Evaluating the Behavioral Intention to Use E-Government Services from Malaysian's Perspective in Kedah State of Malaysia

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Abstract

Recognizing the importance of ICT, e-Government initiatives are rising through public organizations and public administration all over the world. Malaysia as a developing country had started implementing e-Government to improve the public services for the people. Unfortunately, public acceptance and usage towards e-Government are still very limited in most developing countries. The main purpose of this study is to investigate citizen adoption of e-government services in the northern region of Malaysia. Importantly, this study aims to develop a conceptual framework that is based on previous literature on the Unified Theory of Acceptance and Use of Technology (UTAUT) model, by examining the relationships between four factors (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) and Citizen adoption of e-Government services. A self-administered questionnaire was used to obtain data from 22 Malaysian citizens in the state of Kedah, Malaysia, randomly. The findings indicate that Effort expectancy, Social influence and Facilitating conditions are the significant predictors of the Malaysian intention to use an e-Government services, while Performance Expectancy is proven to be an insignificant predictor for the Malaysian's intention to use an e-Government services. The study has made contributions to the body of knowledge at academic and practical levels as an important exploratory study that was conducted in the context of Malaysia, a country which aims to be a developed country by 2020. In addition, this study provides some valuable insights into the adoption of e-Government in Malaysian context which could help government agencies to improve the effectiveness of their services.

Keywords: e-Government; Behavioral intention; Northern region; Malaysia.

1. Introduction

In today's fast globalizing world economy, governments all over the world are recognizing the importance of Information and Communications Technology (ICT) in development. An increasing number of Electronic Government (e-Government) initiatives are being employed to improve the delivery of public services to the people, and to tap the potential synergy from the interaction between new technologies, an educated population and an enabling environment for the attainment of knowledge-based economies (Akman *et al.*, 2005), (Ebrahim and Irani, 2005), (Carter and Bélanger, 2005).

The waves of e-Government are rising through public organizations and public administration across the world. More and more governments are using ICT, especially Internet or web-based network, to provide services between government agencies and citizens, businesses, employees and other non-governmental agencies (Ndou, 2004). The e-Government is the use of ICT and its implementation by government to deliver accessible services to public. It is important for the government to ensure that the public can adopt and adapt to the system to ensure high accessibility. Thus, this study focuses on the key factors that influence the intentional behavior to use e-Government.

Various researchers have offered different definitions to explain the concept of e-Government (Seifert and Petersen, 2002). There is no universally accepted definition of the e-Government concept. Weerakkody and Dhillon (2008) opined that the focus of e-Government centers on technology, citizens, related businesses, and government processes. Horton *et al.* (2001) believed that, e-Government uses technology, particularly the Internet, for the delivery of government information and services to citizens, businesses, government employees, and other agencies.

The most significant characteristics or indicator of any successful e-Government is its quality and accessibility. Acceptance and usage of e-Government are still very limited in most developing countries (Banerjee and Chau, 2004). This, in a way, has a dampening effect to the progressiveness of the e-Government implementation (Bertot and Paul, 2008), which is seen to be one of the best alternatives in improving government services (Jaeger and Paul,

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2003), (Bekkers, 2003). Therefore, the low rates of adoption are the issue and challenges that hinder the effectiveness of e-Government services provided.

This research was conducted to study about the intention to use e-Government services from a Malaysian's perspective on the Kedah state of Malaysia. Since its implementation in 2004, the citizen's adoption of e-Government services are still less than satisfactory (Abdullah *et al.*, 2015). Thus, this study was aimed to identify factors that influence the behavioral intention of e-Government in order to have a better understanding of the link between service delivery and usage.

Theoretical framework in Figure 1 shows the independent variables, namely factors that influence adoption of e-Government services. Together with the figure is the dependent variable, which is the behavioral intention to use e-Government. There have been various theoretical models to explain the concept of e-Government. However, this study adopts the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh *et al.*, 2003) as it is more relevant to this research. UTAUT model built upon and extends beyond the well-established Technology Acceptance Model (TAM) (Davis, 1989), (Davis *et al.*, 1989). Venkatesh *et al.* (2003) have proposed a more comprehensive model, Unified Theory of Acceptance and Use of Technology (UTAUT) model which unified the various model of information technology acceptance that integrated the elements of eight prominent models, namely Theory of Reasoned Action (TRA) (Fishbein *et al.*, 1977), Technology Acceptance Model (TAM) (Davis, 1989), (Davis *et al.*, 1989), Motivational Model (MM) (Davis *et al.*, 1989), as cited in Venkatesh *et al.* (2003), Theory of Planned Behaviour (TPB) (Ajzen, 1991), Combined TAM-TPB, Model of Personnel Computer (PC) Utilization (MPCU) (Thompson *et al.*, 1991), Innovation Diffusion Theory (IDT) (Rogers, 1995), and Social Cognitive Theory (SCT) (Bandura, 2009).

**Figure-1.** Theoretical Framework of the adoption of e-Government services
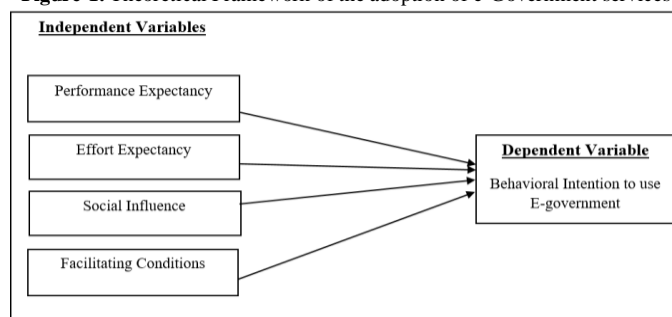
Behavioral intention is defined as a customer's intention to adopt and make use of a certain tool in the future (Ajzen, 1991), (Venkatesh *et al.*, 2003). According to Bandura (2009) the majority of technology adoption researches have utilized behavior intention to predict technology adoption. Additionally, Ajzen (1991) suggested that behavioral intention is counted to have a direct influence on adoption. The measurement of behavioral intention includes the intention, and predicted use of e-Government services.

2. Methodology

A total of 22 samples were collected from self administered quesstionnaire. Although the sample is considered small, but in relation to the variance explained it is reliable.

For the normality of data, the test of Shipiro Wilk was conducted as being suitbale for testing normality when the sample size is 30 or less. The value of $p=0.48$ was obatained which explains that the data is normally distrubuted as null hypotheses is rejeccted.

Futhermore, ai test of sample size was conducted using Power Analysis.
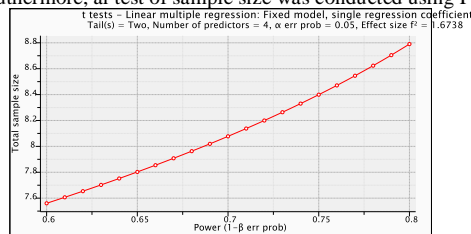
The plot of power analysis shows consistant value points as the power of 0.8 has been achieved with 9 samples, therefore with such high effect size, it acn be concluded that given the normal data and the power analysis, the small sample size does not pose threat to the consistency to results in the future repitation of the study.

The small numbers of respondents were used for the pilot study of this research. The data was then analysed using smart PLS (version 2.0) software to identifiy the relationship between the variables, as suggested by Ringle *et*

al. (2010). PLS has a number of advantages over other forms of analysis based on the particular objectives of this study, the nature of the data used for the study, and the number of samples used in it.

In addition, PLS is appropriate for this research as it can handle constructs with only a few indicator items, as few as two or even one (Hair *et al.*, 2011). It is also less restrictive in its assumptions about the normal distribution of the data (Hair *et al.*, 2011), which is important in this study as normally distributed data exhibit predictable traits and probabilities while, in practice, and specially in social sciences, we are usually confronted with data that is not normal. Thus, it can not be analyzed by general SEM tools that are based on the normal distribution. It is also more appropriate when there are small sample sizes (Chin, 2010), as in the case of this study as traditional co variance based SEM tools require minimum of 200 sets of data, while this study obtained a data set of 22 respondents. Based on these criteria, PLS was selected as the most appropriate choice for analysis.

PLS approach was chosen for its advantages over the covariance approach. The advantages of this soft-modeling approach include theoretical conditions, measurement conditions, distributional considerations, and practical considerations (Chin and Peter, 1999). The PLS approach matches the researcher's prediction-oriented objective, does not require normal data distribution, and accommodates small sample sizes (25). Furthermore, the goal of PLS is to obtain determinate values for latent variables for predictive purposes and minimize the variance of all dependent variables. PLS creates latent variable component scores using the weighted sum of indicators (Cohen, 1988).

3. Results and Discussion

Assessment of PLS models typically follows a two step process. The first step examines the measurement model and the second the structural model (Hair *et al.*, 2011). In an attempt to refine the model, the item loadings were analyzed and item loadings less than the thresholds of 0.7 were deleted, step wise. As the sample size is low with high power analysis, the significant level is set at 0.1 that is 90 percent reliablity.The quality criteria, convergent validy and discriminant validity are shown in Table 1 and Table 2.

Table-1. Convergent Validity and Quality Criteria

	AVE	Composite Reliability	R Square	Cronbach Alpha	Communality	Redundancy
Behavioral Intention	0.81	0.93	0.63	0.88	0.81	0.163213
Effort Expectancy	0.78	0.92		0.86	0.78	
Facilitating Conditions	0.69	0.90		0.85	0.69	
Performance Expectancy	0.68	0.86		0.77	0.68	
Social Influence	0.64	0.84		0.75	0.64	

It is shown that the average variance extracted (AVE) for all the constructs in the model meet the minimum of 0.5 value. Construct reliability assessment routinely, also focuses more on composite reliability as an estimate of a construct's internal consistency. Unlike Cronbach's alpha, composite reliability does not assume that all indicators are equally reliable, making it more suitable for PLS‑SEM, which prioritizes indicators according to their reliability during model estimation. Composite reliability values of 0.60 to 0.70 in exploratory research and values from 0.70 to 0.90 in more advanced stages of research are regarded as satisfactory (Nunnally and Bernstein, 1994), whereas values below 0.60 indicate a lack of reliability (Hair *et al.*, 2011).

The composite reliability is above 0.7 which shows the reliability and quality of the model is satisfactory. R^2 value of 0.63 exceeds the large effect size suggested by Cohen (1988), it also shows that the 63 percent of the variance is explained by the model.

Table-2. Discriminant Validity

|	Behavioral Intention	Effort Expectancy	Facilitating Conditions	Performance Expectancy	Social Influence
Behavioral Intention	0.90				
Effort Expectancy	0.55	0.89			
Facilitating Conditions	0.59	0.21	0.83		
Performance Expectancy	0.46	0.39	0.30	0.82	
Social Influence	0.51	0.54	0.07	0.40	0.80

Discriminant validity is the extent to which each construct is truly distinct from the other constructs in the model. The discriminant validity of all of the constructs was reviewed.

Discriminant validity is tested through exploration of the average variance shared between a construct and its measures (AVE), Fornell and Larcker (1981) recommend values higher than 0.50 with each element in the primary diagonal to be always higher than off-diagonal elements in their related row and column. The pattern supports over all discriminant validity, as the components in the main diagonal are higher than the corresponding off-diagonal components in their equivalent row and column (Halawi and McCarthy, 2008).

A test of discriminant validity is that the AVE of each latent construct should be higher than the construct's highest squared correlation with any other latent construct in the model (Hair *et al.*, 2011), (Chin, 2010). Comparing the AVE of a constructs with that construct's squared correlation with the other latent variables shows that the AVE is higher for all constructs. Therefore the model's latent constructs display discriminant validity.

As for discriminant validity, the model shows that all the constructs are of higher value (as showed in diagonal) meeting the (Fornell and Larcker, 1981) criteria. The path coefficients and the item loadings are shown in Figure 2.

The primary evaluation criteria for the structural model in PLS are the R^2 measures of the dependent or endogenous variables, and the level and significance of the path coefficients (Hair *et al.*, 2011). Since the R^2 explains the variance in the endogenous latent variable, the higher the R^2 the more the variance is explained (Chin, 2010). The path coefficients (Figure 2) in a PLS model are similar to the standardized beta coefficients in a regression analysis (Hair *et al.*, 2011), while strong path weights are indicators of relationships both positive and negative in a PLS model, the significance of the path coefficient must be analyzed through t-tests.

Figure-2. Item Loadings and Model Quality
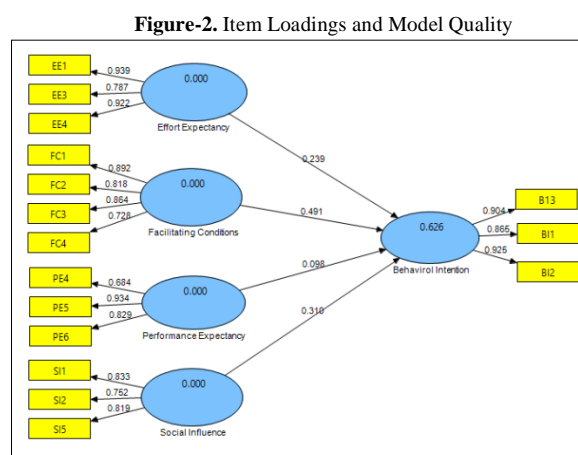
The structural model gives information on how does the theoretical model predicts the hypothesized paths (Halawi and McCarthy, 2008). Smart PLS provides the t-values for each construct in the model and the path coefficients (β).

Since PLS does not assume that data are normally distributed, Smart PLS uses a non-parametric bootstrapping technique to obtain standard errors for hypothesis testing, and for analyzing the significance of the paths (Chin, 2010). Bootstrapping involves taking repeated random samplings of the data with replacement from the original sample to create a bootstrap sample. This involves creating a pre-specified number of bootstrap samples (5,000 in this case) as suggested by Kock (2014). The PLS algorithm estimates the results from each sample, and then creates an empirical sampling distribution for each path. The bootstrapped distribution's standard error is then used in the place of sample distribution (Hair *et al.*, 2011). The number of resample of 5,000 (i.e., number of bootstrap samples) should be large enough to generate estimates that are stable, as recommended by Preacher and Hayes (2008), the t-statistics of the paths were examined. The significance of each t-statistic was then calculated (Chin, 2010). The results are shown in Table 3 and Figure 3.

Table-3. Hypotheses Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STERR|)
Effort Expectancy -> Behavioral Intention	0.24	0.25	0.15	0.15	1.65
Facilitating Conditions -> Behavioral Intention	0.49	0.45	0.12	0.12	4.09

Performance Expectancy -> Behavioral Intention	0.10	0.12	0.16	0.16	0.60
Social Influence -> Behavioral Intention	0.31	0.30	0.15	0.15	2.08

Figure-3. Model Test
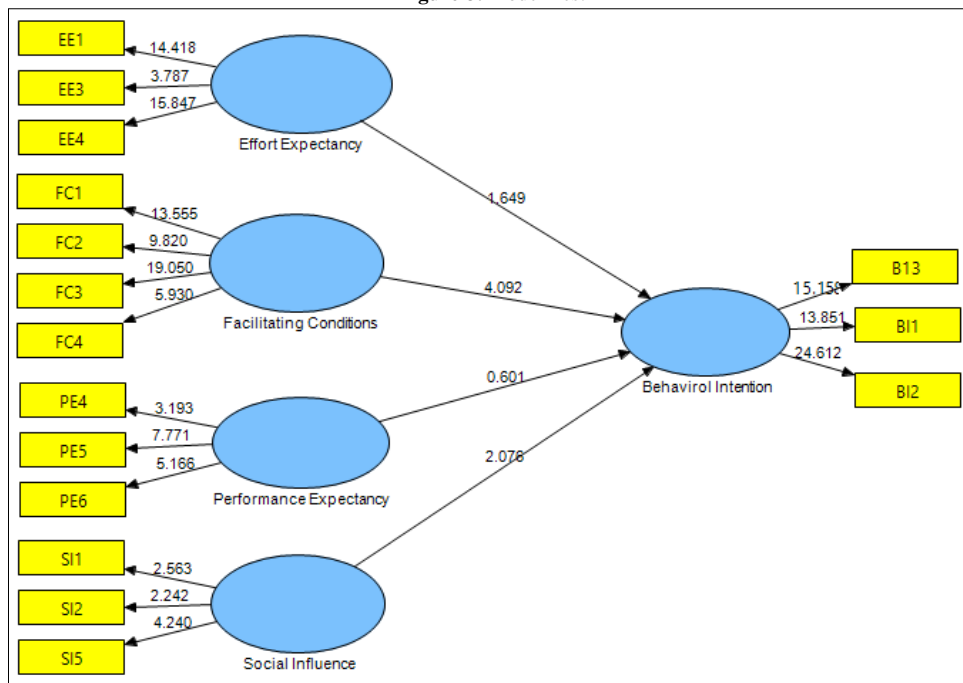
The results show the relationship between Performance Expectancy and Behavioral Intention to be non-significant which means that people have certain set expectations for such behavior and it does not contribute towards the overall behavioral intention with the value of 0.60, this area need to be improved further.

Furthermore, the Effort expectancy as a contributing factor to the behavioral intention is significant at 90% with the value of 1.65 (two-tailed) while Social influence and facilitating conditions are significant at the levels of 95% and 99% respectively.

Another purpose of this research was to arrive at a predictive model of behavioral Intention by conceptualizing and modelling the identified antecedents. The predictive value of a PLS model can be ascertained by using the Stone-Geisser's Q2, which analyzes the predictive value of endogenous latent constructs indicators (Hair *et al.*, 2011). The Q2 value is obtained by using a blindfolding technique in PLS that omits a data point in every pre-determined number of observations, and then uses the resulting estimate to predict the omitted case (Chin, 2010). In general, the pre-determined number of the omitted case (d) is an integer between three and 10, and should not divide evenly into the total number of cases. In this analysis, d=6, as the total sample obtained is 22, and the dependent endogenous construct was analyzed. The result of 0.42 Cross-validated Redundancy shows that the model has very high predictive relevance as Q2 value which is greater than zero indicates the exogenous variables have predictive relevance for the endogenous variable under consideration (Hair *et al.*, 2011).

4. Conclusion

This pilot study was aimed to evaluate the intention to use e-Government services from Malaysian's perspective in Kedah state of Malaysia. Adapting the Unified Theory of Acceptance and Use of Technology (UTAUT) model, this study analyzed four factors as independent variable, which are Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, and Behavioral Intention to use e-Government as the dependent variable.

The analysis showed that the relationship between Performance Expectancy and Behavioral Intention is not significant which means that people have certain set expectations for such behavior and it does not contribute towards the overall behavioral intention. In contrary, the Effort expectancy, Social influence and Facilitating conditions as contributing factors to the behavioral intention are significant.

The limitation of study is the small sample size that was gathered during the data collection, since this study is still at the initial stage. The study might further be continued to get more respondents to get the appropriate figure that represents the intention to use e-Government services in the Northern region of Malaysia. A larger number of

sample size will be advantageous in terms of giving more significant perspective of the intention to use e-Government services in the rural area such as Kedah, Malaysia.

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