a comprehensive understanding of the relationships between attitude adoption intention, performance expectancy, effort expectancy, social influence, environmentalism, and hedonic motivation. SEM facilitates a deeper understanding of the factors influencing customers' adoption intentions with regard to electric smart meters.

4. Data analysis

The study has used various statistical parameters to identify the factors affecting the adoption intention of electric smart meters. The study has analyzed the collected data using Excel, IBM SPSS, and IBM AMOS. Confirmatory factors analysis was used to validate the proposed research model. Furthermore, structural equation modeling was used to determine the impact of independent variables on the dependent variables. An analysis of the characteristics of respondents is presented in **Table 1**.

Table 1. Demographic profile.

Particulars	Frequency	Percentage
Gender		
Male	332	71.86
Female	130	28.14
Total	462	100.0
Age		
18–25	162	35.06
25–30	140	30.31
30–35	126	27.27
35 and above	34	7.36
Total	462	100.0
Qualification		
Undergraduate	71	15.36
Graduate	169	36.58
Post Graduate	146	31.60
Any Other	76	16.46
Total	462	100.0
Monthly Income (INR)		
0–25,000	170	36.79
25,000–50,000	112	24.26
50,000–75,000	117	25.32
75,000–100,000	63	13.63
Total	462	100.0

Table 1 describes the demographic characteristics of the respondents. As far as the gender is concerned, this study has 71.86% male and 28.14% female. Moreover, 35.06% of respondents are in the age group of 18–25, 30.31% are in the age group of 25–30, 27.27% are in the age group of 30–35, 7.36% are in the age group of 35 years and above. Further, 15.36% are undergraduate, 36.58% are graduate, 31.60% are postgraduate, and 16.46% have any other qualification. As far as the monthly income of the respondents is concerned, 36.79% of respondents earn 0–25,000, 24.26% earn 25,000–50,000, 25.32% earn 50,000–75,000 and 13.63% of the respondents earn 75,000–100,000.

4.1. Exploratory factor analysis

This study has used exploratory factor analysis techniques to reduce the dataset and to uncover the underlying factors. EFA is a popular statistical technique among researchers, widely used to explore the appropriate factors for the research work. **Table 2** explains the value of KMO and Bartlett's test. Kaiser-Meyer-Olkin (KMO) measures the sampling adequacy. It determines whether the sample size is enough to carry out further research. The accepted KMO value is 0.5–1. The calculated KMO value for the present study is 0.806 which meets the set criteria. **Table 2** also describes the calculated value of Bartlett's test of Sphericity is <0.05 which again meets the set criteria to conduct further research.

Table 2. KMO and bartlett's test.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.806
Bartlett's Test of Sphericity	Approx. Chi-Square	8582.278
	df	210
	Sig.	0.000

Originally, the research questionnaire had 26 items under six constructs. Based on data obtained from exploratory factor analysis, five items were deleted due to poor factor loading. Lastly, only twenty-one items were selected for further analysis.

4.2. Construct reliability and validity

The research questionnaire must be reliable and capable of measuring the objective of the research study. Reliability is used to check whether the scale used in the questionnaire can measure what it intends to measure. Scale reliability exhibits that it can be measured as per the objective of the research and the result will be consistent. Internal consistency is used by the researchers to check the research questionnaire's reliability. Internal consistency is measured through Cronbach's alpha. Researchers have laid down the acceptance criteria that calculated Cronbach's alpha value must be greater than 0.6 (Hair et al., 1998). In this study, calculate Cronbach's alpha value of adoption intention is 0.851 which is more than the set criteria of 0.6. Calculated Cronbach's alpha value of performance expectancy is 0.942 which is much more than the target value of 0.6. Further, effort expectancy's Cronbach's alpha value is 0.928 which is acceptable since it is more than the set criteria. Cronbach's alpha values for social influence, environmentalism, and hedonic motivation are 0.918, 0.919, and 0.935 respectively which all are more than the set criteria of 0.6. Conversely, validity refers to the ability of the scale used in the questionnaire to produce accurate and consistent results. Average Variance Extracted (AVE) is the popular statistical technique used to examine the scale validity. Average Variance Extracted (AVE) value of more than 0.5 is accepted and considered good. **Table 3** explains that the Average Variance Extracted (AVE) value of adoption intention is 0.738; the Average Variance Extracted (AVE) of performance expectancy is 0.796; Average Variance Extracted (AVE) of efforts expectancy is 0.764; the Average Variance Extracted (AVE) of social influence is 0.774; Average Variance Extracted (AVE) of environmentalism is 0.748; Average Variance Extracted (AVE) of hedonic motivation is 0.839. Thus, the Average Variance Extracted (AVE) value of all constructs is more

Table 3. Construct reliability and validity.

Variable	Indicator	Loading	CR	Cronbach's Alpha	AVE
Intention to Use	IU2	0.883	0.893	0.851	0.738
	IU4	0.817			
	IU5	0.875			
Performance Expectancy	PE1	0.860	0.918	0.942	0.796
	PE2	0.905			
	PE3	0.907			
	PE4	0.921			
	PE5	0.868			
Efforts Expectancy	EE1	0.812	0.928	0.933	0.764
	EE2	0.879			
	EE3	0.918			
	EE4	0.883			
Social Influence	SI1	0.888	0.630	0.918	0.774
	SI2	0.871			
Environmentalism	EVT2	0.888	0.922	0.919	0.748
	EVT3	0.845			
	EVT4	0.852			
	EVT5	0.874			
Hedonic Motivation	HM1	0.909	0.940	0.935	0.839
	HM2	0.928			
	HM4	0.911			

than 0.5 which proves the scale validity. **Table 3** also describes the value of composite reliability (CR) of all constructs used in the study. The accepted value of composite reliability (CR) is 0.7 as set by the researchers. The value of the composite reliability of adoption intention is 0.893; the value of the composite reliability of performance expectancy is 0.918; the value of the composite reliability of efforts expectancy is 0.928; the value of composite reliability of social influence is 0.630; composite reliability value of environmentalism is 0.922; composite reliability value of hedonic

motivation is 0.940. Therefore, the value of all constructs is more than set criteria (0.7) except social influence which is slightly lower than 0.7. The following table explains factor loading, the value of Average Variance Extracted (AVE), and composite reliability values.

4.3. Discriminant validity

Constructs used in the study must be different from each other because each construct measures a different dimension of research. Discriminant validity is used by the researchers to examine how different are the constructs from each other (Hair et al., 2016; Hulland, 1999). Discriminant validity is measured by comparing AVE's square root values must be greater than the correlation values. Furthermore, **Table 4** describes that all six constructs' AVE's square root values are more than the correlation value. Thus, it proved that discriminant validity exists (Fornell and Larcker, 1981; Hair et al., 2016).

Table 4. Discriminant validity (Fornell-Larcker Criterion).

	Intention	Performance	Efforts	Influence	Environment	Motivation
Intention	**0.859**					
Performance	0.338	**0.892**				
Efforts	0.048	0.064	**0.874**			
Influence	0.067	0.009	0.43	**0.880**		
Environment	0.055	0.032	0.463	0.300	**0.865**	
Motivation	0.010	0.041	0.233	0.444	0.257	**0.916**

4.4. Model fit

Structural equation modeling (SEM) was used for data analysis in two phases. The first phase involved validating the overall research model to assess whether the data fit well within the proposed model. This process examines the relationships between observed variables and latent constructs as outlined by Kline (2023), and Weston and Gore (2006). Given the absence of fixed criteria to validate the measurement model, several fit indices were used to ensure its validity. The indices used in this study included CMIN/df, comparative fit index (CFI), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), and parsimonious normed fit index (PNFI). The CMIN/df index, which evaluates model fit by comparing the discrepancy between the sample and fitted covariance matrices, is considered acceptable when values are less than 3 (Schermelleh-Engel et al., 2003) as mentioned in Table 5. The CFI, which assesses how well the data fit the hypothesized model compared to a model with no independence, is considered acceptable with values of 0.90 or higher (Bentler, 1990). The GFI measures the proportion of variance accounted for by the estimated population covariance, with values above 0.90 indicating a good fit (Jöreskog and Sörbom, 1984). Similarly, the AGFI adjusts the GFI for the degrees of freedom in the model, with values above 0.90 being desirable (Tabachnick and Fidell, 2001). Finally, the PNFI adjusts the Normed Fit Index (NFI) for the number of parameters, rewards simpler models, and higher values are preferred (Mulaik et al., 1989). All these indices met the criteria set out in this study, indicating a good model fit. Notably, the fit indices are mentioned in **Table 5**, moreover, it is reflected in **Figure 2** as well. Confirmatory factor analysis (CFA) did not suggest any changes to the overall research model, strengthening its validity. By using multiple fit indices, this study ensured a strong validation of the measurement model, contributing to the transparency and reproducibility of the research findings.

Table 5. Fit indices confirmatory factor analysis.

Fit Indices	Recommended Values	Observed Values	Results
CMIN/df	Less than 5	2.950	Acceptable
CFI (Comparative Fit Index)	0.8–0.9	0.959	Acceptable
GFI (Goodness of Fit Index)	≥0.9	0.905	Acceptable
AGFI (Adjusted Goodness of Fit Index)	≥0.80	0.871	Acceptable
PNFI (Parsimonious Normal Fit)	>0.5	0.757	Acceptable
RMSEA (Root Mean Square Error of Approximation)	Less than 0.08	0.065	Acceptable

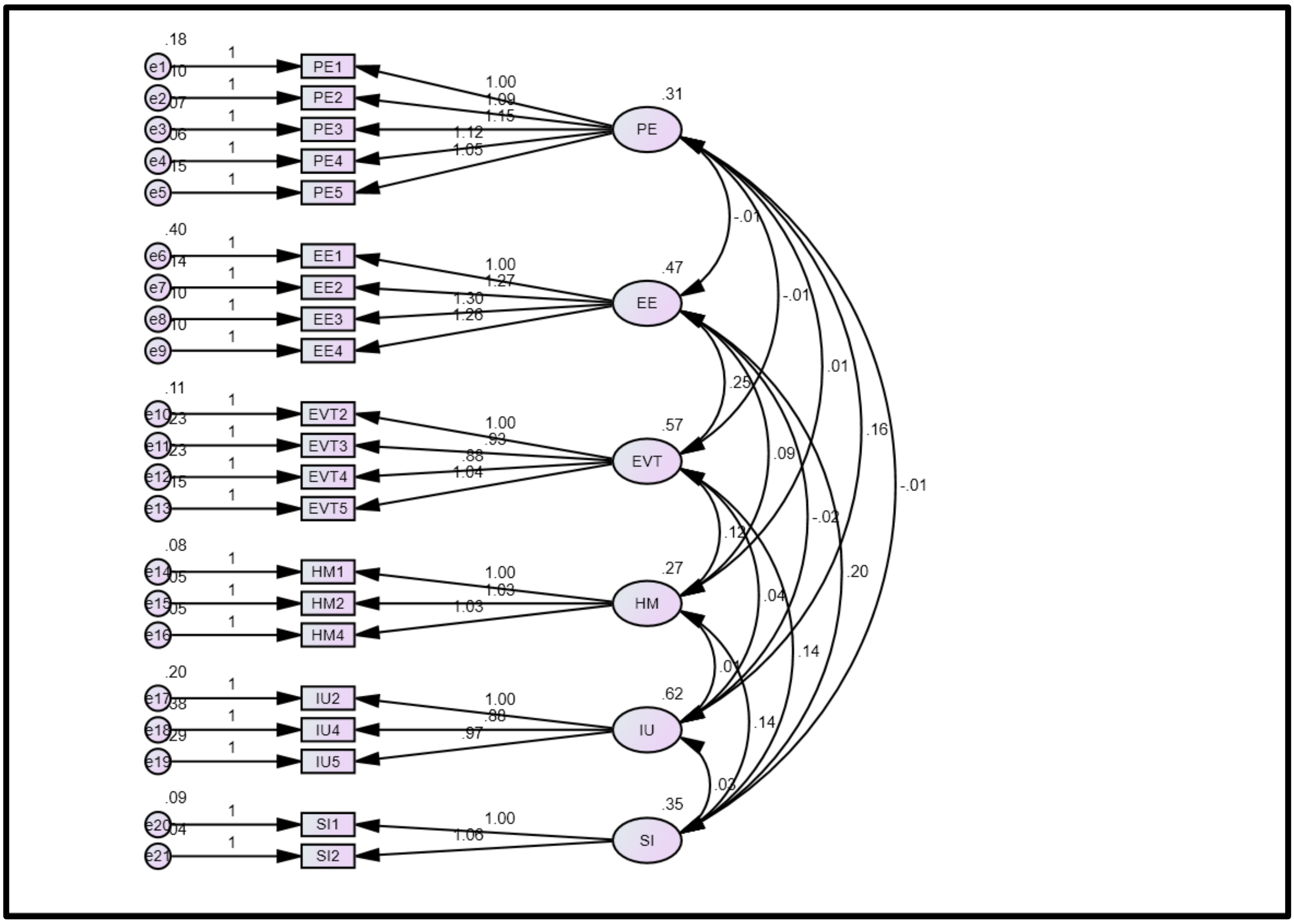

Figure 2. Model fit.

4.5. Structural model

Structural Equation Modelling (SEM) examines the causal relationship between the dependent and independent variables. Structural Equation Modelling (SEM) is highly suitable for determining the strength of relationships among the variables or constructs. SEM is also used in research studies where the sample size is small and there are two or more dependent variables (Sarstedt et al., 2019; Shiau and Chau, 2016). **Table 6** exhibits the results of the path coefficients of the SEM model.

Table 6. Hypotheses conclusion.

Path Coefficients	Estimate	S.E.	C.R.	*P* Value	Status
IU ← PE	0.52	0.07	7.29	0.00	Accepted
IU ← EE	0.10	0.05	1.82	0.06	Rejected
IU ← EVT	0.10	0.05	2.10	0.03	Accepted
IU ← HM	0.10	0.07	1.46	0.14	Rejected
IU ← SI	0.11	0.06	2.77	0.03	Accepted

Table 6 exhibits that there is a significant relationship between adoption intention and performance expectancy because the critical ratio (CR) value is 7.29 ≥ 1.96, and the *P* value is 0.00 < 0.05. However, there is no significant relationship between adoption intention and effort expectancy because the critical ratio (C.R) value is 1.82 ≤ 1.96, and the *P* value is 0.06 > 0.05. Furthermore, there is a significant relationship between adoption intention and environmentalism because the critical ratio (CR) value is 2.10 ≥ 1.96, and the *P* value is 0.03 < 0.05. On the other hand, there is no significant relationship between intention to use and hedonic motivation because the critical ratio (C.R) value is 1.46 ≤ 1.96, and the *P* value is 0.14 > 0.05. Furthermore, there is a significant relationship between adoption intention and social influence because the critical ratio (CR) value is 2.77 ≥ 1.96, and the *P* value is 0.03 < 0.05. These indices are indicated in the **Figure 3** which shows the final structural model.

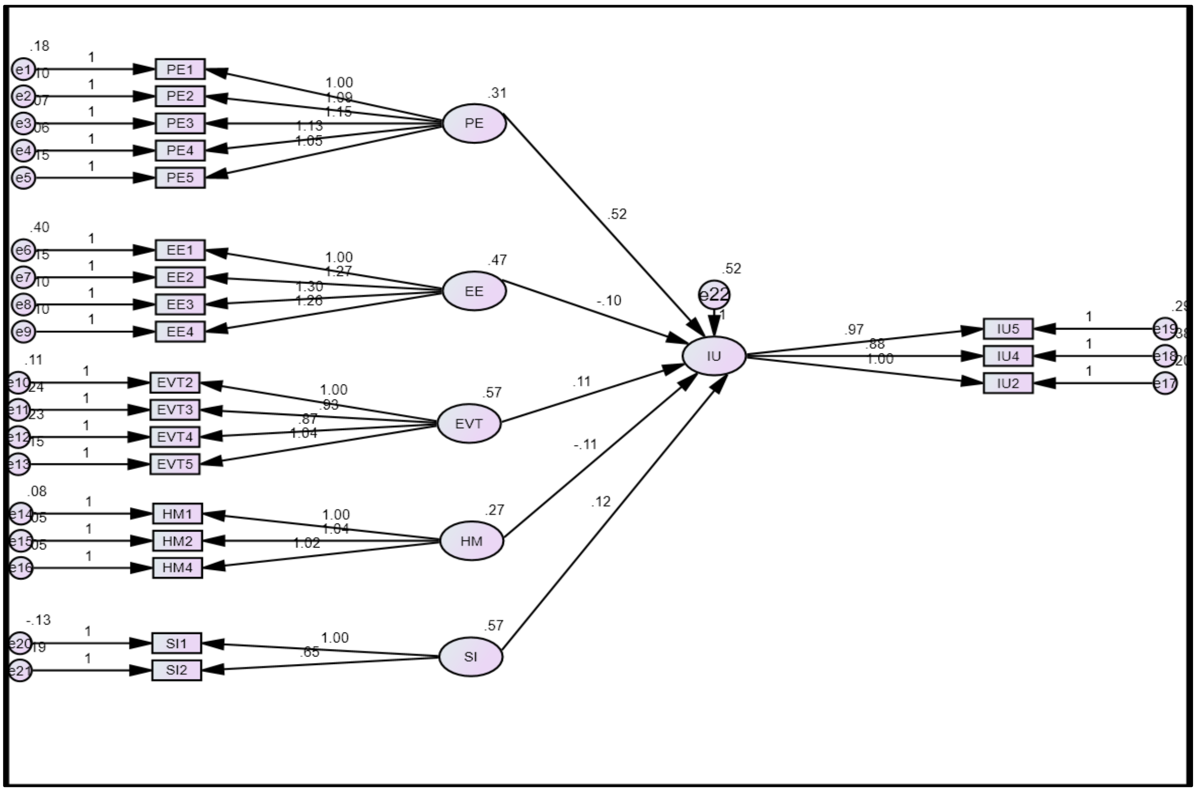

Figure 3. Structural model.

5. Discussion

This study examines the factors affecting the adoption intention of smart electric meters in Indian households. The study endeavored to investigate whether performance expectancy, effort expectancy, social influence, environmentalism, and hedonic motivation affect the adoption intention in the context of smart electric meters. In addition, this study establishes the relationship between the adoption intention and performance expectancy, efforts expectancy, social influence, environmentalism, and hedonic motivation. Furthermore, two main objectives of this research are (i) to identify the impact of demographic variables on the adoption intention of smart electric meters and (ii) to determine the main factors affecting the adoption intention of smart electric meters. This study has emerged as significant because the decarbonization of the Indian economy, protection of the environment, and exhaustible resource conservation are imperative.

This research was initiated with five independent variables (performance expectancy, effort expectancy, social influence, environmentalism, and hedonic motivation) and one dependent variable (adoption intention). Based on these five independent variables, five hypotheses were framed for testing. The measurement model for the study was found statistically significant based on various indices values. However, the hypotheses' testing results were mixed. The results of the study confirmed that performance expectancy positively influences the adoption intention of smart electric meters (CR value is $7.29 \geq 1.96$, and the P value is $0.00 < 0.05$). This result is similar to other previous studies (Cioc et al., 2023; Wunderlich et al., 2019; Kranz et al., 2011). Furthermore, one more study in the context of mobile services (Gofen et al., 2003) confirmed that performance expectancy positively and significantly influences the adoption intention. In addition, effort expectancy was found insignificant concerning influencing the adoption intention of smart electric meters (CR value is $1.82 \leq 1.96$, and P value is $0.06 > 0.05$).

These results are in contradiction to the previous studies (Kowalska-pyzalska and Byrka, 2019; Freitas et al., 2021) which confirmed that effort expectancy influences the adoption intention because customers want such product that they can use easily and without any complication. Moreover, environmentalism is found statistically significant (CR) value is $2.10 \geq 1.96$, and the P value is $0.03 < 0.05$. This result is similar to the previous studies (Balta-Ozkan 2014; Wilson et al., 2017) which confirmed that environmentalism influences the adoption intention because environment-conscious customers prefer to purchase those products that are environment-friendly, contributing to making the economy decarbonized. In the wake of climate change, customers have become more environment-conscious and they are more likely to purchase products that protect the environment and conserve energy resources (Ahn et al., 2016). Furthermore, hedonic motivation was found statistically insignificant (CR) value is $1.46 \leq 1.96$, and the P value is $0.14 > 0.05$. The results of this study differ from the previous studies (Venkatesh et al., 2003) which emphasized that customers expect some extent of funds while adopting the smart electric meter. However, it seems quite impractical that why customers will look for some fun and entertainment while using smart electric meters. Meters are installed in households to monitor the consumption of electricity, not for fun. Thus, the result of the study proved to be more practical and logical. Lastly, social influence positively influences the customers' adoption intention of smart electric meters (CR value is 2.77 ≥ 1.96, and the *P* value is 0.03 < 0.05). The result is similar to the previous studies (Chen et al., 2020) which confirmed that customers take into consideration the advice of friends, family members, and peer groups while adopting the smart electric meter. According to Dutot (2015) also confirmed that social influences have a positive impact on the adoption decision of smart electric meters.

6. Conclusion

The study aims to identify the factors affecting the adoption intention of smart electric meters. Therefore, the study was framed with one dependent variable named adoption intention and with five independent variables namely: performance expectancy, efforts expectancy, social influence, environmentalism, and hedonic motivation. In addition, five hypotheses were framed to better understand the relationship between dependent variables and independent variables. Further, structure equation modeling was employed to test the framed hypotheses. The result of this study confirmed that performance expectancy, environmentalism, and social influence impact the customers' adoption intention. However, the results of the study also indicate that effort expectancy and hedonic motivation do not impact the adoption intention significantly.

Adoption of smart electric meters not only will help the customers and society but also the business organization. Utility providers could easily monitor the electricity consumption behavior of the customers and, the level of electricity demand. In addition, customers can also check the authenticity of the electricity bill and the movement of the meter. The smart electric meter is capable of communicating the energy consumption to both the company and customers simultaneously. The adoption of smart electric meters is beneficial for both business organizations and customers.

7. Limitations and future scope of research

There are numerous inherent limitations that are common to research studies, including this study. These limitations encompass constraints on resources, time, and processes linked to data collection. Significantly, the non-random sampling was chosen from Delhi and the National Capital Region (NCR), thereby reducing its representativeness for the total Indian population. Thus, the findings are constrained to a particular geographical location and may not be applicable to other areas or the entire nation. In addition, the sample size is insufficient, comprising only 462 persons, which is inadequate considering the enormous population of India. The small sample size impedes the capacity to derive precise inferences from the data. The issue of participant involvement was a notable obstacle that required attention, as a considerable number of respondents shown apathy towards completing the questionnaire. Consequently, a substantial portion of the questionnaires collected were missing crucial information, thereby undermining the dependability and accuracy of the study's conclusions.

The study suggests a few areas where future researchers could work. Future researchers could include more independent variables like perceived cost, subsidy, and Government policy. Future researchers could take one mediating variable and examine its impact on the customers' adoption intention. To overcome the limitations of the study, several methodological improvements and data collection techniques can be employed. First, adopting random sampling, including stratified random sampling, will ensure a more representative sample of the Indian population, minimizing the bias introduced by focusing only on Delhi and the NCR. Increasing the sample size through phased surveys and collaboration with local organizations will increase the statistical power and reliability of the findings. Expanding the geographical scope to include diverse regions across India will improve the generalizability of the results. To overcome participant attrition, implementing engagement strategies such as incentives, simplifying questionnaires, and following up with respondents will improve response rates and data quality. Adopting a mixed-method approach by incorporating qualitative data through interviews and focus groups will provide a more comprehensive understanding of the factors influencing smart meter adoption. Finally, conducting a longitudinal study will provide insights into trends and changes over time, thereby increasing the depth of analysis. By incorporating these methodologies and techniques, the limitations of the study can be effectively mitigated, leading to more robust and generalizable findings.

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