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A PLS-SEM Neural Network for Understanding Computer Vision Technical. Apply to Gender Classification System

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Abstract

Analyzing the results from the experimental research environment to the user environment of technology products in the computer science industry is very necessary. In this study, firstly, we applied the local binary pattern and K-Nearest Neighbor method to create a facial gender recognition application with a database of 6000 images divided by male and female, the degree to which the accuracy of the model on recognition is 95.4%. Secondly, we use a 2-layer research model to analyze the results of the user survey about facial gender recognition technology products. Most of the previous studies on facial gender recognition techniques focused on analyzing the impact of factors affecting applications using single-step structure equation modeling (SEM). The purpose of this study, based on the technology acceptance method (TAM) theory, describes the artificial neural network (ANN) method to perform in-depth analysis, yielding more accurate results than the SEM model. The study measures the relationship between the readiness for new technologies (optimism, innovation, discomfort, and insecurity). Technology acceptance (Perceived ease of use, Perceived usefulness). Expectations confirmed and Information systems acceptance (service quality, system quality, and information quality) and user satisfaction on facial gender recognition systems such as personal information declaration systems at customs gates at domestic and international airports. This paper outlines the research model of the multi-analysis approach by combining Partial Least Squares - Structure Equation Modeling (PLS-SEM) and Artificial Neural Network (ANN) analysis. First, the PLS-SEM model evaluates the factors affecting the intention to use the facial gender recognition system. Second, ANN ranks the impact factors of important predictors from the PLS-SEM model. The findings from the PLS-SEM and ANN approach research model confirm the results obtained from PLS-SEM by ANN. In addition, ANN performs linear and non-linear relational modeling with high prediction accuracy compared with the SEM model. In addition, An Importance Performance Map Analysis (IPMA) analyzes the results accurately for factors' important performance.

Keywords: PLS-SEM, Artificial Neural Network , ANN, Face Gender Classification, Structure Equation Modeling

1. Introduction

Computer science develops and applies results from computer science vary widely from economics, engineering, education,... Computer science, developing analytical applications using anthropometrics as the main factor has been and is the main concern of information technology application developers. The application of anthropometric analysis results to security activities is very necessary, because of its uniqueness and irreplaceability in terms of setting the anthropometric characteristics of each individual. In this study, we apply a local binary pattern to extract features on human faces and use the K-Nearest Neighbor algorithm to classify gender on the basis of 6000 comments divided equally between men and women. Next, we apply the PLS-SEM Neural network model to analyze the survey results of users and experts on facial gender recognition applications and analyze the factors affecting the intention to use Continuously the application recognizes the gender of the user's face. The results from the research model are: applied in law enforcement, and commercial businesses and widely used in mobile devices.

(1) Learn features and methods of gender recognition by face, recognize gender recognition techniques through computer science
(2) Using PLS-SEM model combined with neural network to analyze user survey
(3) Model research of 2 stages on PLS-SEM Neural network research shows that the analysis results are more accurate
(4) A new sense of connection from the research environment to the environment in which the research results are used
(5) Analyze user opinions about technology products, assess user acceptance of technology products

1.1 Factor effect to face gender classification

The facial gender recognition technique is one of the methods that many researchers in computer science are interested in doing research. Gender identification is highly appreciated in terms of its wide application such as e-commerce business on user information security systems, identifying user needs to purchase goods at gender discrimination, helping Business people make accurate decisions about the distribution of product layout according to user habits by gender in stores, supermarkets or retail businesses. In judicial administration. Specifically, Declare personal information at border crossings between countries or airports and identify criminals by gender. However, the facial gender recognition system in particular and the anthropometric gender recognition system,

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in general, are still very limited in use in Vietnam as well as in the world.

The researchers believe that, in the future, anthropometric systems will be widely applied and developed. Specifically, the Facial Recognition System will be widely applied in law enforcement, and commercial businesses and widely used in mobile devices.

The Factors that hinder the use of facial gender recognition systems include:

(1) User privacy is not high

(2) Factors about the user's culture and beliefs vary by region and country

(3) The user's level of knowledge and awareness is still not high depending on the region and country or age and gender

Previous studies have shown that religion, beliefs, and user privacy have a strong influence on the limitation of using facial gender recognition systems.

Facial gender recognition system. The satisfaction Index (SAT) measures a user's willingness to accept the use of a gender recognition system. Optimism (OPT) and In-novation (INN) have a positive impact, boosting user satisfaction with the identity system. However, Factors of Insecurity (INS) and Discomfort (DIS) contribute to preventing user satisfaction with the identification system. At the same time, the information technology system [23] (Service quality (SERQ), System quality (SYSQ), and Information quality (INFQ)) positively affect user satisfaction with the gender recognition system by the human face.

In the new technical information system, there are many theories such as the Theory of reasoned action (TRA), the Technology acceptance model (TAM), Theory of planned behavior/decomposed Theory of planned behavior (C-TAM-TPB). However, the most widely used TAM in terms of assessing user satisfaction intention of using a system is made up of new technology. Research evaluating technology integration (discomfort, innovation, optimism, and insecurity) and TAM (perceived system ease of use (Ease of use), expectations of the system (Expectation), and perceived usefulness of the system (Usefulness)) and TAM (testing information technology system on factors such as service quality, system quality, and information quality) to check their impact on user satisfaction with gender identification system by face.

In this study, through TAM to assess user satisfaction on the facial gender recognition system. However, previous studies on TAM showed that using structure equation modeling (SEM) as linear relationship between the structures. In this study, assess the user's satisfaction with the gender recognition system according to the TAM theory by combining two-step approach, those are Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Network (ANN) analysis. ANN generates models with high accuracy with linear and non-linear models compared to SEM models.

The main contributions of the study are shown below:

(1) Evaluation of factors affecting user satisfaction of facial gender recognition systems in terms of techniques and information technology
(2) Using the combined model PLS-SEM ANN to improve the accuracy of the research model
(3) Answering the question why users limit the use of the identification system using anthropometrics in general and facial anthropometry in particular.

The research paper is organized in the following structure: Section 2 presents the background content on the theoretical basis of the facial gender recognition system, which is affected by the user's satisfaction with new technology and information technology systems. Section 3 presents a discussion of the hypotheses that have been developed in the model. Section 4 outlines the content of the research method. Section 6 discusses the findings and implications of the study. Finally, the limitations and future research directions are presented in detail.

2. Related studies and Theoretical background

2.1. Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is used to evaluate technology acceptance. TAM explicitly examines the effects on acceptance and actual use of technology-based on perceived ease of use (PEOU) and perceived usefulness (PU). Previous researchers highly appreciated the robustness of TAMs for assessing technology usage. TAM is extended by integrating individual structures of technical readiness and information systems.

2.2. Technology Model

People of each country have their own freedom of religion. The relevant personal information using anthropometric analysis is considered very difficult for users to accept. Specifically, the facial gender recognition system has only been used limitedly since 2017 in China and is gradually being used by countries such as Russia, India, and Europe in the years after 2018. Facial gender recognition technology has been developed by computer technology experts with a high breakthrough, bringing convenience to users with its usefulness, ease of use, and user expectations. Researchers highly appreciate the development of new technology applications that meet user expectations. Users perceive, feel, and are motivated by the favorable positive performance of products and services that new technology brings. However, the new technology must meet the exclusion of harmful activities for users from negative people such as rating users' personal information.

2.3. Expectation-confirmation model

Expectation-confirmation theory (ECT) was developed in 1980 to validate user expectations before and after purchasing a product or service. Therefore, user satisfaction is decisive for the customer's intention to repurchase or reuse a certain product or service. Specifically, are our customers satisfied when using the facial gender recognition system? In 2001, Bhattacherjee built an Expectation-confirmation model (ECM) based on the foundation of the ECT model to evaluate users' continuous use behavior for products in the information technology industry. The ECM model compares the user's expectations and perceptions after using a technology product, the extent to which the expectation affects the user's useful perception and product satisfaction, directly affects the intention to continue using the technology system. Technological products meet the high expectations of users, which means that products are perceived by users as highly useful, improve user satisfaction, and technology products will always be used by users to improve their intention to use, continued use of the product in the future. Nowadays, many researchers build models to evaluate the validity of ECM for information technology products and services. Enhancing the research model to respond to ever-evolving technology, the studies combine theories such as technology acceptance theory, IS success model, e-commerce trust theory, value perception theory, and self-efficacy theory with ECM to evaluate the user's intention to continuously use information technology products and services.

2.4. Information System Model

DeLone and McLean carried out empirical research on information technology systems and recorded 6 dependent variables as follows: system quality, information quality, system use, user satisfaction, personal influence, and organizational influence. In which, Quality of Service, Quality of System, and Quality of information directly affect the satisfaction of users with technology products. Up to now, the Information System Success Model has been tested and widely used for information technology products.

Chen and Cheng have successfully applied an information technology model to verify online purchasing technology. Gao and Bai apply the IS model to evaluate products related to social networking services.

Although, IS Model is highly feasible for evaluating technology products. However, there has not been any extensive research that shows the IS model in knowledge-sharing platforms. Research on applying IS model to knowledge sharing platforms is the gap in current research. A knowledge-sharing platform is an information system, that applies IS model to the knowledge-sharing system implemented in this study.

2.5. Intergrating the IS model, technical readiness model and ECM

ECM theory is built to test and evaluate the level of user satisfaction. Construction research combines the ECM theoretical model with the technical readiness model and the information technology system model to test the studies. Some authors have researched and demonstrated that the combined ECM model and IS model verify that the service quality, system quality, and information quality factors have a positive impact on user satisfaction with technology products.

The technology readiness model includes factors such as discomfort, innovation, optimism, and insecurity that affect people's satisfaction through two factors: perceived ease of use, perceived usefulness to customer satisfaction to technology products to be verified by ECM Theory.

Previous research results show that the IS model (system quality, service quality, and information quality) and the technology readiness model (perceived ease of use, perceived usefulness) to customer satisfaction with technology products as integration trust, self-integrated effectiveness, social cognitive theory, integrated cognitive value, and subjective criteria. However, there has not been any research evaluating the overall combination of 3 models (technology readiness model, IS model, and ECM theory) to assess the level of satisfaction and intention to use continuously of consumers' technology products. In this study, build an integrated model of the three above models ac-cording to characteristics such as Quality of Service, Quality of System and Quality of information, perceived ease of use, perceived usefulness, and expected confirmation level for the service to consumer satisfaction and the customer's intention to accept continued use of the technology product.

3. Hypotheses development

A tool to predict and measure the reality of consumer behavioral intentions about technology products, developed by Parasuraman and Colby, is called TRI 2.0. The model identifies the motivations and factors that promote the acceptance of technological products. In this study, the technology readiness factor (optimism, innovation, discomfort, and insecurity). The factors of TAM (Perceived ease of use, Perceived usefulness). Expectations are confirmed and are (service quality, system quality, and information quality) model factors have been tested and predicted technology products for facial gender recognition systems, see Figure 1.

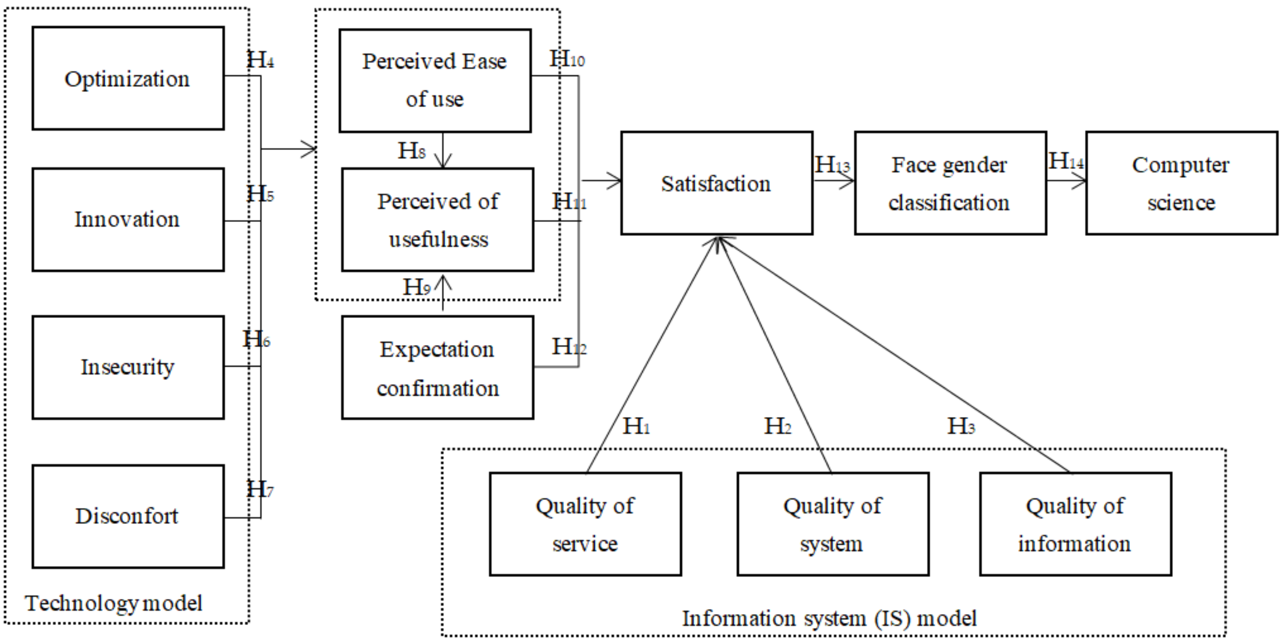

Fig. 1. Reasearch model

3.1. Information system (IS) model

The platform to share with users about technology products that directly affect user satisfaction is widely applied according to the IS model. The elements of the knowledge-sharing platform that technology products have, including platform functions, content quality, and system response speed, are used as indicators of user satisfaction with technology products. Research shows that information quality has a direct impact on user satisfaction. The noise of the signal arising during transmission is a factor that significantly reduces user satisfaction with technology products. Research results also show that the service quality of technology products also has a direct impact on user satisfaction. Specifically, factors such as learning functions, discussion communities, auxiliary learning tools, and other functions of the mobile learning system improve user satisfaction with technology products. Poor system maintenance service such as slow or no spare parts negatively affects user satisfaction. Meanwhile, there is a strong positive correlation between system quality and user satisfaction. However, slow bandwidth and slow link systems between devices of technology products are also factors that adversely affect customer satisfaction. Based on the research, the above discussion and the following hypotheses were formed:

Hypothesis 1 (H1): Quality of service of technology products directly positively affects user satisfaction through knowledge sharing platform.

Hypothesis 2 (H2): Quality of system of technology products has a direct positive impact on user satisfaction through knowledge sharing platform.

Hypothesis 3 (H3): Quality of information of technology products has a direct positive impact on user satisfaction through knowledge sharing platform.

3.2. Technology readiness model

Technology acceptance theory has made users feel about new technology. Previous studies have shown that technology acceptance has two sides positive and negative. Positive people always see technology as a good thing. In contrast, people who are negative about technology are often shy. The facial gender recognition system is a new technology, active people always consider and accept the treatment with a ready attitude. However, the current identification technology is not widely accepted for use because the receiving technology still has many limitations, so users are still negative about the system. Author Parasuraman author has developed a technology readiness index and applied technology with optimism and creativity that always positively affects technology users. The discomfort and insecurity, however, speak to the negativity of adopting new technology. See Figure 1.

- Optimism: New technology brings positivity about improving control of life, bringing flexibility and efficiency to life.
- Innovation: New technology offers new ideas and uses
- Insecure: The technology's intended purpose does not meet personal security, leading users to bring negative intentions toward the new technology.
- Discomfort: New technology makes it difficult or inconvenient for users.

Optimism: New technology always brings a positive feeling to users into technology. Users always have the feeling that technology is easy to use. Specifically, facial gender recognition technology is useful to users and always supports further application development in the user environment. Therefore, optimism always brings positivity to users' satisfaction with new technology.

Innovation: The environment or internal factors of new technology do not cause negative effects on users. Users have always viewed technology as a positive and have always supported novelty in apps. The innovation of gender recognition technology has always been supported, and innovation has always had a positive impact on user satisfaction on the intention to continue using gender recognition technology.

Insecure: User privacy is always the top concern of users in the gender recognition technology system. However, identification technology has not yet brought peace of mind to users about information security, and lack of trust in users in identification technology. Individual users are always in a state of fear and insecurity when using gender recognition technology. The biggest obstacle to identification technology is the security of the personal information of users. Therefore, Insecurity has a negative impact on user satisfaction on intention to continuously use gender recognition technology products.

Discomfort: New technology does not bring comfort to the user. Users feel fluctuating while using gender recognition technology. Users always feel uncomfortable when using technology. Therefore, discomfort always has a negative impact on user satisfaction with the intention to continuously use the gender identity system. Based on the research, the above discussion and the following hypotheses were formed:

Hypothesis 4 (H4): Optimism has a positive effect on the usefulness and convenience of technology on people's satisfaction with the intention to continuously use gender recognition technology.

Hypothesis 5 (H5): Innovation has a positive effect on the usefulness and convenience of technology on people's satisfaction with the intention to continuously use gender recognition technology.

Hypothesis 6 (H6): insecurity has a negative effect on the usefulness and convenience of technology on people's satisfaction with the intention to continuously use gender recognition technology.

Hypothesis 7 (H7): Discomfort has a negative impact on the usefulness and convenience of technology on people's satisfaction with the intention to continuously use gender recognition technology.

Hypothesis 8 (H8): Ease of use has a positive effect on usefulness and a positive effect on user satisfaction on intention to continue using gender recognition technology.

Hypothesis 9 (H9): Expectation has a positive effect on usefulness and a positive effect on user satisfaction on intention to continuously use gender recognition technology.

Hypothesis 10 (H10): Ease of use of new technology has a positive impact on user satisfaction about intention to continue using gender recognition technology.

Hypothesis 11 (H11): The usefulness of new technology has a positive impact on user satisfaction about intention to continue using gender recognition technology.

Hypothesis 12 (H12): Expectations of new technologies have a positive impact on user satisfaction about intention to continuously use gender recognition technology.

Hypothesis 13 (H13): Satisfaction has a positive effect on intention to continuously use gender recognition technology.

Hypothesis 14 (H14): intention to continuously use gender recognition technology positively affects computer science.

4. Research methodology

The data carried out in this study were collected from students, teachers, and technology industry researchers at Ho Chi Minh City Van Lang University. Implement a non-random draw method because it is easy to reach the participants. Most people use smartphones and use the system to turn on and off the phone using facial anthropometry or fingerprints. Criteria that the sampled participants are knowledgeable and find the facial gender recognition system to be useful. Refer to the scales from previous related studies of domestic and foreign authors. Each research variable through at least 4 measurement indicators. The questionnaire was made in English on a 5-point Likert scale to collect data. To ensure that the questionnaire was properly designed, the questionnaire was sent to 3 experts in the field of computer science for comments. The author has adjusted the questionnaire according to the comments of experts.

A total of 300 questions were collected, and 45 questions were removed because there were incorrect or invalid answers, as these people may not have read the questionnaire thoroughly. A total of 255 questionnaires were valid and used smart PLS 3.0 and IBM SPSS Statistics 20. The collected results show that 70.5% are male and 25.5% are female. The age range falls between 18 and 56 years old. Their qualifications are mainly university, accounting for about 75%. The majority are students, accounting for about 70%. For details see Table 1.

Table 1. Sample characteristics

Variables	Items	Frequency	Percentage
Gender	Male	180	80%
	Female	45	20%
Age	21-30	169	75%
	31-40	23	10.22%
	41-50	22	9.9%
	51-60	11	5%
Academic degree	University	158	70%
	Master	151	67.11%
	PhD	4	1.8%
	Professor	3	1.3%

Composite Reliability (CR) is an indicator used to evaluate the reliability and validity of the measurement scales. Cronbach's Alpha value evaluates the reliability of different factors. The evaluation criteria of CR and Cronbach's Alpha is that it must be greater than 0.8, then the survey results are evaluated as reasonable and valid for the analysis of the PLS-SEM model. The analysis results show that all CR and Cronbach's Alpha values are greater than 0.8 and AVE is greater than 0.5. Table 2 shows analytical values showing that the scale is valid and has the confidence level to accept the model. the value of the AVE square root of the research data is greater than the correlation coefficient that proves the validity of the data, see table 3.

Table 2. Convergent validity and reliability

Construct	Indicators	Factor Loading	SMC	AVE	CR	Cronbach's Alpha
Quality of service	SerQ1	0.735	0.598	0.567	0.803	0.845
	SerQ2	0.801	0.609			
	SerQ3	0.783	0.608			
	SerQ4	0.756	0.589			
Quality of system	SysQ1	0.802	0.645	0.547	0.834	0.856
	SysQ2	0.745	0.702			
	SysQ3	0.823	0.608			
	SysQ4	0.789	0.589			
Quality of information	InfQ1	0.821	0.578	0.601	0.823	0.809
	InfQ2	0.798	0.589			
	InfQ3	0.807	0.603			
	InfQ4	0.756	0.603			
Optimization	Opt1	0.809	0.604	0.507	0.835	0.805
	Opt2	0.736	0.708			
	Opt3	0.789	0.658			
	Opt4	0.805	0.638			
Innovation	Inv1	0.769	0.508	0.621	0.823	0.847
	Inv2	0.764	0.623			
	Inv3	0.798	0.645			
	Inv4	0.802	0.628			
Insecurity	Ins1	0.703	0.743	0.589	0.804	0.903
	Ins2	0.765	0.734			
	Ins3	0.703	0.589			
	Ins4	0.789	0.613			

Discomfort	Disc1	0.832	0.616	0.604	0.809	0.846
	Disc2	0.803	0.640			
	Disc3	0.756	0.732			
	Disc4	0.756	0.576			
Perceived Ease of use	Ease1	0.798	0.638	0.578	0.834	0.834
	Ease2	0.831	0.628			
	Ease3	0.805	0.638			
	Ease4	0.746	0.523			
Perceived of usefulness	Useful1	0.709	0.498	0.623	0.834	0.856
	Useful2	0.706	0.573			
	Useful3	0.798	0.579			
	Useful4	0.746	0.694			
Expectation confirmation	Exp1	0.835	0.638	0.672	0.836	0.802
	Exp2	0.832	0.793			
	Exp3	0.831	0.579			
	Exp4	0.734	0.637			
Satisfaction	Sat1	0.768	0.594	0.539	0.805	0.846
	Sat2	0.769	0.640			
	Sat3	0.735	0.598			
	Sat4	0.804	0.634			
Face gender classification	Face1	0.896	0.635	0.647	0.809	0.816
	Face2	0.846	0.679			
	Face3	0.798	0.701			
	Face4	0.746	0.603			

Note: AVE: Average variation extraction, SMC: Squared multiple correlation

Table 3. Discriminant validity analysis

Construct	SerQ	SysQ	InfQ	Opt	Inv	Ins	Disc	Ease	Useful	Exp	Sat	Face
SerQ	**1.000**											
SysQ	0.143	**1.000**										
InfQ	0.231	0.143	**1.000**									
Opt	0.154	0.213	0.213	**1.000**								
Inv	0.145	0.241	0.214	0.121	**1.000**							
Ins	0.267	0.143	0.145	0.231	0.432	**1.000**						
Disc	0.287	0.154	0.189	0.432	0.563	0.342	**1.000**					
Ease	0.376	0.276	0.231	0.324	0.467	0.324	0.234	**1.000**				
Useful	0.145	0.143	0.154	0.178	0.403	0.453	0.323	0.234	**1.000**			
Exp	0.154	0.143	0.156	0.198	0.453	0.251	0.472	0.532	0.402	**1.000**		
Sat	0.178	0.267	0.298	0.398	0.504	0.425	0.532	0.321	0.502	0.324	**1.000**	
Face	0.265	0.253	0.143	0.365	0.435	0.387	0.356	0.432	0.324	0.452	0.321	**1.000**

4.1. Structural model

Use T-Test at a 5% significance level to confirm the path coefficient of the model. The path coefficient and outer loading factor of the bootstrapping model to evaluate the estimated standard error. R square value evaluates the intention to continuously use the facial gender recognition model. See table 4.

This Smart PLS 3.0 software is used to study the PLS-SEM model. The model is evaluated in accordance with the requirements related to the consistency of research data. Experimental results show that information system-related quality (Service quality, system quality, and information quality), optimism, and creativity positively affect the ease of use and usefulness of the new technology on user satisfaction regarding the intention to continue using the facial gender recognition system. However, discomfort and insecurity have the opposite, negative impact. See table 5 and figure 2. The system quality factor (p-value = 0.104) of the information technology model and the discomfort (Dis = 0.427) and insecurity (Ins = 0.612) factor are not supported. We re-analyze the survey results of the three factors above. The results show that placing personal data insecurity (84.35%), the accuracy of technology (93.21%) and religion (10%) affect the intention to continuously use the identification system. gender by face.

Table 4. Results of hypothesis analysis

Hypothesis	Path	Estimate	t-Value	S.E	p-Value	Result
H1	SerQ -> Sat	0.056	4.23	0.067	0.006	Supported
H2	SysQ -> Sat	0.621	3.12	0.032	0.104	**Not Supported**
H3	InfQ -> Sat	0.213	2.65	0.045	0.009	Supported
H4	Opt -> Ease +Useful	0.321	3.23	0.056	0.001	Supported
H5	Inv -> Ease + Useful	0.145	2.14	0.034	0.006	Supported
H6	Ins -> Ease + Useful	-0.876	1.89	0.056	0.612	**Not Supported**
H7	Dis -> Ease + Useful	-0.809	1.98	0.054	0.427	**Not Supported**
H8	Ease -> Useful	0.254	3.24	0.032	0.008	Supported

H9	Exp -> Useful	0.421	2.56	0.054	0.006	Supported
H10	Ease -> Sat	0.278	3.21	0.063	0.005	Supported
H11	Useful -> Sat	0.189	1.67	0.072	0.001	Supported
H12	Exp -> Sat	0.326	1.54	0.037	0.002	Supported
H13	Sat -> Face	0.165	2.01	0.021	0.004	Supported

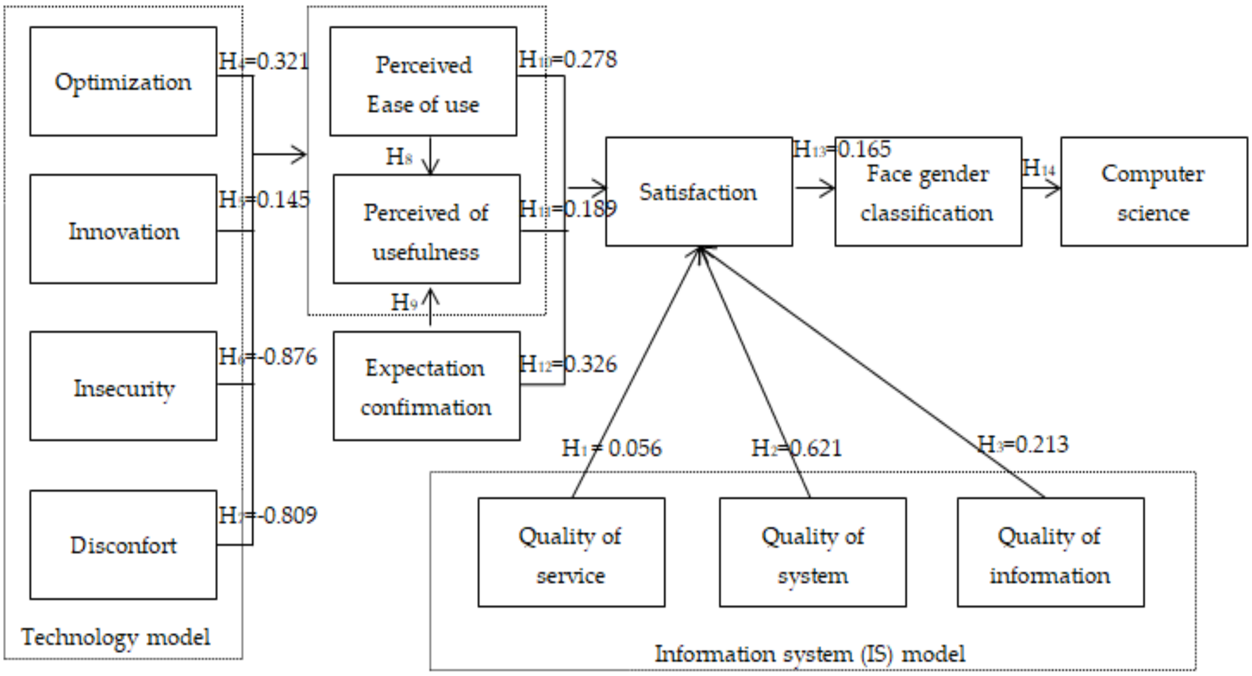

Fig. 2. Result of research model

4.2. Aritificial neural network analysis

Artificial neural network analysis (ANN) was used as the second step in the analysis to complement the PLS-SEM model. In this study, we use the ANN model for in-depth analysis of the technical model, TAM model + Expectation theory, and information technology model affecting customer satisfaction about the intention to continuous use of facial gender recognition technology. ANN gives prediction results with higher accuracy than the PLS-SEM model, because of nonlinear data analysis with the related relationship. PLS-SEM analysis sometimes offers an oversimplified analysis of process complexities. In addition, ANN is recommended to test the relationships of variables. 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 perceptron (MLP) transmission. ANN analysis is performed in 3 layers: input layer, hidden layer, and output layer. In the study, we use IBM SPSS 20 to run the ANN model. The ANN-1 model has an output layer of SAT 1 and has 3 inputs (Quality of service, quality of system, and quality of information) of the information technology model. The ANN-2 model has an output factor of TAM and has four inputs (Optimization, Innovation, Insecurity, and Discomfort) of the technical model. The ANN-3 model has an output factor of SAT 2 and an input factor of 3 (Perceived ease of use and perceived usefulness) of the TAM model and the waiting theory (Expectation confirmation).

The ANN-1 model shown in figure 3, shows auto-generated neurons (nodes) and sigmoid function-activated, used for both hidden and input layers. To ensure the accuracy of the prediction results of the ANN network measured by 10-fold cross-validation. The purpose is to prevent data from generating overfitting errors. We divide the data into 2 parts as follows: One part consists of 85% of data for training and 15% of data for testing. The accuracy of the predictive model is calculated according to the square root index for both the training part (85%) and the test part (15%) of the dataset. The RMSE (Root Square Error) index is calculated using formulas (1) and (2). Where, SSE is the sum of squared error, and MSE is the mean squared prediction error.

$$MSE = \left[\frac{1}{n}\right] \times SSE \tag{1}$$

$$RMSE = \sqrt{MSE} \tag{2}$$

Analysis results from table 5 to table 7, the values of RMSE for training and test data of the dataset representing the ANN model, Accurate model is generated relationship between predictors and output factors. Low RMSE results in more accurate predictions and better data visualization.

Table 5. RMSE values for the ANN-1

Input factors: Quality of Service, Quality of System and Quality of Information.
Output factor: satisfaction

Nerual network	Training (85% of data sample 255); N=217		Testing (15% of data sample 255); N=38	
	SSE	RMSE	SSE	RMSE

ANN1	0.1198	0.036	0.1104	0.0846
ANN2	0.1189	0.0289	0.1060	0.0798
ANN3	0.1156	0.0325	0.1156	0.0892
ANN4	0.1243	0.0301	0.1204	0.0923
ANN5	0.1231	0.0297	0.1156	0.0945
ANN6	0.1164	0.0301	0.1047	0.0904
ANN7	0.1213	0.0302	0.106	0.0835
ANN8	0.1134	0.0303	0.1145	0.0879
ANN9	0.1321	0.0329	0.1143	0.0893
ANN10	0.1231	0.0306	0.1089	0.0897

Table 6. RMSE values for the ANN-2

Input factors: Optimization, Innovation, Insecurity and Discomfort.
Output factor: TAM

Nerual network	Training (85% of data sample 255); N=217		Testing (15% of data sample 255); N=38	
	SSE	SSE	RMSE	RMSE
ANN1	0.1148	0.0302	0.1109	0.0306
ANN2	0.1106	0.0298	0.1173	0.0309
ANN3	0.1078	0.0289	0.1108	0.0305
ANN4	0.1107	0.0286	0.1109	0.0345
ANN5	0.1105	0.0198	0.0899	0.0287
ANN6	0.1167	0.0302	0.1108	0.0298
ANN7	0.1078	0.0302	0.1098	0.0299
ANN8	0.1089	0.0309	0.1132	0.0367
ANN9	0.1104	0.0299	0.1145	0.0308
ANN10	0.1043	0.0378	0.0894	0.0309

Table 7. RMSE values for the ANN-3

Input factors: Perceived ease of use, Perceived of usefulness and Expectation confirmation
Output factor: SAT-2

Nerual network	Training (85% of data sample 255); N=217		Testing (15% of data sample 255); N=38	
	SSE	SSE	RMSE	RMSE
ANN1	0.1098	0.0298	0.1140	0.0309
ANN2	0.1089	0.0314	0.0986	0.0298
ANN3	0.1094	0.0298	0.1097	0.0326
ANN4	0.1231	0.0309	0.1132	0.0395
ANN5	0.1209	0.0356	0.1142	0.0309
ANN6	0.1219	0.0308	0.1159	0.0299
ANN7	0.1106	0.0357	0.1562	0.0298
ANN8	0.1098	0.0302	0.1098	0.0297
ANN9	0.1187	0.0298	0.1167	0.0309
ANN10	0.1289	0.0309	0.0968	0.0392

Table 8. Normalized variable relation importance (Output: SAT-1)

Preditors (Output: SAT-1)	Average relative importance	Normalized relative importance (%)	Ranking
Quality of System	0.621	78.31	2
Quality of Information	0.213	100	1
Quality of Service	0.056	61.79	3

Table 9. Normalized variable relation importance (Output: TAM)

Preditors (Output: TAM)	Average relative importance	Normalized relative importance (%)	Ranking
Insecurity	0.876	100	1
Discomfort	0.809	89.21	2
Optimization	0.321	61.08	3
Innovation	0.145	45.89	4

Table 10 Normalized variable relation importance (Output: SAT-2)

Preditors (Output: SAT-2)	Average relative importance	Normalized relative importance (%)	Ranking
Expectation confirmation	0.326	83.09	2
Perceived ease of use	0.278	45.78	3
Perceived of usefulness	0.189	100	1

The inputs for each model of relative importance were calculated according to a normalized relative importance rank (expressed as a %). Tables 8, 9, and 10 show the sensitivity analysis index. From the analysis results in Figures 9, 10, and 11, the system quality factor of the information technology model and the Insecurity factor, and the Discomfort factor of the technical model are the important factors affecting customer satisfaction. satisfaction and indirect effects on the intention to continue using the gender recognition system of users, in particular smartphone users. Considering 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. ease of use, perceived usefulness of the TAM model, and theoretical expectations, respectively, affect user satisfaction.

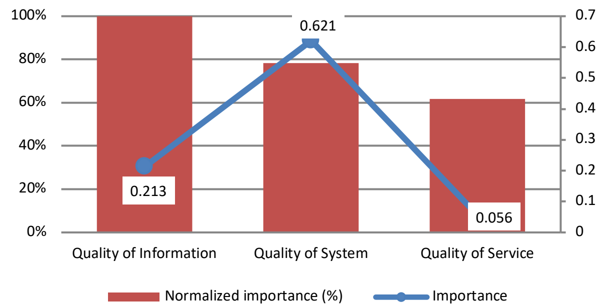

Fig. 3. Normalized variable relation importance (Output: SAT-1)

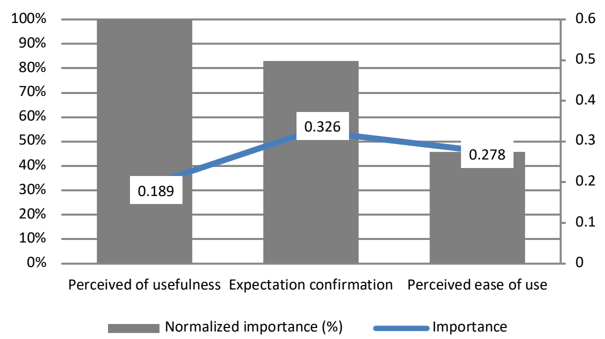

Fig. 4. Normalized variable relation importance (Output: TAM)

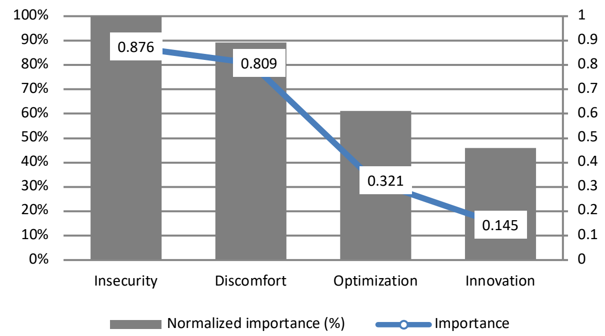

Fig. 5. Normalized variable relation importance (Output: SAT-2)

Table 11. Comparison between PLS-SEM and ANN analysis (Output: INT1)

	Path mean	PLS-SEM Ranking	ANN normalized relative importance (%)	ANN Ranking	Matched?
QSys	0.621	1	78.31	2	No
QInf	0.213	2	100	1	No
QSer	0.056	3	61.79	3	Yes

Table 12. Comparison between PLS-SEM and ANN analysis (Output: TAM)

	Path mean	PLS-SEM Ranking	ANN normalized relative importance (%)	ANN Ranking	Matched?
Insecurity	0.876	1	100	1	Yes
Discomfort	0.809	2	89.21	2	Yes
Optimization	0.321	3	61.08	3	Yes
Innovation	0.145	4	45.89	4	Yes

Table 13. Comparison between PLS-SEM and ANN analysis (Output: INT2)

	Path mean	PLS-SEM Ranking	ANN normalized relative importance (%)	ANN Ranking	Matched?
Expectation confirmation	0.326	1	83.09	2	No
Perceived ease of use	0.278	2	45.78	3	No
Perceived of usefulness	0.189	3	100	1	No

Tables 11, 12, and 13 compare the results of ANN analysis with the results of 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 11 (Output: INT1) service quality factors are ranked for both ANN and PLS-SEM models. However, for PLS-SEM analysis, the first and second results are ranked in order of two factors: system quality and information quality. In contrast, ANN analysis shows that the information quality factor ranks first and the system quality factor second. The ANN model measures linear and nonlinear relationships between variables with high accuracy. Table 12, with 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 13, with output: INT2, 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.

5. Discussion and Conclusion

This study, with technology acceptance theory, with technology acceptance ac-cording to ANN and PLS-SEM analysis. Input values of variables with strength for predicting input (system quality, information quality, and service quality) of the information technology model. The input variables from the engineering model (optimization, innovation, insecurity, and discomfort) and the 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. . However, there is one big difference between ANN and PLS-SEM models, it is the ANN model that gives more accurate analysis results because ANN measures linear and non-linear relationships between variables. Table 12 shows the results of in-depth analysis between the two models ANN and PLS-SEM and gives similar results. Table 12 with output: TAM, 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 of Tables 11 and 13 show that the analysis results between ANN and PLS-SEM are not uniform. Specifically, in table 11 with output: INT1, 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, however, the system quality factor and the information quality factor are ranked from 1 to 2 for the PLS-SEM model and the analysis. 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, and users are shown the importance of considerable user attention to the technical aspects of the facial gender recognition system. The results show that users have high expectations for a facial gender recognition product with high technical factors and ease of use. At the same time, the identification system also ensures ease of use and useful utility for users. Technical factors indirectly affect people's intention to continue using the facial gender recognition system and directly affect the theory of technology acceptance. However, the factors related to the information technology model (information quality, system quality, and service quality) have a direct impact on the satisfaction or intention to continue using the system. gender recognition system by the human face. Users are still afraid and not really secure when accepting the use of the gender recognition system by wearing a face mask. It is these two factors that restrain the development of a series of technology products applying facial gender recognition systems, from the business environment to technology products.

The PLS-SEM model is clearly analyzed using the importance-performance map analysis (IPMA) [29] chart to more clearly assess the relevant impact factors in the PLS-SEM model. IPMA histogram performs analysis based on two parameters, performance, and significance. Specifically, for managers, the importance factor is highly valued and the performance factor is in the range of 0 to 100. Figure 6 shows the correlation between the performance and the importance of the INT1 output factor. The IPMA analysis chart (Figure 6) shows the results related to the target structure determination in the PLS-SEM path model. The system quality factor of the information technology model directly affects customer satisfaction and indirectly on the intention to continuously use the facial gender recognition system. However, this factor has a positive impact on the user's intention to use the identification system continuously. This is one of two elements of the information technology model (system quality, information quality) that requires suppliers and manufacturers of facial gender recognition systems to think more about it. improve product quality. Specifically, improving the quality of information technology systems or digital control systems. Along with that, the good service quality factor of the product supplier applying facial gender recognition technology and 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 with the PLS-SEM model. Regarding the three elements of the information technology model (information quality, system quality and service quality), Table 4 summarizes the content values of the importance of the three factors. in the model of information technology affecting the intention to continuously use the facial gender recognition system.

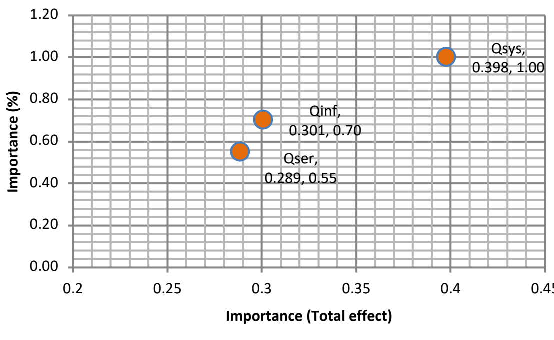

Fig. 6. The correlation between the performance and the importance of the INT1 output factor

Table 14. Summary of relative importance ranking (output: INT1)

Output: INT1	Qser	QSys	QInf
PLS-SEM	3	1	2
ANN sensitivity analysis	3	2	1
IPMA	3	1	2

Figure 7, IPMA diagram with output factor TAM, shows that the optimization factor directly affects the technology acceptance theory model (TAM) [33] and indirectly affects the satisfaction of people and the intention to continuously use the user's identification system. At the same time, the factors of innovation, insecurity, and discomfort have a relative impact on the theoretical model of technology acceptance. Table 15 briefly describes the importance of four factors (optimization, innovation, insecurity, and discomfort) of the engineering model affecting the theoretical model of technology acceptance and the correlation between the ANN analysis and the analysis results. analysis of the PLS-SEM model.

Table 15. Summary of relative importance ranking (output: TAM)

Output: TAM	Opt	Inn	Ins	Dis
PLS-SEM	1	2	3	4
ANN sensitivity analysis	1	2	3	4
IPMA	1	2	3	4

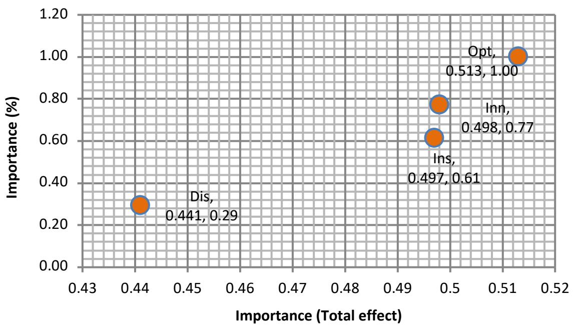

Fig. 7. The correlation between the performance and the importance of the TAM output factor

The Theoretical Technology Acceptance Model (TAM) consists of two main elements: perceived ease of use and perceived usefulness. In which, 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. Figure 8 and Table 16 show that the IPMA and ANN analysis results show the perceived usefulness factor affecting the intention to continuously use the highest recognition system.

Table 16. Summary of relative importance ranking (output: INT2)

Output: INT2	Ease	Useful	Exp
PLS-SEM	2	3	1
ANN sensitivity analysis	3	1	2
IPMA	3	1	2

ANNs can model relationships of complex linear and non-linear relationships and gives more accurate prediction results than the PLS-SEM model. This study discovered that the important factors related to the information technology model are very few for users of products using digital control technology. Specifically, the facial recognition system and contribute to the improvement of product quality for investors, equipment suppliers with the application of facial gender recognition technology in general, and devices using smart technology in private. From a theoretical point of view, very few studies accept the use of a poor-quality information technology system. Especially, for the application of information technology to electronic devices or devices with smart technology applications such as smartphones, computers in countries around the world. The education level in developing countries is still low, and the information technology and internet infrastructure are still limited.

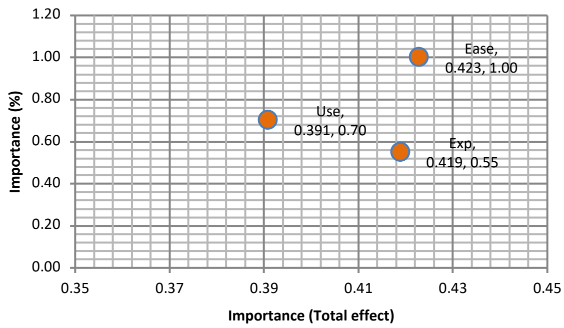

Fig. 8. The correlation between the performance and the importance of the INT2 output factor

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.

Limitation of the research topic. The data were collected in one area, Ho Chi Minh City, Vietnam. The limited point of data space is also a possible reason for our study to be less generalizable. In the future, expand the data to the whole country or across the country with a larger data set. On the other hand, the facial gender recognition system is considered a system that has been used in the present and the future. The establishment of policies and regulations governing the facial gender recognition 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. 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 facial gender recognition systems.

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Appendix A

[Optimization]
OPT1: Facial gender recognition system contributes to a better life.
OPT2: Facial gender recognition system gives people more control in life.
OPT3: Facial gender recognition system makes me more useful in my personal life.

[Innovation]
INN1: Other people come to me asking for advice on using the facial gender recognition system.
INN2: Specifically, I'm seen as a bridge between people and the facial gender recognition system.
INN3: I am always looking for and updating new technical developments such as facial gender recognition systems.

[Insecurity]
INS1: People rely too much on facial gender recognition systems to do many things for them.
INS2: Facial gender recognition system reduces interpersonal interaction.
INS3: I am not confident in doing cost tracking using the Facial Gender Recognition System.

[Discomfort]
DIS1: I received technical support from the facial gender recognition system pro-vider's consulting unit.
DIS2: Advice lines that use facial gender recognition are often not responding to what I understand.
DIS3: There is no easy and understandable manual for using a facial gender recog-nition system.

[Quality of system]
QSys1: The system response speed to knowledge sharing platforms is very fast.
QSys2: Knowledge-sharing platform performance can meet expectations.
QSys3: Performance of a shared knowledge base system meets robustness.

[Quality of information]
QInf1: The output of the knowledge sharing platform system shows high accuracy.
QInf2: Output of an information system from a knowledge-sharing platform that meets high quality in terms of content.
QInf3: The information provided by the knowledge sharing platform is easy to un-derstand.

[Quality of sercive]
QSer1: The service quality of the knowledge sharing platform exceeds expectations.
QSer2: The service quality of the knowledge-sharing platform is excellent.
QSer3: Knowledge sharing platform that provides reliable services to users.

[Perceived ease of use]
Ease1: Learning how to operate and use the facial gender recognition system was easy for me.
Ease2: Using a facial gender recognition system that is easy to understand for me.
Ease3: Clear, easy-to-use facial gender recognition system.

[Perceived of usfulness]
Use1: Using facial gender recognition system makes it easy for me to control opera-tion.
Use2: Using facial gender recognition system helps me increase efficiency in opera-tions.
Use3: The use of facial gender recognition system in daily life helps people.

[Intention to use continuously]
Int1: I plan to use facial gender recognition systems when they become widespread.
Int2: Whenever possible, I always intend to use facial gender recognition system in my daily life.
Int3: I will use the facial gender recognition system when it is legally acceptable in my place of residence or in my country.