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FACTORS INFLUENCING INTENTION TO USE E-LEARNING BY AGRICULTURAL EXTENSION AGENTS IN MALAYSIA

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ABSTRACT

The application of e-learning has extended beyond the traditional educational establishments to various other areas including agricultural sector. In agricultural sector, extension services are perhaps the key beneficiary of e-learning, being in the unique position as an intermediary between agricultural specialists and farmers. Hence the objective of this study was to investigate the relationship between attitude, subjective norm, perceived behavioral control, management support and training; and the intention to use e-learning technology among agricultural extension agents in Malaysian agricultural sector. This quantitative study was based on Theory of Planned Behavior with management support and training as additional constructs. While there were many studies that investigated factors affecting intention to use e-learning in educational institutions, there were limited studies of the same in the context of extension agents in agriculture setting. The results showed that all of the hypotheses developed by the previous authors were supported by the study, and further revealed that management support is the most important determinant of agricultural extension agent's intention to use e-learning, followed by attitude. Finally, the implications of this study were discussed, and further research directions were proposed.

Keywords: *acceptance, agriculture, e-learning, extension agent. theory of planned behavior*

INTRODUCTION

The ever-growing innovation of information communication technology (ICT) has revolutionized the traditional classroom-type face-to-face approach of education and training into electronic learning or e-learning. E-learning is defined as self-study or instructor-led training delivered on a digital device of which the contents and delivery techniques are designed to support individual learning or organizational performance (Clark & Mayer, 2011). The use of e-learning which is traditionally known for its utilization in educational institutions has extended to numerous corporate enterprises and public organizations (Hashim & Tasir, 2014) including agricultural agencies. In agricultural sector, agricultural extension services may benefit most from e-learning because of their role as go-between agricultural researchers and specialists and farmers (Ali & Kumar, 2011). E-learning is increasingly being considered as a feasible approach to help in the development of agriculture education to deliver information and knowledge directly and indirectly to farmers and knowledge intermediaries (such as extension agents) respectively (Agarwal & Kumar, 2013).

STATEMENT OF PROBLEM

According to Yunus and Salim (2013), studies on e-learning in Malaysia were more focused on certain private organizations and institutions of higher learning and there was no comprehensive study to evaluate e-learning in the Malaysian public sector. This finding is further confirmed by Ahmadpour, Mirdamadi, Hosseini and Chizari (2010) who argue that the adoption of e-learning for agricultural development in developing countries is still in the early phases of adoption and has been slow to take off. Extension agents are key actors in conducting an effective agricultural extension education and training therefore, understanding extension agents' attitudes towards the use of technology such as e-learning is important (Afzal, Al-Subaiee, & Mirza, 2016). The findings of the past research have pointed out varying factors that influence e-learning acceptance therefore, it is necessary to have an in-depth study of those factors that influence e-learning acceptance in the context of Malaysian agricultural industry. Hence, this study attempted to achieve the following objectives:

- To develop a framework on e-learning acceptance.
- To investigate the impact of attitude beliefs, subjective norms, perceived behavioral controls, management support and training on intention for e-learning acceptance.

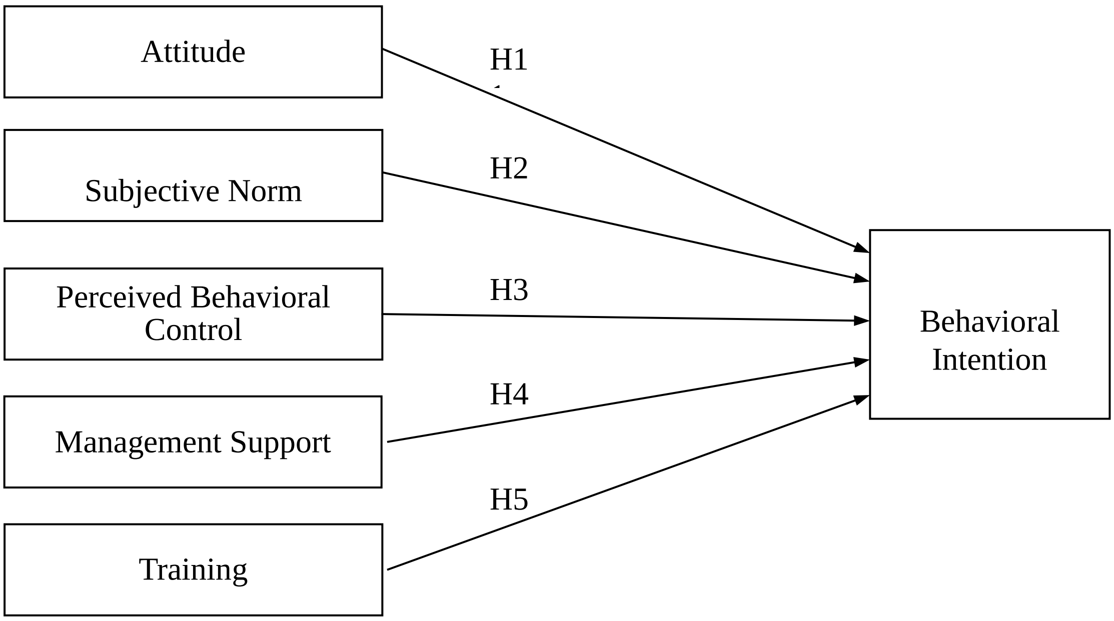
LITERATURE REVIEW

Advances in technology and the interrelation of ICT with educational settings have accelerated the growth of e-learning and fundamentally changed the way of education and learning. The rapid growth of ICT and increasing computer knowledge of the population have led to the usage of many learning and teaching innovative technologies such as e-learning (Vyas & Nirban, 2014). Digital transmission of contents for the purpose of learning and knowledge-seeking known as e-learning is increasingly becoming common workplace learning (Brown & Charlier, 2013). Organizations across the industries time and again have exploited e-learning system to facilitate employee development to sustain organizational competitiveness as e-learning has the capability to deliver knowledge and information to individuals (Yoo & Huang, 2015).

THEORETICAL BACKGROUND

Chu and Chen (2015) noted that researches related to behavioral intention for technology acceptance have been developed around the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Technology Acceptance Model (TAM) (Davis, 1989) and Theory of Planned Behavior (TPB) (Ajzen, 1991). Taylor and Todd (1995a) argue that TPB has been proven to have similar predictive powers as TAM for technology adoption. TAM puts greater emphasis on technology features rather than social influences for examining technology adoption intention. In this study about e-learning acceptance by workplace employees, unlike an individual application it usually involves interaction with trainers and fellow colleagues in the organization. Thus, social influences should not be ignored as e-learning includes interpersonal interactions (Chu & Chen, 2015).

As an antecedent, attitude is linked to behavioral intention as individual forms psychological intentions to perform behaviors toward which they have positive feeling (Ndubisi, 2004). Perceived behavioral control refers to the perception that an individual has the ability, opportunities and resources to perform a certain behavior (Cheng & Huang, 2013). Subjective norm implies individual's wish to act according to the thought or action of the important referent others such as friends and family (Pantano & Di Pietro, 2012). Subjective norms have been observed to be more important prior to, or in the early stages of implementation when users have limited direct experience from which to develop the attitudes towards the innovation (Taylor & Todd, 1995a).



Adapted from Theory of Planned Behavior

Figure 1
Research framework of behavioral intention to e-learning acceptance

Additionally, this study extended the TPB to include two important factors i.e. management support and training. Management support imposes positive effect on acceptance of technology and creates a more conducive environment for information system success thus absence or lack of management support becomes a hindrance in developing, planning and implementing technology initiatives (Al-Haderi, 2014). Frequently examined in past literature, training is a key intervention for implementation of e-learning in developing countries and is one of the top five influential factors that impact e-learning success in developing countries (Bhuasiri, Xaymoungkhoun, Zo, Rho, & Ciganek, 2012; Lee, 2008).

Based on the research framework as illustrated in Figure 1, the hypotheses are postulated as follow:

H1: Attitude has a positive relationship with behavioral intention to e-learning acceptance.
H2: Subjective norm has a positive relationship with behavioral intention to e-learning acceptance.
H3: Perceived behavioral control has a positive relationship with behavioral intention to e-learning acceptance.
H4: Management support has a positive relationship with behavioral intention to e-learning acceptance.
H5: Training has a positive relationship with behavioral intention to e-learning acceptance.

RESEARCH METHODOLOGY

Sampling and data collection

The unit of analysis for this study is individual i.e. agricultural extension agent (AEA) who takes the role of an intermediary for information and knowledge exchange between agricultural specialists and farmers. Sampling frame is as per the list of AEAs from the Department of Agriculture Headquarters in Administrative Capital Putrajaya, Malaysia. The total population size is 559. Cross-sectional random sampling technique was adopted as this method provides better generalizability and to keep bias at the minimum (Sekaran, 2003).

Measurement scale

A survey instrument was developed and pretested by senior executive of extension services at the state agriculture department and academicians. A seven-point Likert scale was used in this study to indicate the degree of agreement for each criterion, with 7 (strongly agree) as the maximum, 4 (neutral) and 1(strongly disagree) as the minimum. The researcher personally administered the data collection by travelling to each state according to the AEA's training schedule. Questionnaires were self-administered i.e. delivered personally to the respondents. A total of 322 questionnaires were extended to the respondents and yielded 322 responses. A total of 53 responses were not usable due to outliers (extreme responses), incomplete and straight-lining responses leaving 269 responses for further analysis.

RESULTS

The Partial Least Squares (PLS) analysis technique was adopted to analyze the research model using the SmartPLS 3 software (Ringle, Wende, & Becker, 2015). As recommended by (Anderson & Gerbing, 1988), two-stage analytical procedures was performed i.e. firstly testing the measurement model to assess the validity and reliability of the measures and secondly the examination of the structural model for assessment of the hypothesized relationships.

Assessment of measurement model

Assessment of measurement model involves processes to establish internal consistency reliability, convergent validity and discriminant validity of the model. Measurement model assessment was performed using PLS algorithm analysis. According to (Hair, Anderson, Tatham, & Black, 1998), Cronbach's alphas and composite reliability statistics must be above 0.7 and AVE must be above 0.5 in order for the scale's reliability to be established. Factor loadings and average variance extracted (AVE) are the two common measures to establish convergent validity with the threshold of 0.70 and 0.50 respectively. Item MS4 and PBC2 were removed from the model as their respective factor loading was less than 0.70. The result as depicted in Table 1 shows that the values of Cronbach's alpha, composite reliability, factor loadings and AVE for all the constructs exceeded the threshold values indicating the establishment of internal consistency reliability and convergent validity.

Table 1

Cronbach's alpha, factor loadings, composite reliability and average variance extracted

Construct	Cronbach's Alpha	Factor Loadings	Composite Reliability	Average Variance Extracted (AVE)
ATT	0.923	0.873 - 0.931	0.946	0.813
BI	0.736	0.702 - 0.777	0.832	0.553
MS	0.947	0.847 - 0.890	0.956	0.757
PBC	0.873	0.771 - 0.892	0.913	0.726
SN	0.932	0.895 - 0.928	0.952	0.831
TRNG	0.948	0.802 - 0.893	0.957	0.735

ATT: Attitude, BI: Behavioral intention, MS: Management support, PBC: Perceived Behavioral Control, SN: Subjective Norm, TRNG: Training.

Table 2

Fornell-Larcker Criterion

Construct	ATT	BI	MS	PBC	SN	TRNG
ATT	**0.902**					
BI	0.619	**0.744**				
MS	0.406	0.706	**0.870**			
PBC	0.477	0.643	0.549	**0.852**		
SN	0.519	0.612	0.553	0.521	**0.912**	
TRNG	0.348	0.566	0.572	0.407	0.429	**0.857**

To establish discriminant validity, two measures are presented namely the Fornell-Larcker criterion (Fornell & Larker, 1981) and Heterotrait-monotrait (HTMT) (Henseler, Ringle, & Sarstedt, 2014). Fornell-Larcker criterion states that the square root of the AVE of each construct should be higher than its highest correlation with any other construct in the model. The Fornell-Larcker criterions for all the constructs exceeded the required threshold as depicted in Table 2. Table 3 shows the HTMT result that shows all values for each construct was below the threshold value of 0.85 (Kline, 2011). As HTMT detects discriminant validity issues reliably, it is concluded that the discriminant validity has been established.

Assessment of structural model

Assessment of structural model involves assessing collinearity issues, significance and relevance of the relationships (path coefficients), level of predictive accuracy (R^2), effect size (f^2) and predictive relevance (Q^2). Collinearity assessment, path

Table 3
Heterotrait-Monotrait (HTMT)

Construct	ATT	BI	MS	PBC	SN
ATT					
BI	0.765				
MS	0.435	0.785			
PBC	0.531	0.776	0.605		
SN	0.559	0.728	0.591	0.578	
TRNG	0.371	0.654	0.604	0.446	0.454

coefficient, R^2 and f^2 values were obtained by performing PLS algorithm analysis while Q^2 value was obtained by using PLS blindfolding procedure. Table 4 shows the collinearity assessment result which the VIF value of predictor constructs are below 5.0, indicating no collinearity issue among the predictor variables.

Table 4
Results of the structural model analysis

Hypothesis	Relationship	Std Beta	VIF	t-value	Decision	R^2	f^2	Q^2
H1	ATT → BI	0.273	1.505	5.074	Supported*		0.161	
H2	SN → BI	0.114	1.791	2.062	Supported**		0.024	
H3	PBC → BI	0.212	1.692	4.769	Supported*	0.690	0.086	0.352
H4	TRNG → BI	0.145	1.550	3.381	Supported*		0.044	
H5	MS → BI	0.332	1.976	5.563	Supported*		0.181	

*: $p < 0.01$, **: $p < 0.05$

Evaluation of R^2, standardized beta and the corresponding t-values was obtained by running bootstrap procedure with 5000 subsamples. The R^2 value ranges from 0 to 1 with higher levels indicating higher levels of predictive accuracy. As a rule of thumb, R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables can be described as substantial, moderate, or weak respectively (Henseler, Ringle, & Sinkovics, 2009). Examining the antecedents to Behavioral Intention i.e. Attitude ($\beta = 0.273$, $p < 0.01$), Subjective Norm ($\beta = 0.114$, $p < 0.05$), Perceived Behavioral Control ($\beta = 0.212$, $p < 0.01$), Training ($\beta = 0.145$, $p < 0.01$) and Management Support ($\beta = 0.332$, $p < 0.01$), together explain 69% of the variance in Behavioral Intention. Management Support was the strongest predictor followed by Attitude, Perceived Behavioral Control, Training and Subjective Norm, hence giving support to the postulated hypotheses H1, H2, H3, H4 and H5 of this study. On the other hand, the R^2 value of 0.690 indicated moderate level of predictive accuracy. For f^2 effect size, the values of 0.02, 0.15, and 0.35 represent small, medium, and large effects respectively (Cohen, 1988) of the exogenous latent variable. As depicted in Table 4, the f^2 value of 0.181 and 0.161 for Management Support and Attitude respectively indicated medium effect sizes while the f^2 value of 0.086, 0.044 and 0.024 for Perceived Behavioral Control, Training and Subjective Norm respectively indicated small effect sizes. The predictive relevance of the model is measured by Q^2 value (Geisser, 1974; Stone, 1974) which was obtained by using blindfolding procedure. Table 4 shows that the Q^2 value for the reflective endogenous latent variable Behavioral Intention is 0.352, larger than zero thus suggesting that the model has sufficient predictive relevance.

DISCUSSION AND IMPLICATIONS

As predicted, all three constructs of the TPB i.e. attitude, subjective norm and perceived behavioral control positively related to intention to accept e-learning confirming the findings from previous study (Lin, Lu, & Liu, 2013; Sawang, Sun, & Salim, 2014). Similarly management support and training also indicated positive relationship with intention. The findings of this study imply that the readiness of AEAs in accepting e-learning is driven primarily by their perception of having the management support toward using the new technology hence testifying to the autonomy of decision makers in top-down organizational structure which is typical in public sector (Shiue, 2007). A research model of e-learning acceptance based on TPB was developed and successfully proven that the model holds true at a different time, place, researchers and subjects of study. In addition, we have also extended the analysis of this study to include more diagnostics such as effect sizes and predictive relevance which mostly were not reported in the earlier study.

In this study it was found that management support and attitude have the most significant positive relationship with intention. Management must create the impression upon the users that e-learning is fully supported by the management to ensure continued and sustained interest among the users. According to Taylor and Todd (1995b), the antecedents of attitude include competency, perception of usefulness and ease of use of the new technology hence higher authority or decision-makers can take some steps to focus in this aspect by reskilling the competency and providing the necessary information and awareness related to the benefits and advantages of e-learning to the AEAs to elevate their intention to use this new technology. Perceived behavioral control also indicated strong predictive capability to behavioral intention to use e-learning suggesting that beside management support, the availability of resources and technical support will certainly influence the acceptance of new technology such as e-learning. Training in addition certainly helps to increase competency and reduce the barrier to e-learning acceptance.

Limitations and suggestions for future research

The research sample this study only represented the perspective of AEAs which could result in potential bias and limit the generalization capability. Hence future studies should consider users from other areas such as agriculture research and training or other government agencies and private organizations in order to capture more generalizable finding. Moreover, this study captured only AEAs' intention to accept e-learning in lieu of actual behavior of acceptance although intention is regarded as a reasonable proxy for actual behavior (Venkatesh & Davis, 2000). At the point of investigation, the agriculture department has yet to develop e-learning system for AEAs as such in future, if e-learning is implemented, it would be worthwhile to examine how AEAs' evaluations of e-learning before and after using e-learning.

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