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Factors Influencing Behavioural Intention of Farmers to Use E-Learning Module on Climate-Smart Horticulture in Arunachal Pradesh

Bai Koyu[1]*, Rajkumar Josmee Singh[2] and Ram Singh[3]

[1]Faculty of Agricultural Sciences, RGU, Rono Hills, Doimukh, Arunachal Pradesh
[2]Assistant Professor, [3]Professor & Head, SSS, CPGS-AS, CAU (I), Umiam, Meghalaya
*Corresponding author e-mail id: bai.koyu07@gmail.com

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ABSTRACT

The study developed a theoretical model based on the technology acceptance model (TAM) called the e-learning acceptance model (ELAM) during 2020. Using structural equation modelling (SEM), farmers' behavioural intention to use (BIU), an e-learning module on Climate-Smart Horticulture was investigated. The facilitating condition, followed by perceived ease of use, attitude toward e-learning, and self-efficacy, was found to be the most influential predictor of behavioural intention to use an e-learning module by the structural equation model (SEM). The endogenous variable BIU having R^2 value of 0.62 indicated that the exogenous variables *viz.*, FC (Facilitating Condition), PEU (Perceived Ease of Use), ATT (Attitude toward e-learning) and SE (Self-Efficacy) had jointly explained and predicted 62 per cent of accuracy on BIU in ELAM.

INTRODUCTION

In order to minimize information and communication asymmetries, as well as the vicious loop of poverty, players in the agriculture supply chain must share intelligence (FAO, 2011). Extension and advisory services have a decisive part to play in connecting farmers with sources of innovative information and tools, and in helping behaviour alteration toward adapted practices among farming populaces (Simpson and Burpee, 2014). Digital breakthroughs have made it feasible to transmit agro-based information more efficiently, to a wider audience, and with more veracity (World Bank, 2017). E-learning has capacity to connect a wide range of people instantly, thus it serves a significant part in extension service. Cultivators benefit greatly from mobile-based delivery since it ensures timeliness (Sandhu et al., 2012). The use of digital technology could also assist to enhance, strengthen, and streamline transmission of information in several systems (Kumar et al., 2019). Agriculture have greatly evolved in recent decades, and extension services must innovate in order to stay relevant and provide farmers with stronger managerial and judgement abilities (Singh et al., 2018; Singh et al., 2020). The value of e-learning lies not only in its ingenuity, but also in the functionality it actually offers in terms of information accessibility, data, and connectivity, all of which are becoming extremely relevant in today's economic and societal interplay. Technological advances open new avenues, but uptake and acceptance of these intriguing emerging innovations has become a key issue for cultivators and research scientists. As a result, it is critical to comprehend the farmers' behavioural intention to use an e-learning module on climate-smart horticulture.

METHODOLOGY

The study proposed a theoretical model called E-learning Acceptance Model (ELAM), which is based on the Technology Acceptance Model (TAM), to measure the intention to use the CSH e-learning module (Davis, 1989). TAM was built on the premise that a technology or framework isn't worth adopting if it doesn't help a user become more efficient. TAM was designed with the idea that if a user can't optimize their performance, they won't accept a tool or framework. TAM has received much interest lately as a model for predicting e-learning modalities (Park, 2009). As shown in Figure 1, ELAM was comprised of seven constructs:

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Attitude toward e-learning (ATT), Self-Efficacy (SE), Facilitating Condition (FC), Perceived Usefulness of Module (PU), Perceived Ease of Use (PEU), Subjective Norm (SN), and Behavioural Intention to Use (BIU).

The study consolidated the path diagram of E-learning Acceptance Model (ELAM) as depicted in Figure 1. Accordingly, eight hypotheses were formulated as illustrated in Table 4; H1: SE has positive influence on PEU; H2: PEU has positive influence on BIU; H3: PEU has positive influence on PU; H4: PU has positive influence on ATT; H5: ATT has positive influence on BIU; H6: SN has positive influence on PU; H7: FC has positive influence on PU and H8: FC has positive influence on BIU.

The study was conducted in the two districts of Arunachal Pradesh; Lower Subansiri and West Kameng. Arunachal Pradesh is India's second-largest cardamom producer. The state is the leading kiwi producer in India (MoFPI, 2017). It is the fourth largest apple producer in India and the first in the North Eastern states (NHB, 2018). Two Community & Rural Development (C & RD) blocks were selected from each district namely Dirang and Kalaktang from West Kameng, and C & RD blocks Ziro-I and Ziro-II from Lower Subansiri. A cluster of two villages was selected from each identified C & RD block, taking into account the horticultural significance and contiguity. Consequently, from the Dirang C & RD block Rungkhung and Zimthung villages were identified. Similarly, the villages of Shergaon and Rupa were identified from Kalaktang C & RD block. Similarly, from the Ziro-I C & RD block, two villages, Hari and Siro, were chosen for investigation, and from the Ziro-II C & RD block, Deed and Yachuli villages were chosen. A total of 200 horticultural farmers which included apple farmers (n_a=67), kiwi farmers (n_k=70) and large cardamom farmers (n_{lc}=63) participated in this study.

RESULTS AND DISCUSSION

Table 1 shows the socioeconomic characteristics of respondents in this study. Apropos to the personal and socio-economic characteristics of the farmers, it was found that a more percentage (42.86–44.78%) of the Apple, Kiwi and Large Cardamom farmers belonged to middle age group (35-50 years). Farmers' educational levels are thought to play an important and active part in the acceptance of any new ICT application in the field. As far as 'Education' of the respondents are concerned, it could be reported that higher percentage (32.86–44.78%) had 'high school' level of

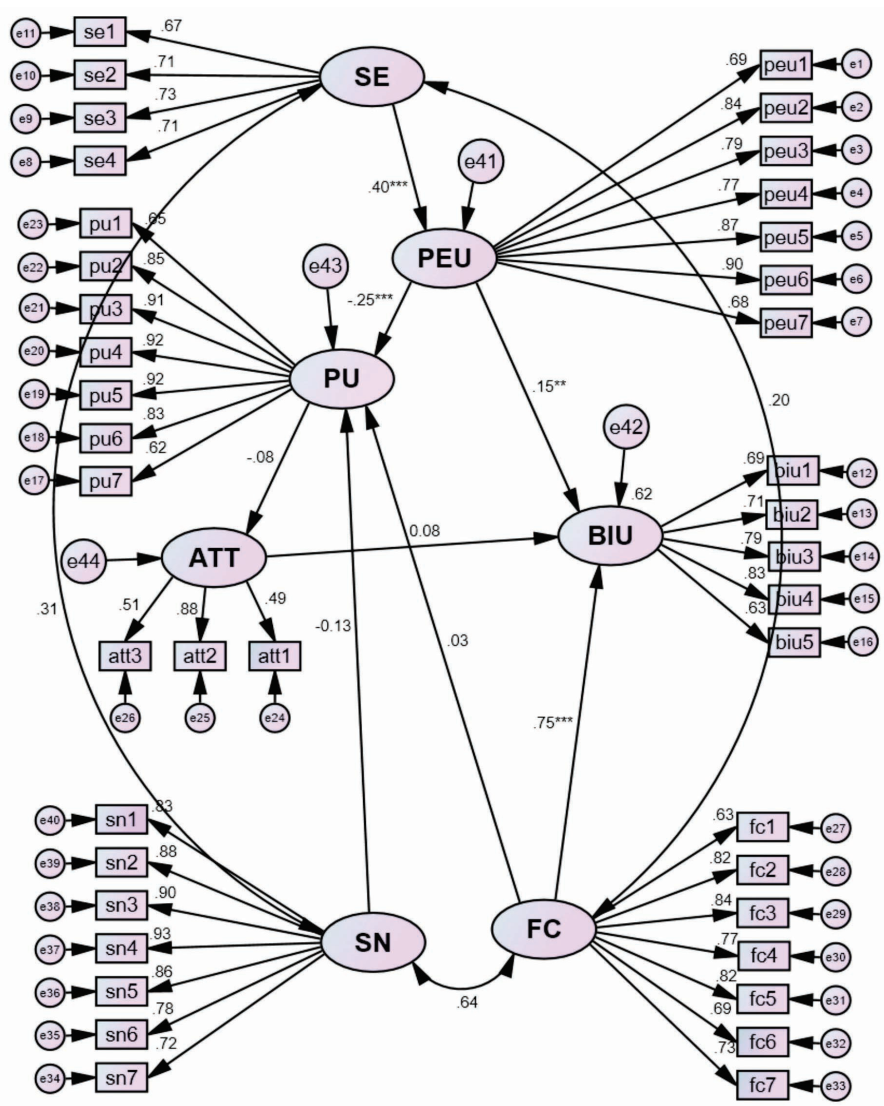

Figure 1. Structural equation model for ELAM; en, where (n = 1-44)

Table 1. Socio-economic and psychological characteristics of respondents

Characteristics	Category	Apple (n=67)	Kiwi (n=70)	Large cardamom (n=63)
Age	Young Age Group (<35 years)	11 (16.42)	12 (17.14)	10 (15.87)
	Middle Age Group (35-50 years)	30 (44.78)	33 (47.14)	27 (42.86)
	Old Age Group (> 50 years)	26 (38.80)	25 (35.72)	26 (41.27)
Education	Primary	10 (14.93)	13 (18.57)	11 (17.46)
	High School	30 (44.78)	23 (32.86)	26 (41.27)
	Higher Secondary	18 (26.86)	21 (30.00)	19 (30.16)
	Graduate	9 (13.43)	13 (18.57)	7 (11.11)
Agricultural land holding	Marginal (<1 ha)	9 (13.43)	9 (12.86)	8 (12.70)
	Small farmers (1-2 ha)	4 (5.97)	5 (7.14)	4 (6.35)
	Semi-medium farmers (2-4 ha)	23 (34.33)	23 (32.86)	22 (34.92)
	Medium farmers (4-10 ha)	28 (41.79)	29 (41.43)	27 (42.86)
	Large farmers (>10 ha)	3 (4.48)	4 (5.71)	2 (3.17)
Annual income	Low annual income (<₹ 33,750)	15 (22.39)	20 (28.58)	18 (28.57)
	Medium annual income (₹ 33,750 - ₹ 1,44,000)	34 (50.74)	35 (50.00)	25 (39.68)
	High annual income (>₹ 1,44,000)	18 (26.87)	15 (21.42)	20 (31.75)
Mass media exposure	Low level of mass media exposure	17 (25.37)	17 (24.29)	12 (19.05)
	Medium level of mass media exposure	30 (44.78)	42 (60.00)	43 (68.25)
	High level of mass media exposure	20 (29.85)	11 (15.71)	8 (12.70)
Cosmopoliteness	Low level of Cosmopoliteness	13 (19.40)	14 (20.00)	11 (17.46)
	Medium level of Cosmopoliteness	34 (50.75)	41 (58.57)	34 (53.97)
	High level of Cosmopoliteness	20 (29.85)	15 (21.43)	18 (28.57)

education. Pertaining to 'Agricultural Land Holding', higher percentage of respondents (41.43–42.86%) had medium agricultural land holding size (4–10 ha). Taking into consideration the 'Annual Income' of respondent, it could be reported that higher percentage of them (39.68–50.74%) had medium level of income (₹ 33,750–1,44,000/-). When level of 'Mass Media Exposure' was examined, it could be revealed that higher percentage (44.78–68.25%) of respondents belonged to medium category. Similarly, higher percentage (50.75–58.57%) of respondents belonged to medium category of 'Cosmopoliteness.'

Total, direct and indirect effect

The standardized total effects as well as the direct and indirect effects of each of the seven variable were evaluated in order to determine the influence of each exogenous on the endogenous variables. The direct effect of a determinant on an endogenous variable is a vector connecting one construct to the other in the research framework. The impact of an indirect effect on a target variable is reflected by its effects on other variables in the model. The sum of the respective direct and indirect effects is a total effect for a given variable. Standardized path coefficients are considered small with values less than 0.1, with values less than 0.3 as medium, and values of 0.5 or more as large (Cohen, 1988). Table 1A summarizes these effects. With a very large total effect, 0.716, the most influential predictor of behavioral intention to use an e-learning module was the facilitating condition. It was accompanied by perceived ease of use, attitude towards e-learning and self-efficacy, with a total impact of 0.107, 0.056 and 0.032, respectively. With standardized path coefficients of 0.026 and 0.032; both facilitating condition and self-efficacy had small indirect effect on behavioral intention to use.

Table 1A. Direct, indirect and total effect of ELAM

Outcome	Determinant	Standardized Estimates		
		Direct	Indirect	Total
BIU (R^2=0.62)	SE	-	0.032	0.032
	PEU	0.107	-	0.107
	ATT	0.056	-	0.056
	FC	0.690	0.026	0.716

Measurement of Validity and Reliability of Scales

Cronbach's α, CR, and AVE were used to assess the reliability of the seven constructs, as shown in Table 2. The Cronbach's α of scales SE, FC, PU, PEU, SN, and BIU have all exceeded the communally accepted level of 0.70, with the exception of ATT (0.64). The composite reliability of all of the constructs ranges from 0.67 to 0.95, which is within the acceptable range of 0.60. Except for ATT (0.42), the majority of the AVE values of the constructs in the study meet the recommended 0.5 level (Fornell and Larcker, 1981).

By referring to Figure 1, it can be seen that the item statements in the scales ATT, SE, FC, PU, PEU, SN, and BIU have factor loadings in the range of '0.49–0.88', '0.67–0.73', '0.63–0.84', '0.62–

Table 2. Validity and Reliability of Scales

Scales	Cronbach's α	Average variance extracted (AVE)	Composite reliability (CR)
ATT	0.64	0.42	0.67
SE	0.80	0.50	0.80
FC	0.90	0.58	0.90
PU	0.93	0.68	0.93
PEU	0.92	0.63	0.92
SN	0.95	0.71	0.95
BIU	0.86	0.54	0.85

Table 3. Model Fitting Indices of ELAM

Model Fit indices	Criterion	Results
χ^2/ df	< 3.00 (Kline, 2005)	1.68
CFI	≥0.90 (Klem, 2000; McDonald and Ho, 2002)	0.91
TLI	≥0.90 (Klem, 2000; McDonald and Ho, 2002)	0.91
SRMR	≤0.08 (Hu and Bentler, 1999)	0.08
RMSEA	<0.07 (Steiger, 2007)	0.06

Table 4. Regression path coefficients (beta values) and significant of direct path

Hypotheses	Path	Actual beta values	Standard error (S.E.)	Critical ratio (C.R.)	p-value	Significance
H1	SE → PEU	0.40	0.07	4.54	0.001	Significant
H2	PEU → BIU	0.15	0.05	2.60	0.01	Significant
H3	PEU → PU	-0.25	0.07	-3.19	0.001	Significant
H4	PU → ATT	-0.08	0.07	-0.93	0.36	Insignificant
H5	ATT → BIU	0.08	0.07	1.31	0.19	Insignificant
H6	SN → PU	-0.13	0.09	-1.33	0.18	Insignificant
H7	FC → PU	0.03	0.09	0.29	0.77	Insignificant
H8	FC → BIU	0.75	0.09	7.27	0.001	Significant

0.92', '0.68–0.90', '0.72–0.93', and '0.63–0.83', respectively. The study's constructs were found to be internally valid due to the specified range of factor loadings (Hair et al., 2010).

Model Fit

Table 3 shows the fit indices for both the measurement and structural models. Table 3 shows that the specified model had a normed chi-square value of 1.68, a CFI of 0.91, a TLI of 0.91, an SRMR of 0.08, and an RMSEA of 0.06, showing good model fit.

The path coefficients of the structural model were evaluated after an acceptable measurement of the model's fit to the measured data. The path coefficients, which indicate the significance of the relationship between variables, were used to test the hypotheses H1 to H8. Table 4 shows that the proposed hypotheses (H1, H2, H3, and H8) were determined to be significant, whereas the remaining hypotheses were found to be insignificant. On performing SEM, it could be concluded that the endogenous variable BIU having R^2 value of 0.62 indicated that the exogenous variables *viz.*, FC, PEU, ATT and SE had jointly explained and predicted 62 per cent of accuracy on BIU in ELAM (Figure 1).

Moreover, the three coefficients of correlation shown by the double headed arrow established in the study were less than 0.85 (Kline, 2005), demonstrating a valid and discriminatory model (Figure 1).

CONCLUSION

The ELAM is an useful model for instructing farmers about climate-smart horticulture. The results of the model fitting indices revealed that the model fits the data adequately. The most crucial factors for the e-learning module to have a significant influence on behavioural intention to use are the facilitating condition, perceived ease of use, attitude toward e-learning, and self-efficacy. The ELAM was found to be valid, and discriminatory.

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