The Role of Institutional Influence in Boosting Smart Meter Acceptance: A Study Using Extended UTAUT2 in Indonesia

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Abstract

Smart meters are a vital technology for enhancing electrical grid efficiency within intelligent grid systems, yet consumer acceptance continues to limit their full potential. This study addresses the research gap in understanding smart meter adoption in Indonesia by applying an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model, modified to include institutional influence as a significant factor. Data was gathered through a survey of 410 individuals and analyzed using partial least squares structural equation modeling (PLS-SEM). The findings highlight that institutional influence is the strongest driver of adoption intention (path coefficient of 0.44), followed by social influence (0.17) and effort expectancy (0.09). Interestingly, performance expectancy, facilitating conditions, and price value did not exhibit significant relationships, suggesting that functional benefits or cost savings are not primary motivators for consumers. These results emphasize the critical role of government policies, regulations, incentives, and educational support in building consumer trust, while also underscoring the importance of user-friendly smart meter designs. Leveraging social encouragement from public figures and community leaders is also recommended to boost adoption rates. Future research could explore the long-term impact of these institutional interventions and examine cultural influences on technology acceptance. Overall, cultivating strong institutional frameworks and supportive social ecosystems is essential for the successful deployment of smart infrastructure in Indonesia, providing key insights for policymakers and practitioners seeking to foster sustainable energy adoption.[1]

Keywords: Institutional Influence; Smart Grid; Smart Meter; Smart Meter Acceptance; Advanced Metering Infrastructure; UTAUT2; Extended UTAUT2.

JEL: D12, L51, L94, O33

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1. Introduction

Smart meters are a key component of the smart grid, enabling efficient management of electrical energy (Wang et al., 2019). In Indonesia, Perusahaan Listrik Negara (PLN), the state-owned electricity company, is implementing a program to replace traditional electricity meters with smart meters, supported by government incentives and facilities (Alkawsi, Ali and Baashar, 2020). Greater understanding and acceptance of the smart meter replacement programme is needed among customers (Nugroho *et al.*, 2017). The successful adoption of smart meters is vital for achieving electrical efficiency and supporting the overall effectiveness of the smart grid system. Various factors, including institutional support and public understanding, influence the acceptance of smart meters in Indonesia. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is an appropriate framework for measuring the acceptance of new technologies, considering factors such as performance expectancy, effort expectancy, social influence, and facilitation conditions (Alkawsi, Ali and Baashar, 2020).

Despite the critical role of smart meters in enhancing electrical grid efficiency, there remains a notable research gap in understanding the specific factors influencing their adoption in Indonesia. Previous studies have largely focused on general technology acceptance models without fully integrating the impact of institutional elements such as government policies, regulations, and incentives, which are particularly relevant in the Indonesian context. This study aims to fill this gap by applying an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model that incorporates institutional influence as a key construct. The primary objective is to empirically investigate how institutional factors, alongside selected UTAUT2 variables, affect consumers' behavioral intention to adopt smart meters in Indonesia. By doing so, the research provides nuanced insights into the socio-technical dynamics shaping smart meter acceptance, offering practical implications for policymakers and utility providers. The remainder of the paper is structured as follows: a literature review and hypothesis development, methodology detailing data collection and analysis, presentation of results with discussion, and finally conclusions, limitations, and directions for future research.(Gumz *et al.*, 2022). The ultimate and broad adoption of smart meters is essential for increasing electrical efficiency and enhancing the performance of the smart grid infrastructure (Sinaga, Sasue and Hutahaean, 2021).

2. Literature Review and Hypothesis Development

2.1. Smart Meter

A smart meter is a crucial component of a smart grid system, enabling real-time electricity consumption measurement and communication to utility companies (Saleem *et al.*, 2019). By incorporating information and communication technology, smart meters optimize grid performance, prevent power outages, and facilitate supply restoration (Glass and Glass, 2019). These advanced digital devices record electricity consumption in real-time, providing valuable data for grid management and maintenance (Arifin, Setyobudi and Elnur, 2023). Smart meters represent a critical technological advancement in the evolution of energy management systems, serving as a foundational element of contemporary energy infrastructure (Humeres, 2022). These innovative devices are not merely tools for measuring electricity usage in real-time but are integral components of the Advanced Metering Infrastructure (AMI) within smart grids (Purnama, Nashiruddin and Murti, 2020). They facilitate the high-frequency collection of electricity consumption data, thereby enabling a multitude of applications that enhance the efficiency, reliability, and sustainability of energy systems (Wang et al., 2019).

The significance of smart meters extends beyond simple data collection (Rita and Fitria, 2021). Their detailed and timely data supports various functionalities crucial for modernizing electrical grids. For instance, they are pivotal in detecting electricity theft, a major issue in many regions, by identifying discrepancies in energy usage patterns (Yan and Wen, 2021). This capability not only aids in reducing losses for utility providers but also contributes to fair billing practices for consumers (Kulkarni *et al.*, 2019).
Smart meters lay the groundwork for innovative energy trading models, such as peer-to-peer (P2P) platforms (Pranadi and SETİAWAN, 2020). These models allow consumers to become prosumers, both producers and consumers of energy, by enabling them to sell excess energy generated from renewable sources back to the grid or directly to other users (Sinaga, Sasue and Hutahaean, 2021). This not only empowers consumers but also promotes the use of renewable energy sources, contributing to the overall sustainability of the energy ecosystem (Wang et al., 2019).

2.2. Integration with IoT and Smart Grid Functions

The convergence of smart meters with Internet of Things (IoT) technologies marks a significant leap forward in energy infrastructure development (Behnam *et al.*, 2023). A more interconnected and automated energy network is realized by integrating smart meters with IoT devices, such as sensors and actuators. This integration facilitates advanced monitoring, control, and optimization of energy consumption at individual and community levels (Adebanji *et al.*, 2022). It supports a range of network functions across the entire energy value chain, from generation and transmission to distribution and consumption, thereby enhancing grid reliability and operational efficiency (Serra *et al.*, 2021).

2.3. Challenges to Consumer Acceptance

Despite their numerous advantages, consumers need help adopting smart meters. A key challenge lies in their limited awareness of smart meters' potential electricity savings and environmental benefits (Chou and Gusti Ayu Novi Yutami, 2014). Addressing this challenge requires targeted educational and communication strategies to improve understanding and appreciation of smart meter benefits (Chamaret, Steyer and Mayer, 2020).

Research has highlighted the influence of personal innovativeness and user experience on the acceptance of smart meter technology. Innovative individuals open to new technologies tend to be more willing to adopt smart meters (Chawla, Kowalska-Pyzalska and Widayat, 2019). Similarly, positive user experiences, facilitated by user-friendly interfaces and transparent information on energy consumption patterns, can significantly boost acceptance rates (Ji and Chan, 2020).

Social factors, including the influence of peers, community norms, and demographic factors like gender, have also been identified as crucial determinants of smart meter acceptance (Waller *et al.*, 2022). Tailoring implementation strategies to account for these social and demographic influences can enhance consumer receptivity to smart meters (Hmielowski *et al.*, 2019).

2.4. Future Directions in Smart Meter Data Analytics

The field of smart meter data analytics is burgeoning, with research delving into methodologies, challenges, and applications for analyzing the vast amounts of data generated by smart meters (Cejka, Frieden and Kitzmüller, 2021). This research is crucial for unlocking smart meters' full potential, enabling utilities and consumers to make more informed decisions about energy production, distribution, and consumption (Castagneto Gissey *et al.*, 2021).

Smart meters transform the energy sector by enabling more efficient and sustainable energy management practices (Dileep, 2020). While consumer acceptance challenges remain, advancements in technology and research continue to pave the way for broader implementation and integration of smart meters into the smart grid. As we move forward, the continued exploration of smart meter data analytics and consumer engagement strategies will be vital to realizing the full potential of this pivotal technology (G. et al., 2021).

2.5. Institutional Influence

The implementation process of smart meters can be influenced by many institutional elements, which can ultimately determine the success and effectiveness of the deployment (Strong, 2018). The sources indicate that these institutional variables encompass: 1. Government policies and regulations: The existence of favorable government policies and regulations can significantly influence the installation of smart meters (Hess, 2014). 2. Involvement of utility companies: The degree of cooperation and active participation from utility companies during the implementation phase can impact the effectiveness of smart meter deployment, such as Financial incentives and funding (Chen, Xu and Arpan, 2017). The availability of financial incentives and funding can facilitate the introduction of smart meters, as it helps cover the expenses involved with installation and infrastructure modifications (Kowalska-Pyzalska, 2018). Institutional factors play an essential role in influencing the implementation of smart meters. Several studies have underlined the significance of various aspects of the acceptance of smart meters. Alkawsi, Ali and Baashar (2020) highlighted the importance of incorporating knowledge about power conservation and environmental consciousness in shaping the willingness of residential consumers to adopt smart. In addition, (Pérez Caballero, 2020) recognized social impact as a significant determinant in adopting smart meters, specifically in the Brazilian setting (Gumz and Fettermann, 2021). Additionally, (Singh, Sinha and Liébana-Cabanillas, 2020) created a smart meter acceptance model to investigate the moderating influence of experience and personal innovativeness variables among residential consumers. These findings underline the multidimensional character of institutional elements that influence the adoption of smart meters, covering social, environmental, and personal dimensions. Moreover, the study by (Talukder *et al.*, 2019) on the acceptability and use predictions of fitness wearable technology underlined the significance of look-and-feel and the availability of fitness apps as major factors impacting adoption. This study primarily examined fitness-wearable technology. However, the results highlight the importance of user experience and the availability of apps in adopting technology (Talukder *et al.*, 2019).

2.6. UTAUT2 Model

The UTAUT2 model, proposed by (Venkatesh *et al.*, 2012), enhances the original UTAUT model by incorporating three additional factors: hedonic motivation, price value, and habit (Baabdullah *et al.*, 2019). These constructs influence individuals' desire to behave and use technology. The UTAUT2 model includes individual characteristics, such as age, gender, and experience, as moderators that affect the influence of these dimensions on behavioral intention and technology use (Kwateng, Osei Atiemo and Appiah, 2019). The model consists of seven essential constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit. These constructs collectively impact individuals' intentions to utilize technology and their subsequent behaviour in actually using it (Baabdullah et al., 2019). The UTAUT2 model has been extensively utilized and expanded in diverse domains, including mobile banking (Raza, Shah and Ali, 2019), food delivery applications (Gunden, Morosan and DeFranco, 2020), mHealth (Duarte and Pinho, 2019), and e-commerce (Hungilo, To and Setyohadi, 2020). For example, (Schretzlmaier and Hecker, 2022) expanded the UTAUT2 model to forecast the adoption of mHealth.

They discovered that the original UTAUT2 model needs to be enhanced by incorporating "perceived disease threat" and "trust" to predict mHealth acceptance more accurately. (Wu *et al.*, 2022) employed an expanded version of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to forecast the likelihood of individuals in China persisting in using mHealth applications. Their study model integrated perceived reliability and online reviews as factors influencing continuing usage behaviour (Wu *et al.*, 2022).

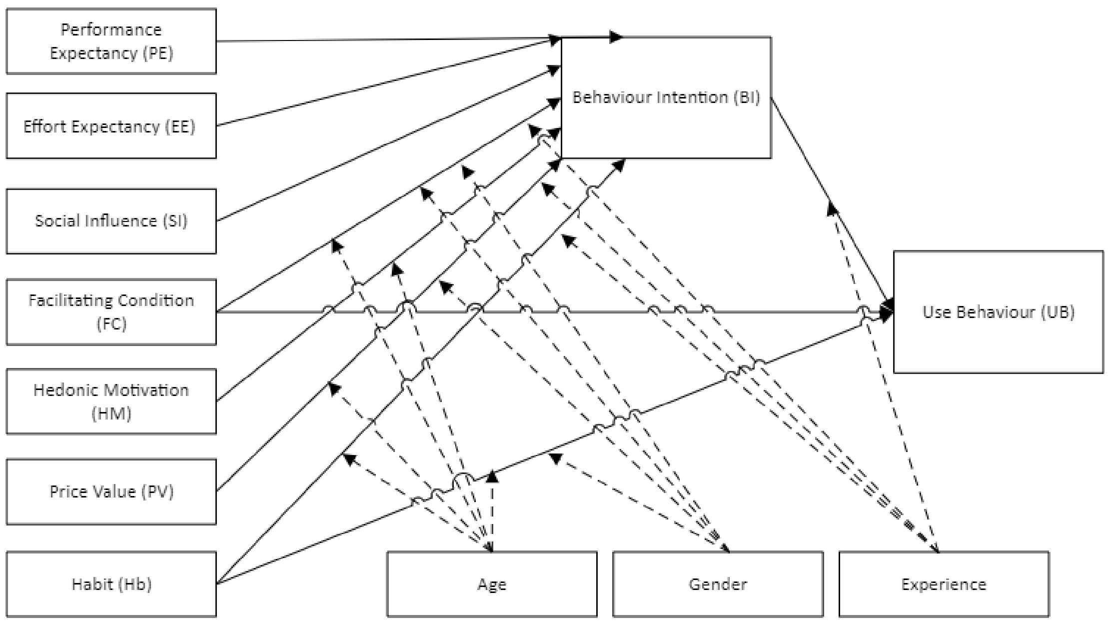

Figure 1. UTAUT2 Model

The UTAUT2 model has been modified to suit other cultural and industry-specific situations, including Islamic banking (Parayil Iqbal, Jose and Tahir, 2023), last-mile delivery (Kapser and Abdelrahman, 2020), and digital entertainment (Aranyossy, 2022). As an illustration, (Eneizan *et al.*, 2019) expanded the UTAUT2 model by integrating trust and risk factors into the framework of customer adoption of mobile marketing in Jordan. In addition, the UTAUT2 model has been employed to evaluate the adoption and seamless integration of cloud-based healthcare facilities from the perspective of healthcare practitioners (Idoga *et al.*, 2019). Overall, the UTAUT2 model has been extensively utilized and expanded in many technological and cultural settings, showcasing its adaptability and significance in comprehending the acceptance and utilization of technology.

2.7. Selected Variables in Extended UTAUT2 for Smart Meter Acceptance

The adoption of smart meters in Indonesia has significant potential to enhance energy management and efficiency (PT. PLN (PERSERO), 2023). Nevertheless, comprehending the variables that impact the adoption and utilization of smart meters is crucial for their effective implementation (Alkawsi et al., 2020). A practical approach to accomplishing this is to use the extended UTAUT2 model proposed (Alkawsi et al., 2020). We will choose selected variables in the Indonesian condition and remove others. The decision to remove three elements: hedonic motivation, habit, and use behaviour from the modified Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model in Indonesia is because the implementation program is merely in the early stage (Arifin, Setyobudi and Elnur, 2023). These stem from the specific context and objectives of the study. Each of these elements has its rationale for exclusion, which can be inferred based on theoretical and practical considerations:

1. **Hedonic Motivation**: This factor refers to the fun or pleasure of using a technology. In the context of smart meters, utility-based technologies primarily focus on energy consumption tracking and management, and hedonic motivation may not be a significant driver of acceptance and use. Utility companies install smart meters and often do not involve active daily engagement or provide entertainment value to the consumer. Therefore, the pleasure or enjoyment aspect may be less relevant in predicting the intention to use smart meters than other technologies where user engagement and experience are more central. Smart meters are still not widely used, so this factor is eliminated (Indrawati and Tohir, 2016).
2. **Habit**: Habit represents the extent to which people tend to perform behaviours automatically because of learning. While habit is a crucial factor in technologies used frequently and voluntarily, such as smartphones or social media platforms, smart meters do not require daily active interaction by the consumer. Once installed, smart meters operate automatically, and the consumer's interaction is often limited to monitoring consumption data. Therefore, the habitual use of smart meters is not a central component of their adoption and use, making this factor less relevant in the model for this specific context. Smart meters are still not widely used in Indonesia, so this factor has been eliminated (Indrawati and Tohir, 2016).
3. **Use Behaviour**: Use behaviuor focuses on the actual usage of the technology. In studies aiming to predict technology acceptance or intention to use, actual use behaviour is often considered an outcome rather than a predictor. Since the primary focus of the modified UTAUT2 model in the context of smart meter implementation may be to understand what drives the intention to accept and support smart meter technology, including actual use behaviour in the model, this could be redundant or beyond the scope of the study's predictive objectives. Because the intensity of use cannot yet be measured, this factor is eliminated (Indrawati and Tohir, 2016).

We will remove three variables because we cannot deep-question the respondents who do not know or have experience with smart meters (Indrawati and Tohir, 2016). Modifying the UTAUT2 model by excluding these elements suggests a tailored approach to understanding smart meter adoption in Indonesia, emphasizing factors that directly influence the acceptance and intention to use within the country's unique sociocultural and infrastructural context. It focuses strategically on the most relevant determinants of technology acceptance, in this case, allowing for a more streamlined and context-specific analysis. By integrating these elements into the expanded UTAUT2 framework, we may thoroughly comprehend the aspects that impact the acceptability and use of smart meters in Indonesia. By incorporating institutional influence as a construct in the extended UTAUT2 model, we can better understand the impact of external factors on the acceptance and use of smart meters in Indonesia. This addition allows for a more comprehensive analysis of the socio-technical ecosystem surrounding smart meter implementation, providing valuable insights for policymakers, utility providers, and researchers in the field. For a deeper understanding of the factors that impact the acceptance and utilization of these meters, an extended UTAUT2 model has been devised with selected constructs.

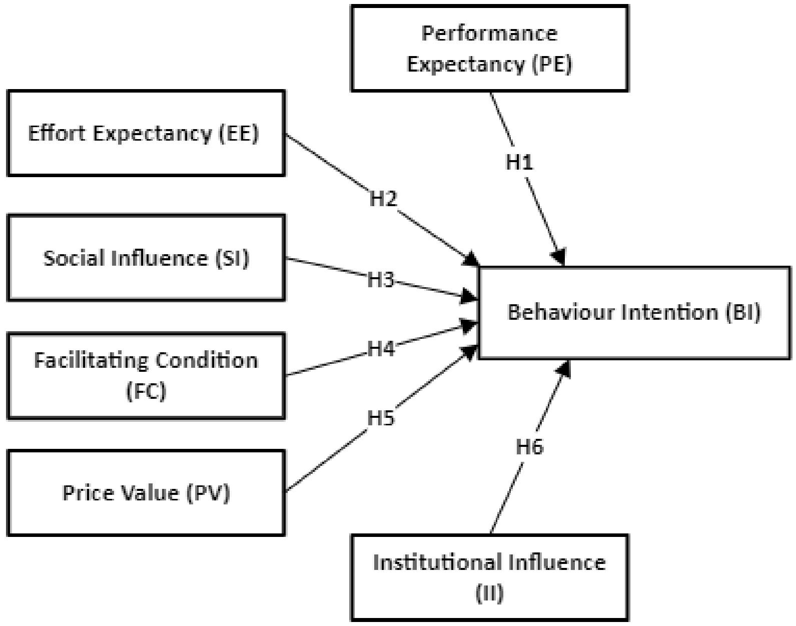

Figure 2. Extended UTAUT2 Model with Selected Variable

2.8. Hypothesis

The hypotheses from the proposed extended UTAUT2 model with Institutional Influence and selected constructs are as follows:

H1: Performance Expectancy (PE) positively influences Behaviour Intention (BI) to use smart meters. Smart meters are expected to improve the quality of electricity management and positively influence their intention to use them. Research generally indicates that when a new technology is perceived to enhance job performance, users are more likely to adopt it.

H2: Effort Expectancy (EE) positively influences Behaviour Intention (BI) to use smart meters. The easier it is to use smart meters, the more likely individuals will adopt them. This hypothesis is based on the idea that if a technology is user-friendly, potential users will have a stronger intention to use it.

H3: Social Influence (SI) positively influences Behaviour Intention (BI) to use smart meters. If an individual's social circle—such as friends, family, or coworkers—believes that they should use smart meters, then the individual is more likely to intend to use them. The social environment can significantly impact technology adoption, especially when the technology is visible within someone's social group.

H4: Facilitating Conditions (FC) positively influence Behaviour Intention (BI) to use smart meters. The presence of support for the service, such as infrastructure, call centers, and offices ready to serve all matters related to smart meters, will impact the desire to adopt this service.

H5: Price Value (PV) positively influences Behaviour Intention (BI) to use smart meters. If individuals feel that smart meters provide greater benefits at a lower cost than traditional meters, this perception will likely influence their intention to use them positively.

H6: Institutional Influence (II) positively influences Behaviour Intention (BI) to use smart meters. The presence of government support, regulations, and institutional backing from relevant institutions will significantly influence the desire to use smart meters.

These hypotheses explore how performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and institutional influence collectively affect the intention to use smart meters. Testing these hypotheses through surveys or interviews with potential users will provide further insights into the factors affecting smart meter adoption.

3. Methodology

3.1. Population and Sample

The PLN Subscriber Survey was conducted to gather feedback from the 80 million PLN subscribers throughout major islands in Indonesia. To analyze the survey data obtained from the PLN Subscriber Survey, we utilized Slovin's formula to calculate the sample size and estimate the characteristics of the entire population of 80 million PLN subscribers. Slovin's theory, also known as Slovin's formula, is a statistical method used to determine the sample size for a research study. It is particularly relevant in survey research and is based on the principle that a small sample can represent the whole population if chosen carefully. The formula is expressed as:

$$n = \frac{N}{1+(Ne^2)} \quad (1)$$

where n represents the required sample size. N represents the overall population size (in this case, 80 million PLN customers). The symbol e represents the acceptable level of error that can be tolerated (often set between 0.01 and 0.05, depending on the desired level of precision). Assuming we use an error rate of e = 0.05 (5%), the calculation becomes:

$$n = \frac{80{,}000{,}000}{1+(80{,}000{,}000 x 0{,}05^2)} \quad (2)$$

Applying this formula yields a required sample size of 399.99, rounded up to 400 respondents. Table 1 presents the demographic characteristics of the respondents.

Table 1. Demography Characteristics Respondent

Item	Category	Amount	Percentage
Gender	Male	274	66,50%
	Female	138	33,50%
Age	≤ 30 Years	96	23,30%
	31 sd 40 Years	265	64,32%
	41 sd 50 Years	50	12,14%
	≥ 51 Years	1	0,24%
Education	≤ Senior High School	96	23,30%
	Under Graduate	264	64,08%
	Graduate/Master	49	11,89%
	Post Graduate	1	0,24%
Electricity Bill (Rupiah per Month)	≤ 200.000 Rp	56	13,59%
	200.001 sd 500.000 Rp	184	44,66%
	501.000 sd 1.000.000 Rp	110	26,70%
	≥ 1.000.000 Rp	62	15,05%
Familiar with Android/Iphone App	Yes	399	96,84%
	No	13	3,16%
Ever Heards of Smart Meter	Yes	155	37,62%
	No	257	62,38%
Ever Tried using Smart Meter	Yes	79	19,17%
	No	333	80,83%
Island to Stay	Jawa	162	39,32%
	Bali	15	3,64%
	Sumatera	83	20,15%
	Sulawesi	96	23,30%
	Kalimantan	28	6,80%
	Others	28	6,80%

The survey results reveal several key findings regarding smart meter awareness and usage:

- **Demographics:** Most respondents were male (66.5%) and between the ages of 31 and 40 (64.32%). Most respondents had at least an undergraduate degree (64.08%) and a monthly electricity bill of between 200,001 and 500,000 rupiah (44.66%).
- **Awareness and usage:** Nearly all respondents (96.84%) were familiar with Android or iPhone apps, but only 37.62% had ever heard of smart meters. Of those who had heard of smart meters, only 19.17% had tried using one.
- **Location:** The respondents were spread out across several Indonesian islands, with the most coming from Java (39.32%) and Sulawesi (23.30%).

3.2. Source Data and Data Collection Instrument

In this study, we aim to gather quantitative data by using a questionnaire to describe and analyze various aspects of our research topic. The questionnaire will consist of carefully crafted questions designed to elicit specific information related to our research objectives.

Table 2. Selected Variable

No	Variable	ID	Items	Source
1	**Performance Expectancy**	**PE**	4	(Venkatesh *et al.*, 2012)
2	**Effort Expectancy**	**EF**	4	(Venkatesh *et al.*, 2012)
3	**Social Influence**	**SI**	3	(Venkatesh *et al.*, 2012)
4	**Facilitating Conditions**	**FC**	4	(Venkatesh *et al.*, 2012)
5	**Price Value**	**PV**	3	(Venkatesh *et al.*, 2012)
6	**Institutional Influence**	**II**	4	***proposed***
7	**Behaviour Intention**	**BI**	3	(Venkatesh *et al.*, 2012)

We employed a Likert scale in our questionnaire to measure respondents' attitudes and perceptions of various constructs. The questionnaire will comprise 29 statement items, each measured using a Likert scale. In January 2024, we distributed questionnaires through internet channels, including email and social media platforms, utilizing Google Forms.

Table 3. Questionnaire

VARIABLE	DESCRIPTION	QUESTION
Performance Expectancy (PE)	Measures which person believes that using a smart electricity meter will benefit them in terms of efficiency, cost management, information accuracy, and overall user experience.	**PE1**. Using a smart electricity meter will improve the efficiency of my electricity usage. **PE2**. A smart electricity meter will help me manage my energy costs better. **PE3**. The smart electricity meter will provide accurate and timely information about my electricity consumption. **PE4**. Smart electricity meters will improve my overall experience in electricity management.
Effort Expectancy	Measures the perception of how easy	**EE1**. Smart meters are easy to learn how to use.

(EE)	it is to use smart meters from the user's perspective, covering aspects such as ease of learning and day-to-day operations.	**EE2**. Smart meters are easy to operate every day. **EE3**. Switching to a smart meter from a traditional electricity meter is easy. **EE4**. I believe that the application to run smart meters must follow the "user interface" of today's applications, which are easy to use.
Social Influence (SI)	Measure perceptions of how much social influence family, friends, and opinion leaders have on individual decisions when using new smart meter technology.	**SI1**. My family and friends would support the use of smart meters if they were available in our area. **SI2**. I recommend using a smart meter if there are recommendations from ads, friends, or family. **SI3**. I feel like I would be technologically left behind if smart meters were available in other areas but not where I live.
Facilitating Condition (FC)	Measure the perceived extent of supporting conditions, such as access to resources, technical support, infrastructure, and availability of information, making smart meters easier for users.	**FC1**. Installing and using smart meters will be easy because of PLN's service readiness. **FC2**. PLN will provide good technical support for implementing the smart meter program. **FC3**. The electrical infrastructure in my neighborhood is ready to support the use of smart meters. **FC4**. Enough information and guidance are available to help me understand and operate smart electricity meters later.
Price Value (PV)	Measure consumer perceptions of whether the costs incurred are proportional to the benefits obtained.	**PV1**. The benefits provided by smart meters are worth the cost. **PV2**. The long-term cost savings of using smart electricity meters outweigh the initial investment. **PV3**. Smart meters are an economical option compared to traditional electricity meters.
Institutional Influence (II)	Assess the influence of institutions, such as government support, policies, and incentive programs, in encouraging smart meters.	**II1**. The government provides sufficient support for the use of smart meters. **II2**. Some policies or regulations will encourage the switch to smart electricity meters. **II3**. Institutions such as power companies or governments will likely provide enough information to support the use of smart meters. **II4**. I believe institutions offer incentives or programs that encourage smart meter adoption.
Behaviour Intention (BI)	To assess users' intention or desire to adopt and recommend the use of smart meters and their commitment	**BI1**. I plan to use smart electricity meters as soon as they become available. **BI2**. I recommend the use of smart meters to others. **BI3**. I am confident that I will continue to use

	to the long-term use of this technology.	smart electricity meters.

3.3. Validity and Reliability Test

The principles of validity and reliability are crucial in research to ensure the accuracy and consistency of measurements and research tools (Ghosal and Conti, 2019). Validity refers to the precise assessment of a notion in a research investigation, and it encompasses various forms, such as content validity, criterion validity, and construct validity. On the other hand, reliability pertains to the consistency of measures, which can be assessed through internal, inter-rater, and test-retest (Ghosal and Conti, 2019). These principles are essential in ensuring the credibility of research data and the precision of interpreting study findings. In the context of data analysis, techniques such as descriptive analysis and Structural Equation Modeling (SEM) are crucial for processing and analyzing the gathered data effectively (Wang et al., 2019). Descriptive analysis systematically arranges and dissects data to comprehensively understand the dataset's attributes and patterns. At the same time, SEM enables researchers to examine causal links between observed and underlying variables, making it valuable for evaluating intricate theoretical frameworks (Wang et al., 2019). In the study of smart meter adoption in Indonesia, descriptive analysis was employed to examine the acceptance of smart meters using the expanded UTAUT2 conceptual framework, providing insights into areas that require enhancement or action (Wang et al., 2019). Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) approach is particularly valuable in exploratory research scenarios and when the data does not entirely adhere to the assumptions of a multivariate normal distribution (Sun and Guo, 2022). This approach allows researchers to effectively connect theoretical concepts with empirical data, as demonstrated in the analysis of the direct impact of factors inside the enlarged UTAUT2 framework in the context of smart meter adoption research in Indonesia (Sun and Guo, 2022).

4. Results and Discussion

Using SmartPLS v4.0.9.9, we will define the PLS model and SEM-PLS results as follows:

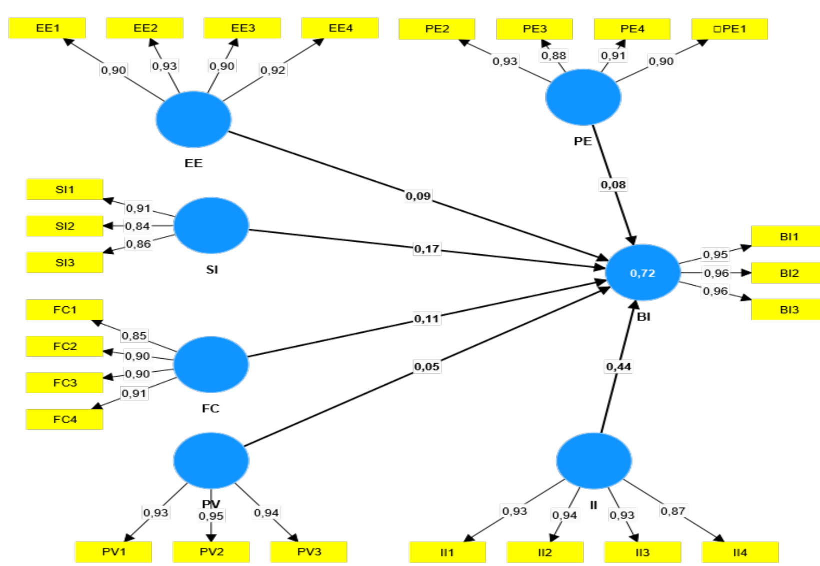

Figure 3. PLS Model

4.1. Measurement Model (Outer Model)

We present the results of the validity and reliability analysis conducted using the SEM-PLS outer model approach to assess the validity of the measurement model and examine the convergence validity by analyzing the average variance extracted (AVE) for each construct. Based on figure 3, all the AVE values exceed the threshold of 0.50, which is commonly deemed acceptable for research purposes. This shows that the measures measure their intended constructs, indicating that the indicator questions used in this study strongly correlate with their respective variables. Similarly, the loading factor values for all indicator questions were higher than 0.7, further confirming the validity of the measurement model.

Table 4. Outer Model

Variable	**Item**	**Cross Loading**	**Cronchbach's Alpha**	**Average Variance Extracted (AVE)**
Performance Expectance (PE)	PE1	0,90	0,93	0,82
	PE2	0,93		
	PE3	0,88		
	PE4	0,91		
Effort Expenctancy (EE)	EE1	0,90	0,93	0,84
	EE2	0,93		
	EE3	0,90		
	EE4	0,92		
Social Influence (SI)	SI1	0,91	0,84	0,76
	SI2	0,84		
	SI3	0,86		
Facilitating Condition (FC)	FC1	0,85	0,91	0,79
	FC2	0,90		
	FC3	0,90		
	FC4	0,91		
Price Value (PV)	PV1	0,93	0,94	0,89
	PV2	0,95		
	PV3	0,94		
Institutional Influence (II)	II1	0,93	0,94	0,84
	II2	0,94		
	II3	0,93		
	II4	0,87		
Behaviour Intention (BI)	BI1	0,95	0,95	0,91
	BI2	0,96		
	BI3	0,96		

The table above contains data related to the measurement model of an SEM-PLS analysis, which includes several variables and respective items. Each variable has been assessed for reliability and validity through Cronbach's Alpha, Cross Loadings, and Average Variance Extracted (AVE). Here is a detailed analysis of each variable: Performance Expectancy (PE) has a Cronbach's Alpha of 0.93 and AVE of 0.82. With all cross-loadings above 0.88 and a high Cronbach's Alpha, PE shows excellent internal consistency, indicating reliable measurement. The AVE is well above the 0.50

threshold, suggesting good convergent validity, which means that the items are well-correlated and measure PE effectively. Effort Expectancy (EE) has a Cronbach's Alpha of 0.93 and AVE of 0.84. Like PE, EE has high internal consistency with a Cronbach's Alpha of 0.93.

The AVE is also above the 0.50 threshold, and all item loadings are above 0.90, indicating that the items measure EE very well. Social Influence (SI) with Cronbach's Alpha: 0.84 and AVE: 0.76 indicates that SI has a slightly lower Cronbach's Alpha but is still within the acceptable range, suggesting good internal consistency. The AVE is above 0.50, and item loadings range from 0.84 to 0.91, showing that the items are reliable indicators of SI. The facilitating Condition (FC) variable has Cronbach's Alpha: 0.91 and an AVE of 0.79, which means that FC shows high internal consistency and an AVE that indicates strong convergent validity. All item loadings are above the 0.85 threshold, confirming that the items are consistent and valid measures of FC. Price Value (PV) has a Cronbach's Alpha: 0.94, AVE: 0.89, so PV demonstrates very high reliability with the highest Cronbach's Alpha in the table. The AVE is also the highest, showing that the items are very strongly related and capture the construct of PV exceptionally well. Institutional Influence (II) has Cronbach's Alpha: 0.94 and AVE: 0.84, which means that II also shows high internal consistency and convergent validity, with all item loadings above 0.87. This indicates that the items are reliable measures of II. Behaviour Intention (BI) has a Cronbach's Alpha of 0.95 and AVE of 0.91. BI has the highest Cronbach's Alpha, indicating excellent internal consistency, and the AVE is significantly above the threshold. The item loadings are exceptionally high (all above 0.95), which indicates a very strong correlation between the items and the BI construct. The overall assessment indicates that the measurement model demonstrates strong internal consistency for all constructs, as indicated by high Cronbach's Alpha values (all above 0.80). The convergent validity is also strong across all constructs, with AVE values well above the 0.50 threshold. This suggests that each set of items correlates well with its respective construct, and the constructs are measured accurately. These results indicate a well-constructed measurement model where the items strongly represent their respective latent constructs. This robustness in the measurement model is essential for ensuring that any subsequent structural model (inner model) analysis is based on reliable and valid measures.

4.2. Structural Model (Inner Model)

The structural model focuses on the theoretical connections between the constructs themselves. The purpose is to elucidate the variation of dependent constructs (endogenous variables) by examining the impact of independent constructs (exogenous variables).

Table 5. R-Square

Variable	**R-square**	**R-square adjusted**
BI	0,72	0,72

R-square: 0.72, which means that the independent variables in the model explain 72% of the variance in BI. This is a strong, positive relationship.

R-square adjusted: 0.72, which is the same as R-square because there is only one independent variable in the model. The adjusted R-square penalizes models with more independent variables to avoid overfitting. The model explains a substantial portion (72%) of the variance in BI.

The path coefficient (β) is a versatile and comprehensive approach based on linear statistics that implies multivariate normality. The path coefficient score determines the strength of the association between variables. A strong and positive link is established when the score β is greater than 0.100.

Table 6. Inner Model

Hypothesis	**Path**	**β (Path)**	**T (Statistik)**	**Information**
H1	Performance Expectancy (PE) -> Behaviour Intention (BI)	0,08	1,22	Negatif - Not Significant
H2	Effort Expenctancy (EE) -> Behaviour Intention (BI)	0,09	5,90	Negatif - Significant
H3	Social Influence (SI) -> Behaviour Intention (BI)	0,17	2,39	Positif - Significant
H4	Facilitating Condition (FC) -> Behaviour Intention (BI)	0,11	1,51	Positif - Not Significant
H5	Price Value (PV) -> Behaviour Intention (BI)	0,05	0,80	Negatif - Not Significant
H6	Institutional Influence (II) -> Behaviour Intention (BI)	0,44	5,90	Positif - Significant

Each hypothesis (H1 to H6) represents a proposed relationship between different independent variables (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Price Value, and Institutional Influence) and a dependent variable (Behaviour Intention). The β (Path) represents the path coefficient, and the T(Statistik) indicates the t-statistic associated with each hypothesis test.
Here is an analysis of the inner model results:

H1: Performance Expectancy (PE) -> Behaviour Intention (BI) Path Coefficient (β): 0.08 T-Statistic: 1.22 Analysis: The path coefficient is relatively low, and the t-statistic is below the common threshold of 1.96 for significance at the 0.05 level, suggesting that this relationship is not statistically significant.
H2: Effort Expectancy (EE) -> Behaviour Intention (BI) Path Coefficient (β): 0.09 T-Statistic: 5.90 Analysis: Although the path coefficient is also low here, the high t-statistic indicates that the relationship between Effort Expectancy and Behaviour Intention is statistically significant.
H3: Social Influence (SI) -> Behaviour Intention (BI) Path Coefficient (β): 0.17 T-Statistic: 2.39 Analysis: The path coefficient is moderate, and the t-statistic is above the threshold for significance, implying a statistically significant positive relationship between Social Influence and Behaviour Intention.
H4: Facilitating Condition (FC) -> Behaviour Intention (BI) Path Coefficient (β): 0.11 T-Statistic: 1.51 Analysis: The relationship here is positive but with a t-statistic that is likely below the threshold for statistical significance, indicating a weaker or non-significant influence of Facilitating Condition on Behaviour Intention.
H5: Price Value (PV) -> Behaviour Intention (BI) Path Coefficient (β): 0.05 T-Statistic: 0.80 Analysis: Both the path coefficient and the t-statistic are low, suggesting that Price Value does not have a significant influence on Behaviour Intention.
H6: Institutional Value (II) -> Behaviour Intention (BI) Path Coefficient (β): 0.44 T-Statistic: 5.90 Analysis: This hypothesis has the highest path coefficient and a high t-statistic, indicating a strong and statistically significant positive relationship between Institutional Influence and Behaviour Intention.
Based on these analyses, it seems that Institutional Influence (H6) has the most substantial influence on Behaviour Intention, followed by Social Influence (H3) and Effort Expectancy (H2). In contrast, performance expectancy (H1), facilitating condition (H4), and price value (H5) do not appear to have

a significant impact on behaviour intention, as suggested by their lower t-statistics. In summary, Institutional Influence is the most meaningful driver of consumers' intention to adopt smart meters, while Effort Expectancy and Social Influence also contribute to positive effects. Performance Expectancy, Facilitating Conditions, and Price Value do not exhibit statistically significant relationships. These results highlight that institutional support factors are pivotal in persuading consumers to accept smart meters. Ease of use and social encouragement also compel intentions, but expectations about functional benefits or economic value do not seem as imperative. The findings provide key implications for policymakers and electricity companies to emphasize institutional participation and incentivization when promoting the large-scale implementation of smart meter infrastructure.

4.3. Discussion

Measurement Model: All constructs showed strong internal consistency, with Cronbach's alpha coefficients above 0.80, indicating that the items within each construct were highly interrelated and adequately captured the underlying concept. In addition, all AVE values exceeded the 0.50 benchmark, providing evidence of good convergent validity and implying that the latent variable was well reflected by its indicators and that it accounted for a substantial portion of their variance. Finally, every item loading was greater than 0.70, demonstrating strong associations between each item and its corresponding construct, which further supports the reliability and validity of the measurement model.

The structural model demonstrates a good fit, with an R-square value of 0.72 indicating that 72% of the variance in Behaviour Intention is explained by the model. In terms of the hypothesised relationships, H2 (Effort Expectancy → Behaviour Intention) and H3 (Social Influence → Behaviour Intention) are positive and statistically significant, indicating that both perceived ease of use and social pressures contribute meaningfully to the intention to adopt smart meters. By contrast, H1 (Performance Expectancy → Behaviour Intention), H4 (Facilitating Conditions → Behaviour Intention), and H5 (Price Value → Behaviour Intention) are not statistically significant, suggesting that expected performance benefits, available support resources, and perceived cost–benefit considerations do not exert a decisive influence on adoption decisions in this context. Most importantly, H6 (Institutional Influence → Behaviour Intention) emerges as the strongest positive and statistically significant predictor, thereby underscoring the central role of institutional factors—such as government involvement, regulatory frameworks, and educational initiatives—in shaping consumers' intentions to adopt smart meters.

The SEM-PLS analysis above produces very interesting data. The performance expectancy variable does not have a significant influence on behaviour intention. This could be due to conditions where respondents already have a level of expectation for the services provided by the provider (PLN), so that whatever the service, they are not affected by the performance of the service to be delivered. Likewise, with the Facilitating Condition, the respondents are confident that all services provided by PLN will be given a very good guarantee. The Price Value variable does not significantly influence respondents' desire to obtain services at affordable costs with good service value.

Conversely, the Effort Expectancy variable positively and significantly influences Behaviour Intention. This is because, among other things, respondents consider the ease of use of smart meters crucial. It also has a variable Facilitating Condition, which has a positive and significant influence. This is because respondents feel that whatever the Condition, they believe the company will provide facilities, as well as possible. The most dominant factor is the institutional factor, which has a significant positive influence. The participation of the government and service provider institutions supported by regulations, education, incentives, and others greatly provides a high level of confidence to accept wholeheartedly if the electricity meter at home is changed from a traditional meter to a smart meter.

Overall Implications:

- Institutional support and incentives are crucial for driving smart meter adoption. Policymakers and electricity companies should prioritize strategies that build trust and confidence in the technology through government participation, clear regulations, and educational initiatives.
- While ease of use (effort expectancy) and social influence positively impact adoption, they are less dominant than institutional factors. Promoting smart meters could benefit from emphasizing user-friendliness and leveraging social networks to encourage peer adoption.
- Factors like functional performance expectancy and price value do not influence adoption decisions significantly. Focusing primarily on these aspects might not be the most effective approach for promoting widespread adoption.

5. Conclusions, Limitations and Further Studies

5.1. Conclusions

The comprehensive conclusion drawn from the collective analysis of the study's findings reveals a multifaceted perspective on the factors influencing the adoption of smart meters among consumers, particularly within the Indonesian context. The overarching conclusion underscores the importance of **institutional influence** in encouraging consumer acceptance of smart meter technologies. Specifically, the involvement of government entities, the establishment of clear and supportive regulations, the provision of incentives, and the execution of targeted educational initiatives have been identified as the most critical factors in fostering a positive behaviour intention toward smart meter adoption. This highlights the necessity for a robust framework of institutional support to enhance consumer trust and confidence in these technologies.

Furthermore, the study illuminates the significance of effort expectancy and social influence as secondary yet positive contributors to adoption intentions. Ease of use, represented by effort expectancy, and the persuasive power of social networks, as encapsulated by social influence, are also crucial in shaping consumers' attitudes towards smart meters. These findings suggest that while smart meters' technical and operational aspects are important, they are less influential than the supportive and regulatory environment created by institutions.

The analysis reveals that performance expectancy, facilitating conditions, and price value do not significantly impact behaviour intention. This indicates that consumers' decisions to adopt smart meters are less driven by the functional performance of the meters, the conditions provided by utility companies to facilitate their use, or the economic implications of their adoption. Instead, the decision-making process is more profoundly influenced by the perceived benefits and support provided by institutional entities. In synthesizing these insights, policymakers and electricity companies should prioritize building a supportive institutional environment to promote the widespread implementation of smart meter infrastructure. Such efforts should ensure that the adoption process is as straightforward as possible for consumers and that there is a strong foundation of trust in the technology facilitated by government and regulatory support. Although the technical benefits and cost savings associated with smart meters are understood, more than these factors are needed to motivate consumer adoption.

The study, therefore, provides a compelling argument for a strategic focus on institutional involvement and incentives, ease of use, and the leveraging of social influence as the most effective means of encouraging the adoption of smart meters in Indonesia and potentially in other similar contexts.

5.2. Limitations

The study's limitations include its reliance on quantitative survey data, which may not capture the deeper motivations and concerns of consumers regarding smart meter adoption. The exclusion of variables such as hedonic motivation, habit, and actual use behaviour, due to the early stage of smart meter implementation in Indonesia, limits the model's comprehensiveness in reflecting user engagement over time. Additionally, the study does not explore potential moderating effects of demographic factors like income or technology experience, which could influence the relationships observed. The cross-sectional design also restricts understanding of how adoption intentions and influencing factors evolve longitudinally. Finally, the focus on Indonesia limits the generalizability of findings to other cultural or institutional contexts. These limitations suggest opportunities for qualitative research, moderation analysis, longitudinal tracking, and cross-country comparisons in future studies. (Source: Selected text)

5.3. Further Studies

- **Qualitative research:** Conduct in-depth interviews or focus groups to understand the reasoning behind consumer choices and delve deeper into their motivations and concerns.
- **Moderation effects:** Explore if factors like demographics, income, or technology experience moderate the relationships observed in the model.
- **Longitudinal study:** Track adoption behaviour over time to see how these factors evolve and their long-term impact.
- **Compare countries:** Investigate if cultural or institutional differences influence adoption patterns across regions.

These further studies can provide richer insights and inform strategies for promoting smart meter adoption, considering the key drivers and potential barriers identified in this initial analysis.

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References

Adebanji, B., Ojo, A., Fasina, T., Adeleye, S. and Abere, J. (2022) 'Integration of renewable energy with smart grid application into the Nigeria's power network: Issues, challenges and opportunities', European Journal of Engineering and Technology Research, 7(3), pp. 18-24. https://doi.org/10.24018/ejeng.2022.7.3.2792

Alkawsi, G.A., Ali, N., Mustafa, A.S., Alhussian, H., Alkahtani, A., Tiong, S.K. and Ekanayake, J. (2020) 'A hybrid SEM-neural network method for identifying acceptance factors of the smart meters in Malaysia: Challenges perspective', Alexandria Engineering Journal. https://doi.org/10.1016/j.aej.2020.07.002

Alkawsi, G.A., Ali, N. and Baashar, Y. (2020) 'An Empirical Study of the Acceptance of IoT-Based Smart Meter in Malaysia: The Effect of Electricity-Saving Knowledge and Environmental Awareness', IEEE Access, 8, pp. 42794-42804. Available at: https://doi.org/10.1109/ACCESS.2020.2977060

Aranyossy, M. (2022) 'Technology Adoption in the Digital Entertainment Industry during the COVID-19 Pandemic: An Extended UTAUT2 Model for Online Theater Streaming', Informatics, 9(3). Available at: https://doi.org/10.3390/informatics9030071

Arifin, Z., Setyobudi, R. and Elnur, K.A. (2023) 'Cost-Benefit Analysis of Advanced Metering Infrastructure Implementation for Strengthening Smart City in Indonesia', in M.D. Lytras, A.A. Housawi, and B.S. Alsaywid (eds) Smart Cities and Digital Transformation: Empowering Communities, Limitless Innovation, Sustainable Development and the Next Generation. Emerald Publishing Limited, pp. 301-317. Available at: https://doi.org/10.1108/978-1-80455-994-920231014

Baabdullah, A.M. et al. (2019) 'Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model', International Journal of Information Management, 44, pp. 38-52. Available at: https://doi.org/10.1016/j.ijinfomgt.2018.09.002

Behnam, A., Azad, S., Daneshvar, M., Anvari-Moghaddam, A. and Marzband, M. (2023) 'Artificial intelligence-enabled Internet of Things technologies in modern energy grids', in Daneshvar, M., Mohammadi-Ivatloo, B., Zare, K. and Anvari-Moghaddam, A. (eds.) IoT Enabled Multi-Energy Systems: From Isolated Energy Grids to Modern Interconnected Networks. London: Academic Press, pp. 69-86. https://doi.org/10.1016/B978-0-323-95421-1.00004-5

Cejka, S., Frieden, D. and Kitzmüller, K. (2021) 'Implementation of self-consumption and energy communities in Austria's and EU member states' national law: A perspective on system integration and grid tariffs', in Proceedings of the 26th International Conference and Exhibition on Electricity Distribution (CIRED 2021), Geneva, Switzerland, 20-23 September 2021, pp. 3254-3258. https://doi.org/10.1049/icp.2021.1526

Chamaret, C., Steyer, V. and Mayer, J.C. (2020) '"Hands off my meter!" when municipalities resist smart meters: Linking arguments and degrees of resistance', Energy Policy, 144. Available at: https://doi.org/10.1016/j.enpol.2020.111556

Chawla, Y., Kowalska-Pyzalska, A. and Widayat, W. (2019) 'Consumer Willingness and Acceptance of Smart Meters in Indonesia', Resources, 8(4), pp. 1-23. Available at: https://doi.org/10.3390/resources8040177

Chen, C. fei, Xu, X. and Arpan, L. (2017) 'Between the technology acceptance model and sustainable energy technology acceptance model: Investigating smart meter acceptance in the United States', Energy Research and Social Science, 25, pp. 93-104. Available at: https://doi.org/10.1016/j.erss.2016.12.011

Chou, J.-S. and Gusti Ayu Novi Yutami, I. (2014) 'Smart meter adoption and deployment strategy for residential buildings in Indonesia', Applied Energy, 128, pp. 336-349. Available at: https://doi.org/10.1016/j.apenergy.2014.04.083

Duarte, P. and Pinho, J.C. (2019) 'A mixed methods UTAUT2-based approach to assess mobile health adoption', Journal of Business Research, 102, pp. 140-150. Available at: https://doi.org/10.1016/j.jbusres.2019.05.022

Eneizan, B., Mohammed, A.G., Alnoor, A., Alabboodi, A.S. and Enaizan, O. (2019) 'Customer acceptance of mobile marketing in Jordan: An extended UTAUT2 model with trust and risk factors', International Journal of Engineering Business Management, 11, pp. 1-10. https://doi.org/10.1177/1847979019889484

Castagneto Gissey, G., Zakeri, B., Dodds, P.E. and Subkhankulova, D. (2021) 'Evaluating consumer investments in distributed energy technologies', Energy Policy, 149, 112008. https://doi.org/10.1016/j.enpol.2020.112008

Glass, E. and Glass, V. (2019) 'Underground power lines can be the least cost option when study biases are corrected', The Electricity Journal, 32(2), pp. 7-12. https://doi.org/10.1016/j.tej.2019.01.015

Gumz, J. et al. (2022) 'Social Influence as a Major Factor in Smart Meters' Acceptance: Findings from Brazil', Results in Engineering, 15(June), p. 100510. Available at: https://doi.org/10.1016/j.rineng.2022.100510

Gumz, J. and Fettermann, D.C. (2021) 'What improves smart meters' implementation? A statistical meta-analysis on smart meters' acceptance', Smart and Sustainable Built Environment, 11(4), pp. 1116-1136. https://doi.org/10.1108/SASBE-05-2021-0080

Gunden, N., Morosan, C. and DeFranco, A. (2020) 'Consumers' intentions to use online food delivery systems in the USA', International Journal of Contemporary Hospitality Management, 32(3), pp. 1325-1345. Available at: https://doi.org/10.1108/IJCHM-06-2019-0595

Hungilo, G.G., To, S. and Setyohadi, D.B. (2020) 'Factors Influencing Acceptance Of Online Shopping In Tanzania Using UTAUT2', Journal of Internet Banking and Commerce, 25(1), pp. 1-23. Available at: http://www.icommercecentral.com.

Hess, D.J. (2014) 'Smart meters and public acceptance: Comparative analysis and governance implications', Health, Risk and Society, 16(3), pp. 243-258. Available at: https://doi.org/10.1080/13698575.2014.911821

Hmielowski, J.D. et al. (2019) 'The social dimensions of smart meters in the United States: Demographics, privacy, and technology readiness', Energy Research & Social Science, 55, pp. 189-197. Available at: https://doi.org/10.1016/j.erss.2019.05.003

Humeres, M. (2022) '"Meters can be wonderful": The relevance of democracy and technical aspects for user acceptance of smart meter policy in Chile', Energy Research and Social Science, 90. https://doi.org/10.1016/j.erss.2022.102613

Idoga, P.E. et al. (2019) 'Assessing factors militating against the acceptance and successful implementation of a cloud based health center from the healthcare professionals' perspective: A survey of hospitals in Benue state, northcentral Nigeria', BMC Medical Informatics and Decision Making, 19(1). Available at: https://doi.org/10.1186/s12911-019-0751-x

Indrawati, I. and Tohir, L.M. (2016) 'Predicting smart metering acceptance by residential consumers: An Indonesian perspective', in Proceedings of the 2016 4th International Conference on Information and Communication Technology (ICoICT), Bandung, Indonesia, 25-27 May 2016, pp. 1-6. https://doi.org/10.1109/ICoICT.2016.7571892

Ji, W. and Chan, E.H.W. (2020) 'Between users, functions, and evaluations: Exploring the social acceptance of smart energy homes in China', Energy Research and Social Science, 69. Available at: https://doi.org/10.1016/j.erss.2020.101637

Kapser, S. and Abdelrahman, M. (2020) 'Acceptance of autonomous delivery vehicles for last-mile delivery in Germany - Extending UTAUT2 with risk perceptions', Transportation Research Part C: Emerging Technologies, 111, pp. 210-225. Available at: https://doi.org/10.1016/j.trc.2019.12.016

Kowalska-Pyzalska, A. (2018) 'What makes consumers adopt to innovative energy services in the energy market? A review of incentives and barriers', Renewable and Sustainable Energy Reviews, 82(Part 3), pp. 3570-3581. https://doi.org/10.1016/j.rser.2017.10.103

Kulkarni, S., Myers, E., Lipták, S. and Divan, D.M. (2019) 'A novel approach to implement low-cost AMI functionality using delay-tolerant communication', in 2019 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 18-21 February 2019, pp. 1-5. https://doi.org/10.1109/ISGT.2019.8791621

Kwateng, K.O., Osei Atiemo, K.A. and Appiah, C. (2019) 'Acceptance and use of mobile banking: an application of UTAUT2', Journal of Enterprise Information Management, 32(1), pp. 118-151. https://doi.org/10.1108/JEIM-03-2018-0055

Pérez Caballero, L.M. (2020) Social impact matters: Towards a methodological framework for the social impact assessment of energy projects. Master's thesis. Eindhoven University of Technology

Nugroho, S.B., Zusman, E., Nakano, R., Takahashi, K., Koakutsu, K., Kaswanto, R.L., Arifin, N., Arifin, H.S., Munandar, A., Muchtar, M., Gomi, K. and Fujita, T. (2017) 'The effect of prepaid electricity system on household energy consumption - The case of Bogor, Indonesia', Procedia Engineering, 198, pp. 642-653. https://doi.org/10.1016/j.proeng.2017.07.117

Parayil Iqbal, U., Jose, S.M. and Tahir, M. (2023) 'Integrating trust with extended UTAUT model: a study on Islamic banking customers' m-banking adoption in the Maldives', Journal of Islamic Marketing, 14(7), pp. 1836-1858. Available at: https://doi.org/10.1108/JIMA-01-2022-0030

Pranadi, A.D. and Setiawan, E. (2020) 'Cost benefit analysis for peer-to-peer mechanism in residential sector of a single buyer electricity market', Journal of Energy Systems, 4(4), pp. 179-195. https://doi.org/10.30521/jes.748138

PT. PLN (PERSERO) (2023) PLN Segera Gunakan " AMI " Tahun Ini , Meteran Canggih yang Bikin Pelanggan Bisa Monitor Penggunaan Listrik Secara Realtime. Available at: https://web.pln.co.id/...-segera-gunakan-ami-tahun-ini-meteran-canggih-yang-bikin-pelanggan-bisa-monitor-penggunaan-listrik-secara-realtime.

Purnama, A.A.F., Nashiruddin, M.I. and Murti, M.A. (2020) 'Feasibility Study of the IoT-Connectivity Deployment for AMI Service: A Case Study in Surabaya City', 2020 IEEE International Conference on Communication, Networks and Satellite, Comnetsat 2020 - Proceedings, (January), pp. 61-66. Available at: https://doi.org/10.1109/Comnetsat50391.2020.9328934

Raza, S.A., Shah, N. and Ali, M. (2019) 'Acceptance of mobile banking in Islamic banks: evidence from modified UTAUT model', Journal of Islamic Marketing, 10(1), pp. 357-376. Available at: https://doi.org/10.1108/JIMA-04-2017-0038

Rita, R. and Fitria, M.H. (2021) 'Analisis Faktor-Faktor UTAUT dan Trust Terhadap Behavioral Intention Pengguna BNI Mobile Banking Pada Pekerja Migran Indonesia', Jesya (Jurnal Ekonomi & Ekonomi Syariah), 4(2), pp. 926-939. Available at: https://doi.org/10.36778/jesya.v4i2.453

Saleem, Y. et al. (2019) 'Internet of Things-Aided Smart Grid: Technologies, Architectures, Applications, Prototypes, and Future Research Directions', IEEE Access, 7, pp. 62962-63003. Available at: https://doi.org/10.1109/ACCESS.2019.2913984

Schretzlmaier, P., Hecker, A. and Ammenwerth, E. (2022) 'Extension of the Unified Theory of Acceptance and Use of Technology 2 model for predicting mHealth acceptance using diabetes as an example: a cross-sectional validation study', BMJ Health & Care Informatics, 29(1), e100640. https://doi.org/10.1136/bmjhci-2022-100640

Serra, D., Mardero, D., Di Stefano, L. and Grillo, S. (2021) 'Post-metering value-added services for low voltage electricity users: Lessons learned from the Italian experience of CHAIN 2', Applied Energy, 304, 117806. https://doi.org/10.1016/j.apenergy.2021.117806

Sinaga, D.H., Sasue, R.R.O. and Hutahaean, H.D. (2021) 'Pemanfaatan energi terbarukan dengan menerapkan smart grid sebagai jaringan listrik masa depan', Journal Zetroem, 3(1), pp. 11-17. doi: 10.36526/ztr.v3i1.1251.Dileep, G. (2020) 'A survey on smart grid technologies and applications', Renewable Energy, 146, pp. 2589-2625. Available at: https://doi.org/10.1016/j.renene.2019.08.092

Singh, N., Sinha, N. and Liébana-Cabanillas, F.J. (2020) 'Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence', International Journal of Information Management, 50, pp. 191-205. Available at: https://doi.org/10.1016/j.ijinfomgt.2019.05.022

Strong, D.R. (2018) 'The Early Diffusion of Smart Meters in the US Electric Power Industry'. https://doi.org/10.31237/osf.io/7zprk

Talukder, M.S., Chiong, R., Bao, Y. and Hayat Malik, B. (2019) 'Acceptance and use predictors of fitness wearable technology and intention to recommend: An empirical study', Industrial Management & Data Systems, 119(1), pp. 170-188. https://doi.org/10.1108/IMDS-01-2018-0009

Venkatesh, V., Thong, J.Y.L. and Xu, X. (2012) 'Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology', MIS Quarterly, 36(1), pp. 157-178. https://doi.org/10.2307/41410412

Waller, G., Crosbie, T., Newbury-Birch, D., Bandyopadhyay, S., Ghanem, D.A., Jana, A., Pillai, G.G., Priya, G.S.K., Sarkar, A., Thomas, N., Diba, P. and Divers, A. (2022) 'What is in a meter? A qualitative exploration into the implementation of electricity metering across Mumbai communities using Normalisation Process Theory', Global Implementation Research and Applications, 2(4), pp. 361-370. https://doi.org/10.1007/s43477-022-00059-y

Wang, Y., Chen, Q., Hong, T. and Kang, C. (2019) 'Review of smart meter data analytics: Applications, methodologies, and challenges', IEEE Transactions on Smart Grid, 10(3), pp. 3125-3148. https://doi.org/10.1109/TSG.2018.2818167

Wu, P., Zhang, R., Zhu, X. and Liu, M. (2022) 'Factors influencing continued usage behavior on mobile health applications', Healthcare, 10(2), 208. https://doi.org/10.3390/healthcare10020208

Yan, Z. and Wen, H. (2021) 'Electricity Theft Detection Base on Extreme Gradient Boosting in AMI', IEEE Transactions on Instrumentation and Measurement, 70. Available at: https://doi.org/10.1109/TIM.2020.3048784