Hybrid SEM-neural networks for predicting electronics logistics information system adoption in Thailand healthcare supply chain

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Abstract: The aim of this work is to examine the adoption of the electronics logistics information system in healthcare industry in Thailand by using structural equation modelling (SEM) approach. Neural network is then employed to test and confirm the research model. These approaches are applied to analyse the effect of all independent constructs and behavioural intention to adopt e-logistics information system by healthcare workers. Unified theory of acceptance and use of technology 2 (UTAUT2) was used to examine electronics logistics information system adoption in the hospitals. Confirmatory factor analysis (CFA) was applied to determine how well the measured variables represent the constructs. SEM was then introduced to analyse the relationship among the variables. Lastly, neural network was applied to predict the relative importance of each independent variable. The study from SEM revealed that seven potential variables of behavioural intention from UTAUT2 for the adoption of e-logistics can be compressed into six variables (performance expectancy, perceived value and support, price value, social influence and facilitating conditions, perceived ease of use and habit). Three significant variables for the e-logistics in hospital adoption in Thailand (performance expectancy, effort expectancy, and habit) are proven to be statistically significant.

Keywords: structural equation modelling; SEM; electronics logistics; e-logistics; information system; neural network; healthcare; Thailand.

Reference to this paper should be made as follows: Kunnapapdeelert, S. and Pitchayadejanant, K. (2020) 'Hybrid SEM-neural networks for predicting electronics logistics information system adoption in Thailand healthcare supply chain', *Int. J. Business Performance and Supply Chain Modelling*, Vol. 11, No. 1, pp.54–68.

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1 Introduction

Healthcare industry have been developed very fast in the last decade since people care more about their health. Medical technologies have been developed for providing the better services and treatments to the patients which causes a higher treatment cost. Various hospitals and physician practices are trying to find the way for reducing the expense while improving the service quality. Therefore, supply chain management have been adopted into the healthcare sector. Healthcare supply chain management focus on the managing supplies and delivering goods and services to the patients. It is the flow management of physical goods, medical product information and services through numerous stakeholders such as manufacturers, hospitals, logistics providers, insurance companies, purchasing staffs and other agencies to get the right healthcare service/supply items, in the right place, at the right time and in a lowest possible cost. Subsequently, numerous researchers have paid attention to the healthcare supply chain recently (Tamir at al., 2019).

Electronics logistics (e-logistics) information system in healthcare is another vital tool for supporting healthcare supply chain. In the past, information flow through paper-based which leads to the delay, error and unreliable information. The adoption of information systems in healthcare logistics system is the strategic that enhance the performance of healthcare industry. However, some of healthcare staffs might not familiar with the use of IT system and do not want to use the technology for their work. According to the literatures, there are various countries have tried to enhance the operational performance in healthcare industries by adopting IT systems to use in many sectors in healthcare supply chain (Pai and Huang, 2011; Gaardboe et al., 2017; Khamisi et al., 2019; Pennathur, 2020). The results revealed that some organisations success whereas some of them fail to adopt IT system in their organisation. Despite the use of IT system can enhance working ability of the organisation, some of the operators who have to use the new technology are fear to change their routine work and learn to use the new technology.

As Thailand is developing country couple with now is digital disruption era. Every organisations have to adopt themselves to compete with the competitors by reducing time, cost and improving the service level. The most efficient way to survive in this urge and challenge of current situation is to adopt IT systems to the supply chain management. Some of the organisation just apply IT system into the organisation without giving knowledges or ideas to the operators because it is the decision of the top management level. This would cause unsuccessful in the use of technology in the organisation. Subsequently, technology acceptance model (TAM) should be applied for examining behavioural intention to adopt e-logistics information system from hospital medical practitioners. Numerous factors are considered to be the information technology acceptance such as social influence (SI), perceived eased of use, motivation, etc. (Talukder et al., 2020; Lu et al., 2020). However, the cultural differences on the healthcare operator's perception of information technology acceptance is another issue that needed to be considered (Lin, 2014).

Further, the study of technology acceptance of Thailand healthcare industries has left to be deal with. Consequently, a powerful tool as a hybridisation of structural equation modelling – artificial neural networks (SEM-ANN) is applied to examine the relationship among performance expectancy (PE), effort expectancy (EE), SI, hedonic motivation (HM), price value (PV) and behavioural intention of electronics logistics information system adoption in the hospitals by exploring direct and indirect effects in this study. The empirical results from the study would assist to identify the suggestions for enhancing the use of e-logistics information system of hospitals in Thailand.

This work is organised as follows. Literature review of the use of information technology in healthcare industry, TAMs and neural network analysis in IT adoption for healthcare industry are described in Section 2. Section 3 explains methodology of the research. Results and discussion are presented in Section 4. Lastly, conclusions and further research are drawn in Section 5.

2 Literature review

Information and communications technology (ICT) are a very important tool for enhancing performance in many sectors not only in industrial sector but in service sector as well. Hospital information system (HIS) has been gradually introduced for automating business processes in a hospital. It could be developed for supporting several modules in the hospital (Handayani et al., 2016). HIS has been used in registration module for queuing of both inpatient and outpatient, scheduling and in emergency room. Order communication system module has been used for assisting medical staff about medical record, current patient health and support activities (results from laboratory and radiology). Further, HIS can support medical recode of patient identification, diagnosis and treatment procedure. In case of financial, HIS has been adopted for supporting calculation and preparation of bill and payment. These imply that HIS becomes an important supporting system for driving the hospital to compete with the other hospitals. Users of HIS are classified into two main classes (Ribière et al., 1999). The first class is called as internal user such as hospital managers, physicians, nurses, pharmacists, administrative staffs, laboratory staffs, and other operators in healthcare industry. Whereas, patients, their family, insurance providers, suppliers and researchers in healthcare service are considered as external user.

Later, experts classified health information technology (HIT) into three bundles as administrative HIT, clinical HIT and augmented clinical HIT (Sharma et al., 2016a). Administrative HIT is related to the administrative information flows within hospital. It composes of financial and accounting systems of hospital. This system is used for integrating hospital support functions as enterprise resource planning (ERP). It can also perform staff scheduling for hospital staff which assign work based on skill, shifts and seniority of staff. Clinical HIT is developed for enhancing patient care by collecting, testing, and processing the patient data for treating purpose which can be acquired from X-ray, CT scan, etc. This system provides faster diagnosis, more accurate treatment and better compliance to treatments specific to the patient conditions. In case of, augmented clinical HIT, this system integrates various clinical HIT systems, reports and provides decision support for caregivers.

Nowadays, there is another function in HIS called as e-logistics information system that has applied for increasing performance of the hospital especially in procurement process. It is the development of integration between information and technology and logistics support business processes that apply in various healthcare activities.

E-logistics is the use of systems, informatics tools and internet as medium for servicing logistics processes. It can cooperate with several tools such as internet portal, electronics platform, transactions system, purchasing system, electronics catalogue, data warehouse, information service, etc. (Barcik and Jakubiec, 2012; Sundar et al., 2018; Tu et al., 2018; Panova and Hongsheng, 2019). E-logistics is used for supporting many activities such as production, order processing, procurement, warehouse and distribution management to reduce operational time and cost. It also plays an important role in terms of ecology, sustainability and reverse logistics. E-logistics reduces the environmental impact when navigation systems and/or global positioning system (GPS) are used. The user can select the most efficient route for delivering goods based on optimisation software which reduce energy consumption, overall cost, and travelling time (Luić and Milić, 2015). E-procurement allows the suppliers to increase competitiveness in raw material market. Procurement processes become faster, easier, and more efficient than the traditional method by e-commerce (Toktaş-Palut et al., 2014; Senarathna et al., 2014). E-logistics combines a lot of storage functions into a single warehouse. It reduces complexity of process in warehouse while increases the effectiveness of warehouse activities. E-logistics is very useful for managing logistics activities in medical industry includes procurement, material management, and inventory management (Tung et al., 2008). The system monitors and manages inventory levels based on replenishment policy which can avoid material shortage problem. Physicians, nurses and pharmacists can examine inventory level any time that they want.

Researchers have studied on the assessment of information system adoption for healthcare industry in developed countries (Sweden, Scotland, Norway, Netherlands, Germany, England, etc.). They reported that such countries have widely adopted information system in healthcare industry. Ahmadi et al. (2015, 2017) studied HIS adoption from expert's perspective in Malaysian public hospitals by considering four different dimensions. The first dimension is technological dimension which considering relative advantages of HIS adoption (i.e., hospital operating cost reduction, patient care quality improvement, productivity of hospital staff enhancement, and time reduction), compatibility with the existing system in the hospital, complexity of HIS and security concern. The second dimension is organisational dimension. It consists of existing telecommunication and database facilities, supporting from top management level, hospital size, and financial resources. The next dimension is environmental dimension which are the pressure from competitors, the pressure form government and the support from vendor. The last dimension belongs to human dimension. This dimension considers two different views from the perceived technical competence and knowledge of staff. They found that relative advantage, compatibility, security concern, size of hospital, pressure from competitors, supporting from vendor, perceived technical, perceived technical competence and knowledge of staff affect to HIS adoption. In case of Iran, HIS has been used for a decade but it seems not be very successful from user's viewpoint. Hospital's staff does not want to use the HIS for their work because they do not know how to use HIS efficiently (Alipour et al., 2017).

TAM was firstly introduced by Davis in 1985 based on the idea of theory of reasoned action (TRA) and theory of planned behaviour (TPB) from Ajzen and Fishbein (1975) and Ajzen (1985), respectively. TAM was proven to be a model for analysing behavioural intention toward the use of information systems (Davis et al., 1989). The actual use of technology is influenced by external factors, perceived usefulness of the system, perceived ease of use, and attitude. However, TAM was accepted by the user only 10% to 50%. TAM was further extended by Venkatesh and Davis (2000) as TAM2. The model emphasises more about perceived usefulness, intention to use, and perceived ease of use in technology. TAM2 showed that the subjective norm has more direct effect on usage intention than perceived usefulness and perceived ease of used in technology. In 2003, Venkatesh et al. proposed the unified theory of use and acceptance of technology (UTAUT) for predicting the customer adoption of technology. UTAUT was developed by integrating the fragmented theory and research on individual acceptance of IT from eight existing models. Later, an extension of UTAUT, UTAUT2 was introduced for more accurately examine information technology acceptance and usage by adding PE in to the previous proposed UTAUT. Venkatesh et al. (2012) pointed out that PE, EE, SI, facilitating conditions (FC), HM, PV, and habit are affected to behavioural intention as explained below.

- *PE:* PE is the degree that individual believes that the use of information system is useful for completing their task. It will assist the individual in attaining desired performance goal (Vroom, 1964). Variable for expressing PE is perceived usefulness.
- *EE:* EE is explained as the degree of ease of the use of the IT system. It was originally proposed in TAM. Researcher found that the application which is easier to use will be more likely to be accepted by the user (Davis, 1989).
- *SI:* SI is defined as the degree of the user perceived that using information technology system can enhance the image or status of user in one's social group. It concerns intentional and unintentional efforts to change person's beliefs, attitudes or behaviour (Gass, 2015).
- *FC:* FC refers to the degree that the user believes that the organisational technical infrastructure available for supporting the use of the system (Venkatesh et al., 2003).
- *HM:* HM is the degree of pleasure that the user received from using of the information technology system. It was found to be directly affected to technology acceptance and use (Brown and Venkatesh, 2005; Childers et al., 2002).
- *PV:* Venkatesh et al. (2012) explained PV as the consumers' cognitive trade-off between benefits that user perceives from the use of technology system and the monetary cost for using such system.
- *Habit:* habit is the automated behaviour of the user from the start learning to the regular use of the technology (Venkatesh et al., 2012).

According to the concept of SEM, SEM checks linear relationship between the independent variables and dependent variables which might not be efficient enough to make decision (Sin et al., 2015). Subsequently, backpropagation neural network is applied to determine both linear and nonlinear relationships between variables from UTAUT2 and e-logistics adoption. However, the neural network is not suitable for hypothesis testing because neural network behaves like black box. Therefore, the hybridisation of SEM and neural network is developed to complement each other in this work.

Artificial neural network which generally known as neural network. It has been used in variety fields such as in engineering, logistics, medical etc. (Lolli et al., 2017; Kwon, 2017). Further, it has been successfully applied to predict the importance of IT/IS adoption factors in several areas such as mobile commerce, Facebook usage, radio frequency identification device (RFID), inter-organisational system (IOS) and mobile payment (Liébana-Cabanillas et al., 2017a; Sharma et al., 2016b; Chong et al., 2015; Chong and Bai, 2014). Neural network is the computational approach that imitate the structure and function of biological neural networks (Fu, 1995). Neural network tries to learn relationships between input and output data. It composes of three different layers: input layer, hidden layer and output layer. The learning process consists of two main phases as follows. The first phase is to train the network base on input and output dataset. Once training data are introduced into network, learning experience is kept from the difference between the actual out and trained output from the network. The difference (error value) will be decreased during the training process by adjusting the weights of the connections between layers. Training process is continued iteratively until the error value is low enough. Although several training approaches are available, the commonly used is the backpropagation. The backpropagation is a supervise leaning (Monfroglio, 1994). The network is trained to optimise the weights between neurons by minimising the prediction error. The learning process relies on a set of the inputs and outputs therefore performance of the trained network should not set to provide the best results. If the training performance is too high, the network will be overfitted and lack of generalisation.

The combination of SEM and artificial neural network has been developed for predicting technology acceptance. Hybrid structural equation modelling – artificial neural networks (SEM-ANN) was proposed to investigate the influencing factors for the user's intention to mobile learning (m-learning) adoption (Tan et al., 2014). TAM was used as a model to explain the acceptance and use of m-learning. The hypotheses were examined by SEM at the first stage. Neural network based on supervised learning was then applied to rank the importance of such significant factors obtained from SEM.

Liébana-Cabanillas et al. (2017b) predicted the most significant influencing factor to use m-payment. SEM was proposed to evaluate the significant variable that effect on mobile payment adoption. The relative influence significant predictors that obtained from SEM were then ranked by neural network. The results presented that the rank obtained from neural network provided slightly different order obtained from SEM.

3 Methodology

The purpose of this work is to examine the adoption of e-logistics information system of hospitals in Thailand by using hybrid SEM-neural networks. SEM is used for analysing the acceptance of e-logistics information system in Thailand's hospitals. Neural network is then used for confirming the results from SEM. This research study the technology acceptance in healthcare sector of Thailand. The research was conducted for four months during July to October 2017. This study was conducted in both public and private hospitals for exploring the possibility of implementing e-logistics in their operations such as procurement, inventory control, order processing, tracking of patients' record, etc. The sampling method used in this research was convenience sampling. The survey was distributed to 520 medical staffs in Thai hospitals and 371 questionnaires were returned. The survey composes of two main sections. The first sections are the questions related to demographic structure of the respondents. Another section is involved with research model includes seven independent and one dependent variables as explained in Figure 1. Five-point Likert scale was used in the questionnaire. Research model based on seven hypotheses are developed as follows.

H1 PE influences the behavioural intention to adopt e-logistics in hospital.

H2 EE influences the behavioural intention to adopt e-logistics in hospital.

H3 SI influences the behavioural intention to adopt e-logistics in hospital.

H4 Facility condition (FC) influences the behavioural intention to adopt e-logistics in hospital.

H5 HM influences the behavioural intention to adopt e-logistics in hospital.

H6 PV influences the behavioural intention to adopt e-logistics in hospital.

H7 Habit (H) influences the behavioural intention to adopt e-logistics in hospital.

Data analysis was conducted by AMOS-SPSS. The consistent of each construct in the model is tested by Cronbach's alpha. Cronbach's alpha value generally ranges from 0 to 1. Two major types of factor analysis, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were performed in the early stage. EFA was applied to:

1 explore the pattern of data

2 determine relationship between patterns

3 data reduction.

In this case Kaier-Mayer-Olkin (KMO) measurement of sampling adequacy and Bartlett's test of sphericity were used as the measurement of data appropriateness. KMO value more than 0.7 is always acceptable. KMO value in between 0.7 and 0.8 are good, value between 0.8 and 0.9 are great and the KMO value that more than 0.9 are excellent. The CFA is used to estimate the reliability and validity of the measurements. Generally, the model chi-square (χ^2), normed chi-square (CMIN/DF, χ^2/df), root mean square residual (RMR), goodness-of-fit index (GFI), adjusted goodness of fit index (AGFI), normed fit index (NFI), comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardised root mean residual (SRMR) are used to measure fit in structural equation modelling (SEM). The appropriate value of goodness of fit are represented in Table 1.

SEM was then applied to analyse the effect of all independent constructs and behavioural intention to adopt e-logistics. After that, error back-propagation neural network was applied for confirming ability of SEM in this study. Structure of neural network composes of three layers: input layer, hidden layer and output layer. Input layer involved with independent variables from UTAUT2 that was processed by SEM. Hidden layer consists of several hidden modes. Output layer of this problem is the behavioural intention of e-logistics information system adoption in Thai hospital as presented in Figure 2.

Figure 1 Research model

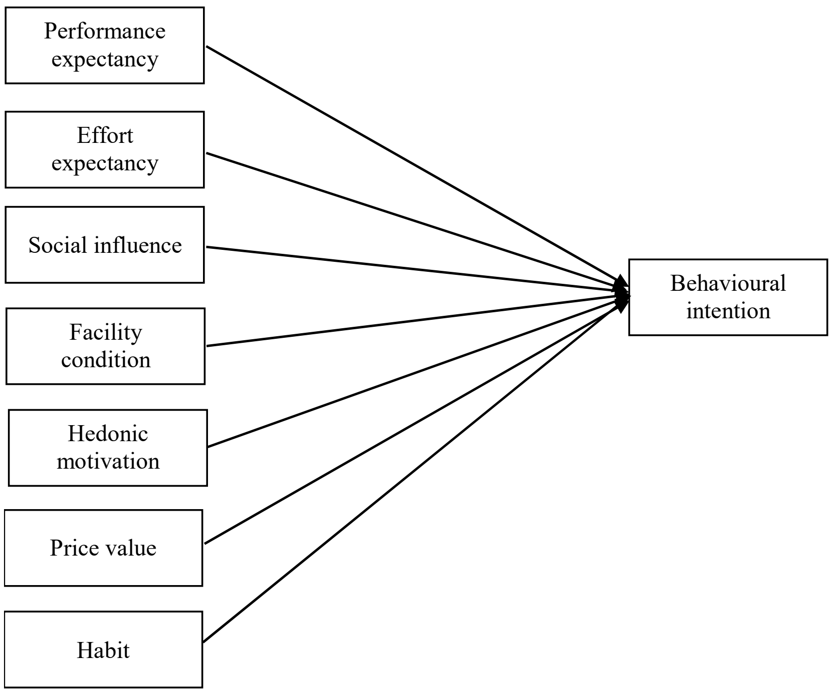
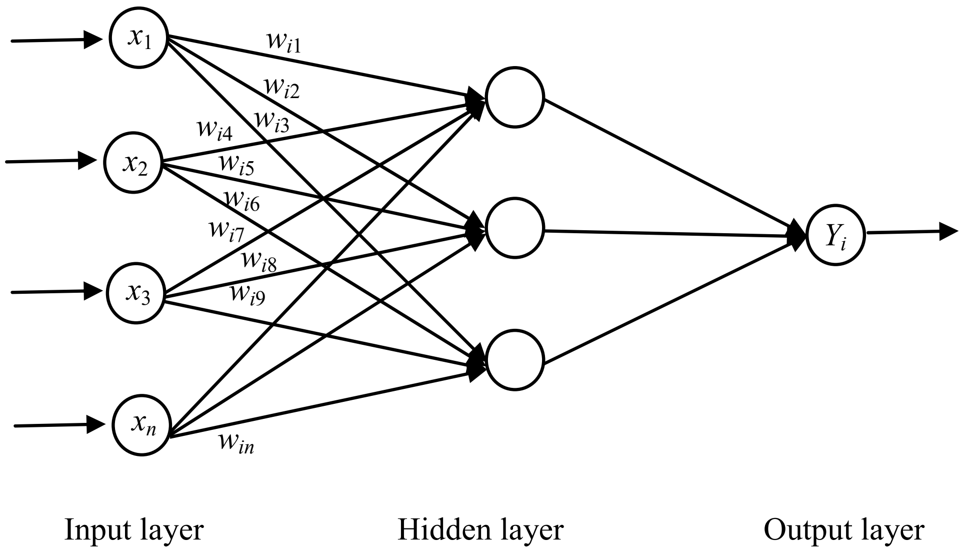


Table 1 Model fit statistics indicators and its threshold levels

Measurements	*Value*	*References*
Chi-square (χ^2)	Low chi-square relative to degrees of freedom with an insignificant value	Bollen (1989)
Normed chi-square (CMIN/DF, χ^2/df)	Less than 3	Bollen (1989)
Root mean square residual (RMR)	Less than 0.05	Kline (2005)
Goodness-of-fit index (GFI)	Greater than 0.90	Kline (2005)
Adjusted goodness of fit index (AGFI)	Greater than 0.90	Sharma et al. (2005)
Normed fit index (NFI)	Greater than 0.90	Kline (2005)
Comparative fit index (CFI)	Greater than 0.90	Hu and Bentler (1999)
Root mean square error of approximation (RMSEA)	Between 0.05 and 0.08	Browne and Cudeck (1993) and MacCallum et al. (1996)

Figure 2 Neural network structure



4 Results and discussion

The first part of the survey is the personnel details of the respondents. 117 respondents are males (31.5%) and 254 respondents are females (68.5%). Distribution of respondents according to five main age groups are 21 to 25, 26 to 30, 31 to 35, 36 to 40 and more than 40 years old. Majority (27%) of the respondents are young adult aged from 31 to 35 years. 278 (74.9%) of respondents have used e-logistics while 93 (25.1%) of respondents have never used e-logistics. Another part of the survey is seeking for the opinion regarding to the affecting factors to the adoption of e-logistics. A five-point Likert scale (score 1 indicates strongly disagree, while score 5 indicates strongly agree with the statement) was used to rate each statement of the model.

Reliability of the questionnaire was tested based on composite reliability to measure the consistent of each construct. PE attained the highest value with 0.935 while PV achieved the lowest value of 0.864. Composite reliability of each construct is in between 0.8 to 0.9 which confirms that this construct is a good construct.

Considering KMO value, the results illustrate that KMO and Bartlett's test value is 0.974 which significantly more than 0.7 and satisfactory for further analysis. Principal component analysis (PCA) is applied for data reduction. The rotated component matrix which converged in 8 iterations presented that this set of constructs can be reduced into six predictors of intention (PE, perceived value and support, PV, SI and FC, perceived ease of use and habit). The reliability test results for six new predictors of intention is presented in Table 2.

Next, the fit of the proposed model is assessed based on goodness-of-fit indices as explained below. The value of chi-square $(\chi^2_{371}) = 573.331$, and $\chi^2/df = 1.809$, $p < 0.000$ show that the model is significance. Root mean square residual (RMR) = 0.027 is less than the threshold value indicates that the model is close fit. The other fit index:

GFI = 0.902; AGFI = 0.875; NFI = 0.946; CFI = 0.975 which exceed the recommended threshold. RMSEA = 0.047 represents a good fit. These reveals that all criterion index lies in acceptable range.

Table 2 Reliability analysis

Variables	*Measurement variables*	*Factor loading*	*Composite reliability*
Performance expectancy	E-logistics is beneficial to me	0.766	0.935
	E-logistics saves my time	0.758	
	E-logistics increases the productivity	0.747	
	E-logistics make me work easily	0.739	
	E-logistics allows completing transaction faster	0.706	
Hedonic motivation	E-logistics is interesting	0.732	0.930
	E-logistics supports me	0.665	
	E-logistics is value to me	0.655	
	E-logistics is compatible	0.581	
Price value	E-logistics has the reasonable price	0.716	0.929
	E-logistics is value to money spent	0.647	
	Price of e-logistics system is suitable	0.642	
Social influence and Facilitating conditions	The other persons agree when I use e-logistics	0.695	0.921
	The other persons think that I should e-logistics	0.665	
	There is limited resource to use e-logistics	0.604	
	I have knowledge to use e-logistics	0.580	
Effort expectancy	Learning to use e-logistics is easy for me	0.733	0.887
	I do clearly understand how to use e-logistics	0.708	
	I can use e-logistics professionally	0.707	
Habit	I have to use e-logistics	0.706	0.864
	I am used to use e-logistics	0.701	
Behavioural intention	I intend to use e-logistics	0.884	0.896
	I plan to use e-logistics everyday	0.930	
	I will suggest the others to use e-logistics	0.916	

Structural equation model (SEM) was applied to test hypothesis relationship of the proposed model. As stated earlier, PCA was applied for dimension reduction. The results from PCA recommended to reduce the set of constructs into six predictors of intention (PE, perceived value and support, PV, SI and FC, perceived ease of use and habit) as explained in Table 2. The strength and significance of direct effect on six independent variables (PE, HM, PV, SI and FC, EE and habit) on behavioural intention were examined as showed in Table 3. Three out of six variables were statically significant. PE has proven to be a significant predictor of behavioural intention with the estimate value of 0.151 and *p*-value of 0.035. This shows that the respondents are willing to use e-logistics information system due to the performance that e-logistics information system provides. Hypothesis H2 was rejected due to the fact that there was not statistically significant effect of HM on behavioural intention in the model (estimates 0.192 and *p*-value > 0.05). Further, there has not been confirmed significant effect of PV on behavioural intention in the study (estimates 0.013 and *p*-value > 0.05). PV has an insignificant direct impact on the adoption of e-logistics information system (estimates –0.056 and *p*-value > 0.05). However, two variables that are found to have the strongest direct impact on e-logistics information system adoption are EE (estimates 0.013 and *p*-value < 0.299) and habit (estimates 0.425 and *p*-value < 0.05).

Table 3 Hypothesised relationship

Hypotheses	*Estimates*	*Standardised estimates*	*C.R.*	*Sig.*
H1: Performance expectancy → behavioural intention	0.151	0.071	2.108	0.035
H2: Hedonic motivation → behavioural intention	0.192	0.138	1.391	0.164
H3: Price value → behavioural intention	0.013	0.098	0.135	0.893
H4: Social influence and facilitating conditions → behavioural intention	–0.056	0.104	–0.535	0.592
H5: Effort expectancy → behavioural intention	0.299	0.063	4.708	***
H6: Habit → behavioural intention	0.425	0.081	5.227	***

Note: ***0.01 of significant.

Table 4 RMSE for the neural networks

Neural network	*Training*	*Testing*
1	0.510132	0.49155
2	0.523686	0.494343
3	0.464395	0.634339
4	0.498983	0.517586
5	0.492382	0.488023
6	0.520319	0.490438
7	0.489255	0.476978
8	0.493893	0.474397
9	0.496192	0.47782
10	0.492209	0.563499
Average	*0.498145*	*0.510897*
Standard deviation	*0.016987*	*0.05079*

Neural network was developed to ensure the performance of SEM. The input layer consists of three independent significant variables from SEM (PE, EE and habit) while the output layer consists of only one variable (behavioural intention). Sigmoid function was used as the activation function in both hidden layer and output layer. Error backpropagation was employed to train the neural network. A ten-fold cross validation was applied to avoid the overfitting of the model. Ninety percent of the data was used for training the network while the remaining 10% was used as the tested set. The accuracy of the model was measured by root mean square error (RMSE) as presented in Table 4.

Average value of RMSE from the neural network model are 0.498145 for training set and 0.510897 for testing set which are small. The results implied that the neural network performs a quite accurate prediction. The normalised importance measuring how much the value predicted by the model varies for different values of the predictors. It is the ratio of the importance of each predictor (input variables) to the highest importance value as indicated in Table 5.

Table 5 Normalised variable importance

Predictors	*Normalised importance*
Performance expectancy	0.82443843
Effort expectancy	0.88165088
Habit	1

The analysis found that habit is the most significant predictor of e-logistics adoption, followed by EE and PE, respectively.

5 Conclusions

UTAUT2 was applied to examine the predictors of e-logistics adoption. Seven potential predictors of behavioural intention (i.e., PE, EE, SI, FC, HM, PV, and habit) for the adoption of e-logistics in Thailand hospital tested. The study from SEM found that seven potential variables can be reduced into six variables such as PE, HM, PV, SI and FC, EE and habit. Three significant variables for the e-logistics in hospital adoption (PE, EE, and habit) are proven to be statistically significant. In contrast, no significant effect of HM, PV, and SI and FC on behavioural intention was confirmed in this study.

The backpropagation neural network was employed to examine the research model to improve the understanding of consumer technology adoption decisions. The results from neural network illustrated that habit, PE, and EE are the important factor for the adoption of e-logistics in Thailand hospital. This research is useful for the e-logistics system providers and researchers to understand customer behaviour from the perspective of Thai consumers.

There are three limitations in this study. First, the data used in this study is collected only in Thailand, therefore it would be useful to conduct the future research to other countries and compare the preference of various countries. Secondly, it would be very interesting to compare each independent variable with different demographic groups. Thirdly, the model would be stronger to add more independent variable such as perceived security/risk into the model.

Acknowledgements

This work was fully supported by the Burapha University International College, for providing recommendations which helped to improve this study and granting financial support.

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