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Smart Meter Application Analysis using PLS-SEM Deep Neural Network: A Case Study

Nguyen Thi Phuong Thao[1], Minh Ly Duc[2, 3,*] and Petr Bilik[3]

[1]Faculty of Electrical and Electronics Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam
[2]Faculty of Commerce, Van Lang University, Ho Chi Minh City, Vietnam
[3]Department of Cybernetics and Biomedical Engineering, Faculty of Electrical Engineering and Computer Science, VSB–Technical University of Ostrava, 17. Listopadu2172/ 15, 708 00 Ostrava, Czech Republic

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Abstract

Smart meters measure, control, analyze, and predict the amount of electricity, water, and gas used. In developing countries, where there is no consensus to accept the use of smart meters, there are many possible risks when using smart meters. However, there are also many benefits of smart meters. This study conducts an overall assessment of the demand and impact of the smart meter in the southern region of Vietnam through a survey of 500 samples. This article examines information technology system (IS) related factors and engineering model-related factors according to technical readiness such as optimism, innovation, insecurity, and discomfort. Accompanying that is the expectation of smart meters, for Vietnamese people's intention to constantly use smart meters. Most of the previous studies on smart meter systems have focused on analyzing the impact of factors affecting the application using single-step structural equation modeling (SEM). In this study, it is proposed to use a 2-layer model between the research model of the multi-analysis method by combining the Partial Least Squares - Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANN) model was performed for additional analysis for the results of PLS-SEM, and ANN has higher predictive accuracy than PLS-SEM because ANN has the ability to perform well for both linear relational model and linear relationship model and non-linear with high prediction. First, the PLS-SEM model evaluates the factors affecting the intention to use the smart meter system. Second, the ANN ranks the impact factors of the critical predictors from the PLS-SEM model, and the Critical Performance Map Analysis (IPMA) analyzes the exact results for the critical performance of the variables elements. The results of this study show that the quality of information and quality of system factors of the IS model have a negative impact on users' intention to use smart meters. At the same time, factors of Optimization and innovation have a strong positive impact on users' intention to use smart meters.

Keywords: Partial Least Squares- Structural Equation Modeling ; PLS-SEM; Artificial Neural Networks ; ANN; IPMA; Smart Meter

1 Introduction

A smart meter is a device connected to a Wi-Fi system and has many advantages over a traditional electricity meter, it helps to measure and monitor energy consumption in real-time with accuracy ± 1%. In addition, users can open and close the smart meter's switch flexibly thanks to its Wi-Fi connection system [1-3]. This makes deploying a smart home system simple and affordable for many families in Vietnam. Vietnam's economy is a developing socialist-oriented market economy, heavily dependent on agriculture, tourism, raw exports, and foreign direct investment. In October 2020, according to estimates of the International Monetary Fund (IMF), the size of Vietnam's economy with 97.3 million people according to nominal GDP reached 340.6 billion USD, purchasing power parity reached 1,047 billion USD, GDP per capita in nominal terms is 3,498 USD/person and in purchasing power is 10,755 USD/person. Saving costs in production and operation to create more profits and develop the country is the top goal of Vietnam. In people's lives, saving daily living costs is necessary, especially saving costs for using energy sources such as electric energy, water energy, and gas energy. Equipment using electricity in each house of people accounts for 90% of the equipment used by Vietnamese people in daily life. Continuous monitoring of consumption in electricity use is the top concern of people. The electricity meter and the index recording system are the "weighers" to measure the output for Electricity to bill and calculate the monthly electricity usage of customers. Therefore, ensuring the accuracy and transparency of data on meter readings is a top priority of Vietnam Electricity and its member Power Corporations. Record meter readings always require 2 people, in which 1 person holds the ladder, and 1 person climbs the electric pole to read the reading. Data is recorded in the notebook, brought back to the computer, and converted into invoices for customers. Such a process of indexing and issuing invoices takes many days, is labor intensive, and potentially dangerous for electrical workers because they often have to climb high. The size of the smart electricity meter is relatively small with the portable assembly feature that is easy to install and replace when necessary to make your smart home, and more convenient, the most important feature [4-6]. The most important thing is to control power consumption accurately and reduce power consumption when away from home, helping to reduce the family's electricity costs. The accuracy of smart electricity meters is ±1% compared to traditional electricity meters is ±2%. In addition, the smart meter can also measure the consumption of the smallest consuming devices such as chili

*E-mail address: minh.ld@vlu.edu.vn
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lamps, and night lights with high accuracy. The Liquid Crystal Display (LCD) network is designed to be able to see parameters such as U, I, Q of the power supply or connect to a mobile phone via Wi-Fi network [7]. The function of energizing up to 60A over the Internet anywhere and anytime [8], ensuring absolute safety for your home along with the development of a voice processing application program in the computer science industry that helps the clock Smart electricity meter is allowed to schedule on and off automatically and easily by connecting with virtual assistants, processing by voice such as Alexa, Google Assistant.

A smart meter is a digital system that records the amount of energy used, helping to effectively manage the smart grid, and supporting the user to make an easy decision or decide whether to continue to use the electricity [9]. On the other hand, smart meters help to estimate temperature set points because of the heat transfer coefficient for large buildings. At the same time, smart meters also help energy users and suppliers in controlling, predicting energy loads and deciding on whether to continue using electrical energy or suspend various regulatory policies to view smart data [10]. However, in developing countries, the data exchange is done between the user and the electricity supplier. Synchronizing smart devices helps to distinguish the electric energy efficiency of each device and facilitates data transmission between smart devices in the home for better, more efficient operation. This is a new smart technology, smart devices are controlled by a control button in the center and improve the efficiency of electrical energy use, saving energy costs [11-13]. Many energy supply companies have restructured their production processes providing energy derived from fossil fuels and nuclear to renewable energy sources such as wind, solar, geothermal, and biomass. Energy-using companies consider process optimization and optimal use of energy sources to reduce electricity consumption and use energy more efficiently. This requires the integration of information technology and telecommunications systems into the power grid to form a "smart grid" technology [14]. Such systems further enhance the power sector's efficient supply chain load management. Consumers can access energy usage data at websites for application to analyze power consumption. They have been using it to decide whether to continue using it or not[15]. Stop using energy or temporarily stop using some smart devices in their home to increase flexibility in measuring and monitoring energy use. The use of smart meters can determine the hourly cost of energy usage to the user. Users can convert peak hours of electronic use to suitable time frames to reduce energy costs and use electrical energy at a cheaper price. In addition, the very important function of smart grids and smart meters also supports the management of complex power networks [16-17]. Other benefits that smart grids or smart meters bring are environmental factors, namely improving energy efficiency, mitigating climate change, and balancing supply and demand[18]. If the smart grid or smart meter is widely used in Vietnam, it will contribute to positive climate change or solve climate change related problems. A user survey in Hong Kong showed that 97.4% of smart meter users perceive benefits related to the environment such as data security, data quality, and data availability. The cost-effective energy use and ability of smart meters to connect with other smart devices play an integral role in the smart grid. They are the premise to move toward implementing a smart grid with smart metering [19].

It is important to clearly identify the factors that influence a customer's intention to continue using a smart meter that demonstrates the device’s usefulness while meeting the user's expectations. Specifically, technical readiness about optimism, innovation, insecurity, discomfort, and factors that smart electrical measuring devices can create an information technology (IS) models involve factors such as service quality, system quality, and information quality that affect the intention to use continuously users. Information technology-related factors contribute significantly to the user's intention to continue using. Identify problem points affecting users' intention to use continuously and provide directions to improve user satisfaction with smart electrical meters and improve users' intention to use continuously [20]. In general, developed countries have been perfecting the use of smart electricity metering devices in the smart grid. However, compared to developing countries like Vietnam, which is gradually entering the use of smart devices in the smart grid, many negative factors arise, and the benefits from smart metering devices are not high to the user's intention to continue using. Some challenges of using smart grids or smart meters in Vietnam such as high locations, rural areas, and not being equipped with enough smart metering equipment, are related to smart infrastructure. User awareness about smart metering equipment is still limited, which is a significant influencing factor between energy suppliers, smart grid service devices and users [21]. Specifically, in the past few years, electricity users have sent many complaints to the city-level electricity corporation about the unusually high payment content and the incorrect numbers on the payment slip of the electricity that the user uses and the user does not know and cannot control over time the daily used electricity indicators. The need for a smart meter that meets the expectations of monitoring electricity usage over time is urgent. The objective of this study is to analyze the causes leading to the influence of electricity consumption indicators that do not match the actual amount of users and analyze the influencing factors on the security of the personal information of users when they use smart meters and users' apprehension about smart meters. Smart meters do not guarantee a more rational use of natural resources. However, user interaction with the smart meter is easy and the Smart meter contributes to real-time control of electricity usage with the goal of reducing energy usage.[22-24].This study, in addition to understanding and raising users' awareness of smart metering devices, also provides a clearer understanding of the potential for developing the application of smart devices to the power grid in Vietnam.

The research is organized according to the following organization: Section 2 presents the literature review and development of hypothesis. Section 3 presents the research model. Section 4 presents results and discussion. Section 5 presents conclusions and directions for future research.

2. Literature Review

2.1. Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM)[25] was developed by Davis (1986) based on the theory of reasonable action (TRA) to predict the acceptability of an information technology system. TAM is a model for predicting and explaining customer acceptance of new technology [26-27] and is used to study consumer acceptance of SG products and services [28-32]. The purpose of validating the modification of an information technology system to make it acceptable to users is based on two main factors: (1) perceived usefulness and (2) Perceived ease of use. Perceived usefulness is the extent to which users believe that using the system will improve their performance. Perceived ease of use refers to the extent to which users believe that using the system will be easy. The Technology Acceptance Model (TAM) depends on the behavioral intentions of consumers[33].

2.2. Information Technology Model (IS)

A smart meter is integrated with digital control and Wi-Fi connection~~,~~ to control and monitor electricity consumption in real-time[34-36]. The information technology network system requires quality assurance because the equipment to operate the network system such as the internet connection is not interrupted by the information transmission line of the smart device and is large enough to transmit data between devices. Smart equipment in the power system and the maintenance system needs to have a good implementation plan and ensure stable operation of the system [37], [2]. However, in rural, highland, deep-lying areas, islands in Vietnam, etc., the information technology infrastructure system is still limited, which can be said to be outdated. That is the main reason for the difficulty in smart meter implementation. Information transmission systems such as those of Wi-Ficonnected devices affect the information quality of smart devices when transmitting data between smart devices, speed of response and data transmission of information systems. In particular, the transmission of power consumption data from the smart meter to the user's management device such as a smartphone is the top concern of the user [26]. In addition, the user has an opening and closing function of the electric ladder switch through the transmission line. If the quality of information is not guaranteed to work well, the user's requirements will not be satisfied. Although smart meter suppliers regularly have customer appreciation programs for providing quality service, digital technology related services, positively affect the perceived intention of the user [38]. Many previous studies show that the information technology model depends on 3 main factors: (1) service quality, (2) system quality, and (3) information quality that affects intentions. To determine useful product users, using digital control platforms to share knowledge about digital control technology products which not many studies have shown. Specifically, with smart meter products, the sharing platform about smart meter products in Vietnam is very limited. This study helps to contribute to a clearer understanding of the knowledge-sharing platform on product usage by using digital technology, specifically smart electricity meters. Based on the above research and discussion, the following hypotheses are formed (Fig. 1). Hypothesis 1(H1): Service quality of the information technology model has a direct positive impact on the intention to use continuously of users. Hypothesis 2 (H2): The system quality of the information technology model directly affects the user's intention to use continuously. Hypothesis 3 (H3): The information quality of an information technology system directly affects the user's intention to use it continuously.

2.3. Technology Model

Meters are determined by four factors: Optimization, Innovation, Insecurity, and Discomfort. These four factors affect the technology acceptance model (TAM) [17]. Technology acceptance theory shows that users perceive technology in two ways, which are positive and negative[25-26]. Users accept to use the product in a more positive way of finding the smart meter product useful for them (Fig. 1)[33]. However, users facing the negative side will be hesitant to accept the use of smart meters. They do not agree to change the traditional electricity meter to a smart meter. Vietnamese awareness about smart meters is not high and they have not clearly seen the benefits as well as the usefulness and ease of operation of smart electricity meters. Users can use smart-phones to connect to smart meters through the network and control their power consumption over time. It helps them save costs when automatically adjusting the power consumption according to the actual time [34]. In addition, the innovation factor of smart electricity meters in increasingly optimizing operating methods, controlling the operation of digitally controlled products, for example: using voice to control intelligent electrical system control outside the house, where their area Wi-Fi network connection system and a smartphone, the user can control the opening and closing of smart power consuming devices in the house through smart electricity meters [13].

Users use personal information to operate and open smart devices in a smart grid or a smart home. This is useful information that hackers can infiltrate and steal user information to serve negative benefits for users like hackers can open the user's home door when they are away, or hackers use the personal information of users to steal banking information [33]. The head of the household (who is primarily responsible) for the management of appliances use electricity or is responsible for paying living expenses in the family. In the middle age from 47 to 55 years old, peoplewho use smartphones are often aware that seeing with their eyes and touching with their hands are afraid to change their living environment like they are afraid to change from a traditional electricity meter to a smart meter. Because they are still concerned about security or clarity about the results of digital control technology products, namely smart electricity meters [18]. This is annoying user content related to smart meters. The technical model of the digital control product consists of four main elements. (1) Optimization: New technology brings positivity to activities, improves control over life, and bring flexibility and efficiency to life.(2)Innovation: New technology offers new ideas and uses, and increases the flexibility of products using digital controls.(3)Insecurity: The intended purpose of the technology does not meet the individual users' standards, causes negative user intent toward a digitally controlled product.(4)Discomfort: Digital control technology makes it difficult for users to operate, causing inconvenience to users[35-36].

Users consider the theoretically related positive and negative factors to perceive the intention to continuously use the smart meter product. On the other hand, users' expectations about a digitally controlled product affect technology acceptance theory (TAM)[17], and expectations also directly affect users' intention to use continuously. The theory of expectation was proposed by Victor Vroom in 1964 and was supplemented [26], and edited to complete the theory of expectation by Porter and Lawler in 1968 [33]. Expectation theory shows that the act of using a smart meter brings a result and attractiveness to the user. Specifically, users using smart meters meet the expectation of optimizing the cost of using electrical energy, and eliminating waste of energy sources [34]. This 4-factor technical model affects the theory of user acceptance of technology, in terms of 2 negative and positive aspects. Expectation theory[12] shows that users accept the use of technology such as smart electricity meters, bringing the benefits of controlling electricity consumption and saving electricity costs for users. At the same time, the information technology model that supports users when using smart electricity meters is easier and meets users' expectations of smart electricity meters. Based on the above discussion, the following hypotheses are formed.

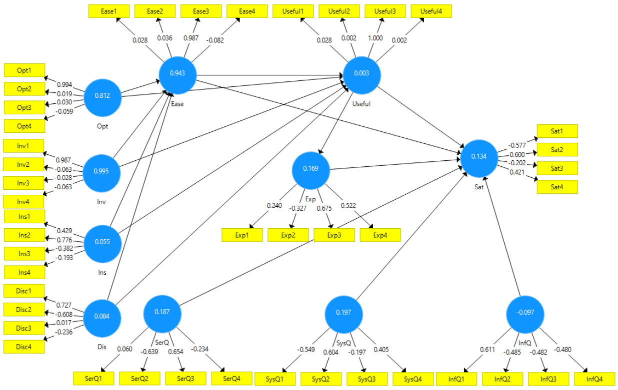

Fig. 1. Research model.

Hypothesis 4 (H4): The optimization factor has a positive impact on the theory of technology acceptance and indirectly has a positive impact on the user's intention to use continuously.Hypothesis 5 (H5): The innovation factor directly affects the theory of technology acceptance and indirectly affects the continuous use intention of users.Hypothesis 6 (H6): Insecurity factors directly affect technology acceptance theory and indirectly affect users' intention to use continuously.Hypothesis 7 (H7): The discomfort factor directly affects the theory of technology acceptance and indirectly affects users' intention to use continuously.Hypothesis 8 (H8): The Perceived ease of use factor directly affects the Perceived usefulness factor and indirectly affects the user's intention to use continuously. (H10).Hypothesis 9 (H9): The factor in the theory of expectation is the Expectation Confirmation factor that directly affects the Perceived usefulness factor and indirectly affects the user's intention to use continuously. (H12).Hypothesis 11(H11): Perceived usefulness has a direct impact on the user's intention to use continuously.

3. Research Method

The data carried out in this study were collected from people living in the Ho Chi Minh City area and the Tay Ninh province area in Vietnam. The survey sample is conducted haphazardly because it is easy for the survey participants. Survey participants are married and have their own houses and are using electric energy, making monthly electricity payments to the electricity supplier. Most survey participants found it useful to monitor electricity usage results with traditional and smart electricity meters. The survey scale is measured in the survey table from previous studies by domestic and foreign authors in Vietnam. Each research variable participates in at least 3 measurement variables. The questionnaire is made entirely in Vietnamese and according to the Likert 5 scale. To ensure the appropriate design of the questionnaire, the questionnaire was sent to 3 experts in the field of computer science related to electricity for comments and the author completed the questionnaire according to the comments of experts [39-40]. Composite reliability (CR) (Eq. 1) is the index applied to evaluate the reliability and validity of the scale, Cronbach's Alpha (Eq. 2) value is the index used to evaluate the reliability of other factors. The evaluation criteria of the CR index and Cronbach's Alpha index must be greater than 0.8 for the survey results to be assessed as reasonable values and then included in the PLS-SEM analysis model [25-27]. The results of the survey panel analysis are that the CR index and Cronbach's Alpha index are both greater than 0.8 and the Average (AVE) (Eq. 3) index is greater than 0.5 [40]. This proves that the survey panel has a valid scale analysis value and has a high level of reliability for the research model the square root of the AVE index is larger than the correlation coefficient, proving the validity of the data.

$$CR = \frac{(ld_1+ld_2+\cdots+ld_m)^2}{(ld_1+ld_2+\cdots+ld_m)^2+\sigma_1^2+\sigma_2^2+\cdots+\sigma_m^2} \quad (1)$$

Where: CR: composite reliability CR of latent variable A, ld_1, ld_2, ld_m: the normalized load coefficient of the observed variable belonging to the latent variable A, m: number of observed variables of latent variable A, $\sigma_1^2, \sigma_2^2, \sigma_m^2$: variance of the measurement error of the observed variable belong to the latent variable A with $\sigma_m^2 = 1 - ld_m^2$.

$$\alpha = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^{k}\sigma_y^2}{\sigma_x^2}\right) \quad (2)$$

Where: k: the number of items, σ_y^2: variance associated, σ_x^2: variance associated.

$$AVE = \frac{\sum_{i=1}^{k}\partial_i^2}{\sum_{i=1}^{k}\partial_i^2+\sum_{i=1}^{k}Var(e_i)} \quad (3)$$

Where: k is the number of items, ∂_i: the factor loading of item i, $Var(e_i)$: the variance of the error of item i.

The probabilistic sampling method is error-controlled and highly representative of the population, used for descriptive research. The non-probability sampling method is time and cost-saving. Sample size (Eq.4) and number of samples (Eq.5) are used to evaluate the appropriate sampling method for a study.

$$n = \frac{[q(1-q)]Z_{\alpha/2}^2}{D^2} \quad (4)$$

Where: q: Sampling rate equals target occurrence rate. $0 \leq q \leq 1$.

$$n = \left(\frac{Z.s}{a.\bar{x}}\right)^2 \quad (5)$$

Where: Z: Reliability. s: Standard deviation. $\bar{x}$: Average of sample. a: bias rate. The process of carrying out the survey is shown in Figure 2.

A total of 500 questions were collected and 45 questions were discarded because there were incorrect or invalid answers, it is possible that these people did not carefully read the questionnaire with a total of 455 valid questionnaires used in Smart PLS 3.0 and IBM SPSS Statistic 20 software, to analyze the research model. The collected results show that 71% are female and 29% are male. The age range falls between 21 and 60 years old. The main level of education is upper higher education. For details see Table 1.

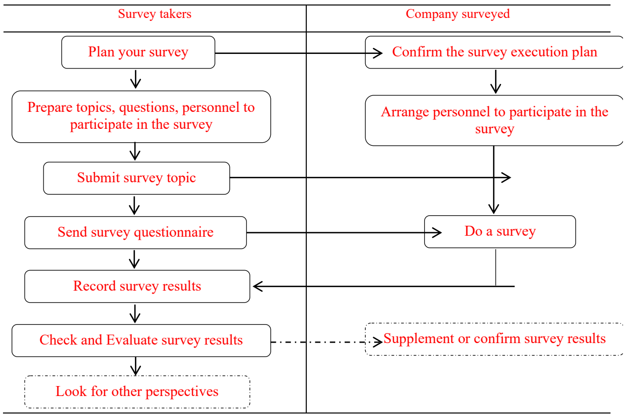

Fig. 2. Process to prepare to take a survey.

Table 1. Sample characteristics.

Variables	Items	Frequency	Percentage
Gender	Male	323	71%
	Female	132	29%
Age	21-30	68	15%
	31-40	137	30%
	41-50	228	50%
	51-60	22	5%
Academic degree	Below University	91	20%
	University	318	70%
	Master	23	5%
	PhD	18	4%
	Professor	5	1%

3.1. Structural Model

Using the T-test statistical analysis model to evaluate and confirm the model's path coefficient, the R-squared value is used to evaluate the user's intention to continuously use the smart electricity meter in Vietnam. Smart PLS 3.0 software is used to study the PLS-SEM model [41-42]. The model is evaluated with data consistency requirements. The research results after being analyzed show that the quality related to the information system such as service quality, system quality, and information quality have a direct impact on users' intention to continuously use the watch product smart meter [43-44]. According to the analysis results from Table 4, the system quality factor (P-Value = 0.102) and the information quality factor (P-Value = 0.213) of the information technology model is not supported (Tab. 2).

Table 2. Result of hypothesis analysis.

Hypothesis	Path	Estimate	T-value	S. E	P-value	Result
H1	Qser→ Int	0.156	4.21	0.058	0.003	Supported
H2	**Qsys→ Int**	**0.631**	**3.50**	**0.035**	**0.102**	**Not Supported**
H3	**Qinf → Int**	**0.549**	**4.03**	**0.047**	**0.213**	**Not Supported**
H4	Opt → Eas + Use	0.513	4.13	0.039	0.000	Supported
H5	Inn → Eas + Use	0.498	4.51	0.042	0.001	Supported
H6	Ins → Eas + Use	0.397	4.01	0.032	0.002	Supported
H7	Dis → Eas + Use	0.441	4.05	0.039	0.003	Supported
H8	Eas → Use	0.332	3.98	0.041	0.000	Supported
H9	Exp → Eas + Use	0.339	4.01	0.052	0.001	Supported
H10	Eas → Int	0.423	3.98	0.041	0.006	Supported
H11	Use → Int	0.391	4.07	0.052	0.008	Supported
H12	Exp → Int	0.419	3.95	0.061	0.003	Supported

Note: S.E: Standard Error,

3.2. Artificial Neural Network Analysis

ANN (Artificial Neural Network) [3] is used as the second mesh in the analysis to complement the PLS-SEM model. This study uses the ANN model for an in-depth analysis of the information technology model that affects the intention to use a smart meter continuously [4]. ANN shows the prediction results with higher accuracy than the PLS-SEM model because of the non-linear relationship analysis data[44]. SEM analysis sometimes offers an oversimplified analysis of process complexities [45]. In addition, ANN is recommended to be used to test the interest of the factors [46-47]. Therefore, the combined use of the PLS-SEM model with the ANN model the main purpose is that they complement each other. During ANN analysis, data is supported by Multilayer perception (MLP) [27]. ANN analysis is performed in 3 layers: input layer, hidden layer, and output layer (Fig. 3). This study used IBM SPSS 20 to run the ANN model [27]. The ANN-1 model has an output class of Int-1 and has 3 inputs of the information technology model: quality of service, quality of the system, and quality of information. The ANN-2 model has an output factor of TAM and has four inputs from the technical model: Optimization, Innovation, Insecurity, and Discomfort. The ANN-3 model has an output factor of Int-2 and has three inputs, Perceived Ease of use, Perceived usefulness, and Expectation confirmation. The ANN-1 model shows the neurons (Node) generated automatically and activated by the sigmoid function used for both the hidden layer and the output layer. To ensure the accuracy of the prediction results of the ANN as measured by 10 times cross-validation for the purpose of preventing data from over-fitting errors, the study divide the data into two parts as follows: a part 85% of the data is for training and 15% of the data is for testing. The accuracy of the predictive model is calculated according to the index after the square of the square root for both the training part (85%) and the test part (15%) of the dataset, the RMSE index (Root square error) is calculated by the formula (1) and (2). In which, SSE is the sum of squared error and MSE is the mean squared prediction [45].Analysis results from table 3 to table 5 of RMSE values for training and test data of the dataset representing the ANN model, exactly the model generated relationship between predictors and output factors. Low RMSE results in more accurate predictions and better data visualization [48].

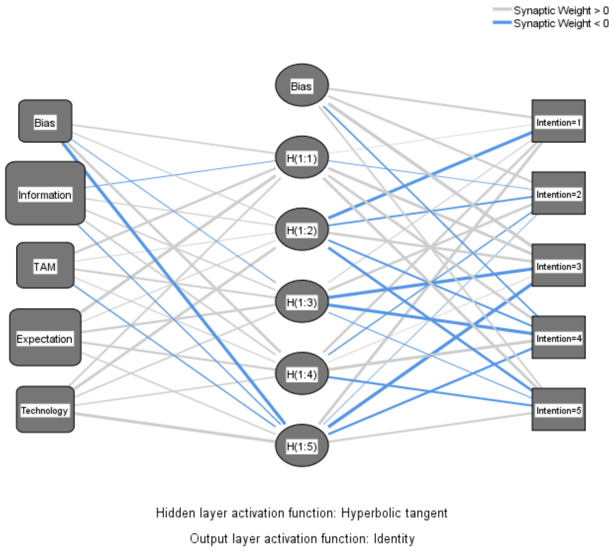

Fig. 3. Artificial Neural Network (ANN) research model.

Table 3. RMSE values for the ANN-1 model.

Input factors: Quality of Service, Quality of System and Quality of Information. Output factor: Intention to use of continuously				
Neural Network	**Training (85% of data sample 455) ; N = 387**		**Testing (15% of data sample 455) ; N = 68**	
	MSE	**RMSE**	**MSE**	**RMSE**
ANN1	0.1199	0.0318	0.1101	0.0887
ANN2	0.1231	0.0316	0.1080	0.0873
ANN3	0.1274	0.0317	0.1160	0.0911
ANN3	0.1321	0.0321	0.1290	0.0910
ANN4	0.1316	0.0323	0.1170	0.0960
ANN5	0.1153	0.0299	0.1060	0.0918
ANN6	0.1241	0.0298	0.1090	0.0879
ANN7	0.1127	0.0301	0.1190	0.0921
ANN8	0.1213	0.0299	0.1180	0.0906
ANN9	0.1135	0.0303	0.1090	0.0910
ANN10	0.1124	0.0289	0.0998	0.0897

Note: Root Mean Squared Error (RMSE), Mean Squared Error (MSE)

Table 4. RMSE values for the ANN-2 model.

Input: Optimization, Innovation, Discomfort, Sercurity Output: TAM				
Neural Network	**Training (85% of data sample 455) ; N = 387**		**Testing (15% of data sample 455) ; N = 68**	
	MSE	**RMSE**	**MSE**	**RMSE**
ANN1	0.1161	0.0301	0.1172	0.0359
ANN2	0.1152	0.0304	0.1181	0.0293
ANN3	0.1098	0.0305	0.1109	0.0301
ANN3	0.1151	0.0291	0.1106	0.0351
ANN4	0.1012	0.0287	0.0991	0.0299
ANN5	0.1053	0.0298	0.0983	0.0342
ANN6	0.1041	0.0296	0.1173	0.0335
ANN7	0.1091	0.0308	0.1131	0.0347
ANN8	0.1043	0.0305	0.1129	0.0298
ANN9	0.1031	0.0299	0.0991	0.0345
ANN10	0.1132	0.0189	0.1012	0.0298

Table 5. RMSE values for the ANN-1 model.

Input: Perceived ease of use, Perceived usefulness, Expectation confirmation Output: Intention to use Continuously				
Neural Network	**Training (85% of data sample 455) ; N = 387**		**Testing (15% of data sample 455) ; N = 68**	
	MSE	**RMSE**	**MSE**	**RMSE**
ANN1	0.113	0.0312	0.115	0.0338

ANN2	0.109	0.0308	0.119	0.0347
ANN3	0.115	0.0313	0.109	0.0395
ANN3	0.117	0.0301	0.112	0.0381
ANN4	0.108	0.0299	0.115	0.0373
ANN5	0.109	0.0308	0.117	0.0352
ANN6	0.115	0.0309	0.109	0.0361
ANN7	0.119	0.0313	0.108	0.0339
ANN8	0.118	0.0309	0.117	0.0342
ANN9	0.109	0.0314	0.109	0.0359
ANN10	0.099	0.0301	0.129	0.0299

Tables 6-8 show the sensitivity analysis index. Fig. 4, Fig. 5, and Fig. 6 show the system quality factor of the information technology model, the Insecurity factor, and the Discomfort factor of the technical model are the effects of the important factors on the intention to continue using the smart meter system of users, in particular smartphone users [49]. Consider the importance of the next standardized variable, the service quality factor, the information quality factor of the information technology model and the optimization factor, the Innovation factor of the technical model, and the perceived factor of ease of use, perceived usefulness of the TAM model, and theoretical expectations, respectively, affect user satisfaction.

Table 6. Normalized variable relation importance (Output: Int-1).

Predictors (Output: Int-1)	Average relative importance	Normalized relative importance (%)	Ranking
Quality of System	0.631	100	1
Quality of Information	0.549	81.94	2
Quality of Service	0.156	61.79	3

Table 7. Normalized variable relation importance (Output: TAM).

Predictors (Output: TAM)	Average relative importance	Normalized relative importance (%)	Ranking
Insecurity	0.397	45.46	4
Discomfort	0.441	67.23	3
Optimization	0.513	100	1
Innovation	0.498	89.21	2

Table 8. Normalized variable relation importance (Output: Int-2).

Predictors (Output: Int-2)	Average relative importance	Normalized relative importance (%)	Ranking
Expectation confirmation	0.419	83.09	2
Perceived ease of use	0.423	100	1
Perceived usefulness	0.391	64.26	3

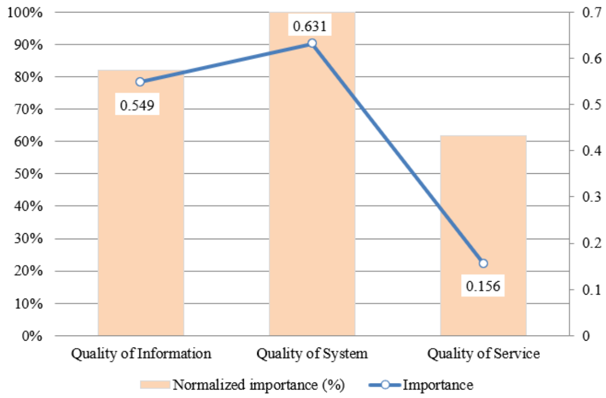

Fig. 4. Normalized variable relation importance (Output: SAT-1).

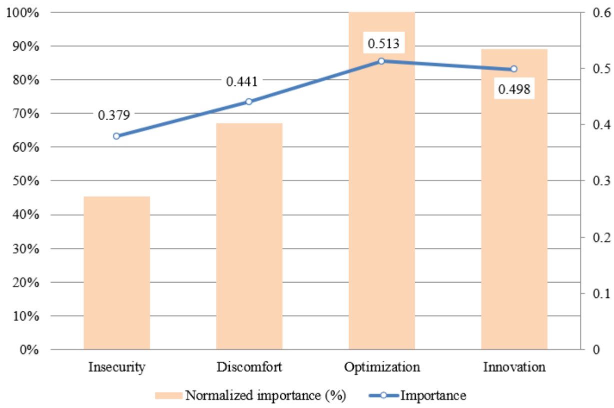

Fig. 5. Normalized variable relation importance (Output: TAM).

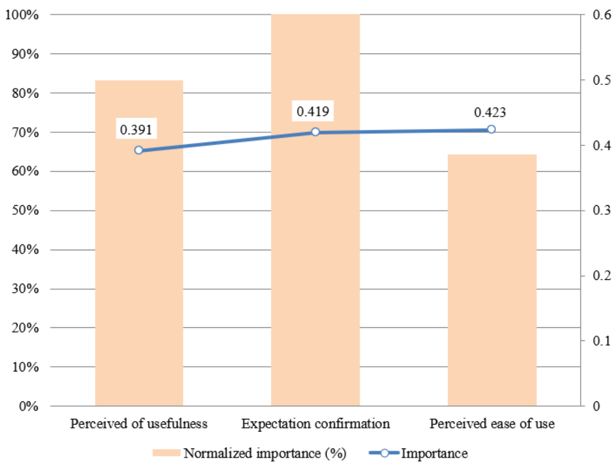

Fig. 6. Normalized variable relation importance (Output: SAT-2).

Tables 9-11 compare the results of ANN analysis to PLS-SEM analysis based on the coefficient-ranked path strength of the PLS-SEM and the significance of the ANN's normalized relative index. Comparison results from Table 9 (Output: INT-1) service quality factors are ranked for both ANN and PLS-SEM models. However, in PLS-SEM analysis, the first and second results are ranked in order of two factors: quality of the system and quality of information.ANN analysis shows that the information quality factor ranks first and the system quality factor ranks second. The ANN model measures linear and nonlinear relationships between variables with high accuracy[50]. Table 10, (Output: TAM), the factors of optimization, innovation insecurity, and discomfort are ranked from 1 to 4 for both ANN and PLS-SEM models. The ANN model measures linear and nonlinear relationships between variables with high accuracy. Table 11, (Output: INT-2), Expectation confirmation, Perceived ease of use, and Perceived usefulness factors are ranked 1 to 3 for the PLS-SEM analysis model. However, the analysis results from ANN give completely opposite results and are ranked in order from 1 to 3 as follows: Perceived usefulness, Expectation confirmation, and Perceived ease of use. The ANN model measures linear and nonlinear relationships between variables with high accuracy.

Table 9. Comparison between PLS-SEM and ANN analysis (Output: INT-1).

	Path means	**PLS-SEM Ranking**	**ANN normalized relative importance (%)**	**ANN Ranking**	**Matched?**
QSys	0.631	1	81.94	2	No
QInf	0.549	2	100	1	No
QSer	0.156	3	61.79	3	Yes

Table 10. Comparison between PLS-SEM and ANN analysis (Output: TAM).

	Path means	**PLS-SEM Ranking**	**ANN normalized relative importance (%)**	**ANN Ranking**	**Matched?**
Insecurity	0.379	4	45.46	4	Yes
Discomfort	0.441	3	67.23	3	Yes
Optimization	0.513	1	100	1	Yes
Innovation	0.498	2	89.21	2	Yes

Table 11. Comparison between PLS-SEM and ANN analysis (Output: INT2).

	Path means	**PLS-SEM Ranking**	**ANN normalized relative importance (%)**	**ANN Ranking**	**Matched?**
Expectation confirmation	0.419	2	83.09	2	Yes
Perceived ease of use	0.423	1	100	1	Yes
Perceived of usefulness	0.391	3	64.26	3	Yes

4. Result and Discussion

The analysis results of the PLS-SEM model in Table .1, the quality of the system factor (Qsys ->Int) has a value of P-Value = 0.102 greater than 0.05, indicating that the quality of the applied information technology system for smart meter negative influence. and at the same time, the quality of the information factor (Qinf ->Int) has a value of P-Value = 0.213 greater than 0.05, also indicating that the quality of information technology system negatively affects the smart meter and weak The quality of service factor (Qser ->Int) has a P-Value = 0.003 less than 0.05, which proves that the quality of service factor positively affects smart meter. This finding was also found in the study Social Influence as a Major Factor in Smart Meters' Acceptance: Findings from Brazil [41]. The factors in the technology model and the expectation model factor as well as the technical acceptance theory, about the P-Value reached the maximum value of 0.008 and less than 0.05, which proves that all factors in terms of optimization, innovation, insecurity, discomfort, convenience, usefulness, and expectations have a positive impact on smart meters. This research result is also found in studies on factor analysis of smart meter and is consistent with research results [26], [40-41].

This study has input variables from the engineering model (optimization, innovation, insecurity, and discomfort) and inputs from the TAM (perceived ease of use and perceived usefulness) model and the expected factor. The above factors are ranked based on the results of sensitivity analysis of the ANN model to determine the results of PLS-SEM. The detected results from the ANN model help verify the results from the PLS-SEM model analysis [34-35]. However, the ANN model gives more accurate analysis results because of linear and non-linear relationships between variables. The factors of the technical model (optimization, innovation, insecurity, and discomfort) are ranked in order from 1 to 4 for both ANN and PLS-SEM analysis models. However, the analysis results between ANN and PLS-SEM are not uniform [39], [51-53]. Specifically, the elements of the information technology model (QSys, QInf, QSer) are ranked in order from 1 to 3 for the PLS-SEM analysis model. However, the results from the ANN analysis model of the elements of the information technology model (QInf, QSys, QSer) are ranked in order from 1 to 3. This result shows that the service quality factor ranks third among the three factors. The system quality factor and the information quality factor are ranked from 1 to 2 for the PLS-SEM model and ANN gives the opposite result, which is information quality (QInf) first and system quality factor (QSys) ranked second. This study shows that the factors related to technology (optimization, innovation, insecurity, and discomfort) directly affect the theoretical model of technology acceptance of users. Users have high expectations for a smart meter product with high technical factors and ease of use. At the same time, the smart meter system also ensures ease of use and useful utility. Technical factors indirectly affect people's intention to continue using the smart meter system and directly affect the theory of technology acceptance. However, the factors related to the information technology model (quality of information, quality of system, and quality of service) have a direct impact on the satisfaction or intention to continue using the smart meter system. Users are still afraid and not secure when accepting the use of the smart meter system.

5. Conclusion

The ANN research model in this study is evaluated by the MSE value (Mean squared error). The MSE of an estimator is the average of the difference between the estimates and what is evaluated. The results of the ANN analysis show that the standard deviation of the MSE values of training and testing ranges from 0.005 to 0.008. This result shows the impact of observed variables on the latent variable that meets the requirements, there is no difference. The Importance Performance Map Analysis (IPMA) chart helps us to identify latent variables in the model that have relatively high importance but low performance. The PLS-SEM model is clearly analyzed using the importance-performance map analysis (IPMA) chart to assess the relevant impact factors more clearly in the PLS-SEM model [54]. IPMA histogram performs analysis based on two parameters, performance, and significance. The IPMA analysis chart (Fig.7) shows the results related to the target structure determination in the PLS-SEM path model [55-57]. The quality of the information technology model directly affects customer satisfaction and indirectly on the intention of continuously using the smart meter system. However, this factor has a positive impact on the user's intention to use the identification system continuously [58-59]. This is one of two elements of the information technology model (quality of system, quality of information) that requires suppliers and manufacturers of smart meter systems to think more about it [60]. Improving product quality, the good service quality factor of the product supplier applying smart meter technology, according to ANN's ranking shows the consensus on the service quality factor, but in terms of information quality and system quality, they do not agree the PLS-SEM model regarding the three elements of the information technology model (quality of information, quality of system and quality of service).

However, factors Qinf ->Int and Qsys ->Int have a strong negative impact on users' interest in using smart meter because their P-Value in the PLS-SEM model is greater than 0.05, IPMA analysis shows high influence of Qinf and Asys factors. This result is consistent with PLS-SEM and ANN analysis. Proving that the element of ensuring the quality of information in technology (information security) and the quality of information transmission in the system or operating the information system are issues that need to be researched and found solutions to raise users' interest in smart meters in the future. At the same time, the factors of innovation, insecurity, and discomfort have a relative impact on the theoretical model of technology acceptance. The importance of four factors (optimization, innovation, insecurity, and discomfort) of the engineering model affectsthe theoretical model of technology acceptance and the correlation between the ANN analysis and the analysis results of the PLS-SEM model.The results of IPMA analysis (Fig. 8) show that optimization and innovation factors have a great influence on the interest of smart meter users. This analytical result is consistent with the analysis results of PLS-SEM and ANN and the research results of recent smart meter studies [33-36]. This proves that smart meter advanced research techniques are always interested and developed continuously. The results of the IPMA analysis in Figure 8 show the convenience factor and the expectation that the new technology applied in smart meters has the greatest impact. This implies the expectation of a new technological technique to improve the smart meter, which is more and more simple to use and convenient in thousands of operations. This is also a promising research direction for future researchers.

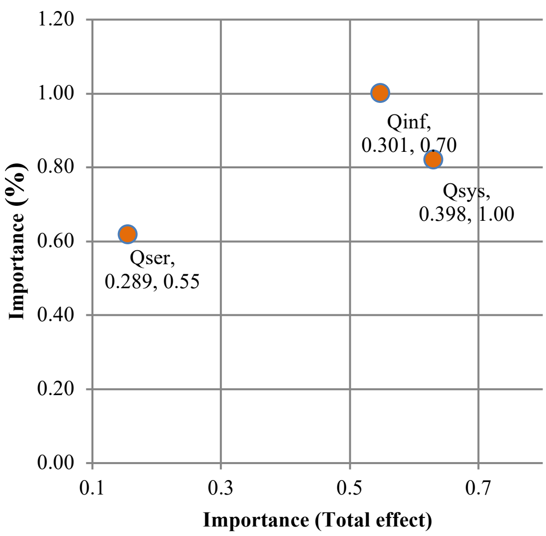

Fig. 7. The correlation between the performance and the importance of the INT-1.

The Theoretical Technology Acceptance Model (TAM) consists of two main elements: perceived ease of use and perceived usefulness. The perceived ease of use factor that affects the user's continuous intention to use is higher than that of usefulness but is ranked as the 2nd and 3rd according to the PLS-SEM model, the first is the confirmation factor (Fig. 9).

ANNs can model relationships of complex linear and non-linear relationships and give more accurate prediction results than the PLS-SEM model. This study discovered the important factors related to the information technology model are very few for product users using digital control technology. From a theoretical point of view, very few studies accept the use of a poor-quality information technology system. The education level in developing countries is still low, and the information technology and internet infrastructure are still limited. The 2-step research model including two models, PLS-SEM and ANN helps to create the following benefits: ANN helps to evaluate and verify the analysis results from the PLS-SEM model. In addition, ANN is also capable of modeling complex linear and non-linear relationships with high predictive accuracy compared to the PLS-SEM model. In summary, the 2-step analysis model PLS-SEM Neural network gives better and more accurate analysis results than the 1-step analysis model PLS-SEM. In addition, the analysis results from IPMA show that the findings from the PLS-SEM model provide an understanding of the relative importance and performance of each factor, and the ANN helps to further verify the outcome factors analysis results from the PLS-SEM model.

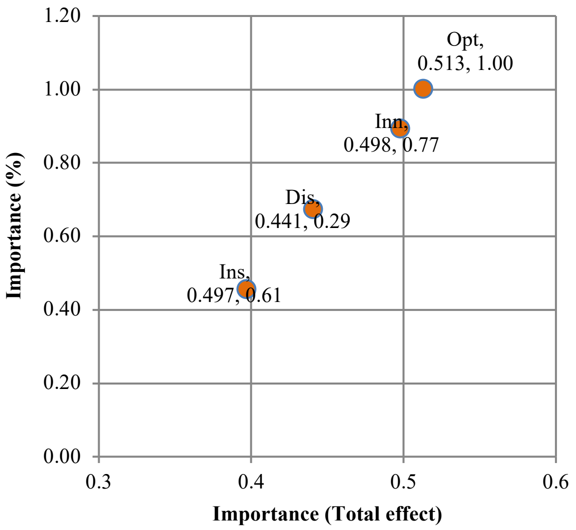

Fig. 8. The correlation between the performance and the importance of the TAM factor.

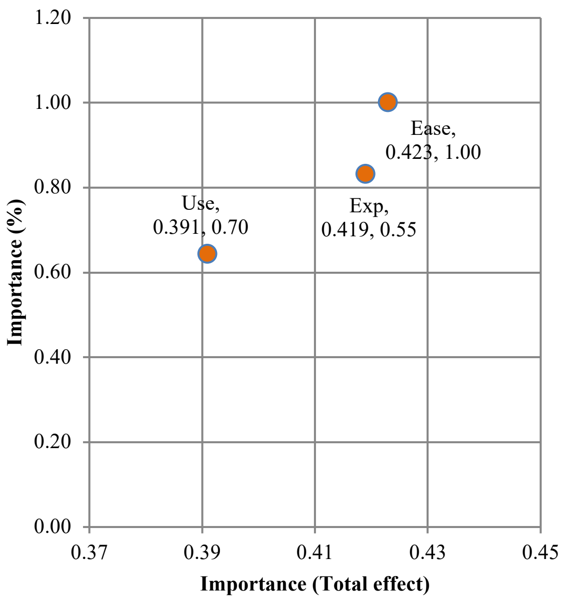

Fig. 9. The correlation between the performance and the importance of the INT-2 factors.

Research results show that users are very interested in deploying and using smart meters in measuring and controlling the amount of electrical energy used in production and people's daily life. The results show that controlling electricity index data by modern technology has been developed in Vietnam. Specifically, according to EVN's Business Department, the Group manages all data indexes of more than 29 million meters on CMIS software, without manual recording and calculation of data. For electronic meters with remote data collection, the readings are automatically updated for CMIS to calculate invoices. With mechanical meters, workers will record readings in the field using a tablet computer with a CMIS connection. Regardless of the data collected from any type of meter, EVN is fully controlled by information technology. Within 24 hours after recording the index, Electricity will send a notice in the form of SMS/Email/Zalo/Web Customer Service/App Customer Service... to the customer so that the customer can monitor the meter reading of the Electricity. On the other hand, users are also worried about the security of their personal information when using smart meters. However, because the results are very convincing when using smart meters, users still decide to deploy and use smart meters and wait for information security experts to find the optimal method of information security.

Limitations of the research topic: The data were collected in 2 areas, Ho Chi Minh City and Tay Ninh province, Vietnam. The limited point of data space is also a possible reason for this study to be less generalizable. Users who use smart meters are in measuring and controlling electrical energy need to know a certain amount of wireless communication systems and handle unusual situations related to wireless systems when disconnected. Users living in highlands and rural areas in midland and mountainous provinces often have low education and do not have much access to wireless science and technology. The survey and measurement samples in this study have not been carried out in the low-educated population areas as above, so the results of this study are not really generalizable. In the future, it needs to expand the data to the whole country or across the country with a larger data set. On the other hand, the smart meter system is considered a system that has been used in the present and in the future. Smart meter is a device using smart information technology by Internet of Things devices connected to mobile devices, input data information provided to the smart meter is a source of real-time collected signals, The data obtained from the smart meter is processed by the information system through the application software, the data is processed and transmitted to the smart meter user and the data is stored in the server gradually data sources become big data sources. The system of measuring and controlling electrical energy using smart meters is completely different from the previous human method. Because of the newly developed operation, authorities at all levels need to re-stipulate operating and control policies and ensure that the smart meter system is operated according to a common standard for users. The establishment of policies and regulations governing the smart meter system is also a direction that needs to be considered for future research. In addition, the element of information technology control rights or factors related to the security of users' personal information or creating a firewall to prevent components with nefarious intentions such as hacking the personal information of users, this is also a hot topic for researchers and scientists. Finally, the Technology Organizational Environment (TOE) model used in the activity examines various factors influencing the acceptance and use of smart meter systems.

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