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Acceptance of an E-learning Module on Climate-smart Horticulture: A Structural Equation Model

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ABSTRACT

Background: E-learning is now being used in a variety of industries, including agriculture. The use of information and communication technologies (ICTs) is seen as essential for overcoming the barriers that a developing country faces in all areas and closing the digital divide. Farmers must be prepared with the most recent breakthroughs in ICTs in order to take advantage of new opportunities in the global market.

Methods: By designing an e-learning module and providing farmers with a self-learning framework, the study focuses on the use of ICT instruments in climate-smart horticulture. The psychological factors in this study were investigated using the E-Learning Acceptance Model (ELAM), which was derived from the Technology Acceptance Model (TAM). A quantitative survey of 200 farmers were conducted. Structural equation modelling (SEM) was used to test the research hypotheses.

Result: ELAM has enough predictive ability to explain farmers' behavioural intention to utilise an e-learning module in a real world. In total, the result supports five ELAM hypotheses. The SEM findings indicate that ELAM is a valid model. In ELAM, partial mediation was also observed.

Key words: Climate-smart horticulture, E-learning acceptance model, E-learning module, Structural equation modeling, Trchnology acceptance model.

INTRODUCTION

Information and communication technologies (ICTs) are promoting quick exchange of information and innovations, as well as functioning as a critical factor for transforming the agrarian scenario and farmers' livelihoods through boosting access to farm data (Parganiha *et al.,* 2012). E-learning has the potential to reach a wider audience including the learners who are geographically dispersed with limited time and doesn't have any resource to travel (FAO 2021). Authorities, agricultural consultancies, non-governmental organisations, producer organisations and corporate bodies, or any stakeholder in the digital economy, could use e-learning to reach vast numbers of cultivators and enabling them to engage with each other. Content may be readily updated to deliver better results. E-learning could promote new learner-centric strategies in designing and executing the educational experiences by involving producers and their community, as well as adult learners (World Bank, 2017). E-learning can be demarcated as delivery of a learning, training or education program by electronic means. It encompasses the usage of a computer or electronic device (*e.g.,* a mobile phone) in particular mode to deliver training, educational or learning material (Stockley, 2003). Traditionally exclusive to academic institutions, the use of e-learning has spread to a wide range of enterprises and government organizations (Hashim and Tasir, 2014). E-learning would be the most crucial to scientific advancement for its relevance as a link between agricultural scientists, subject matter experts and farmers (Ali and Kumar, 2011). E-learning is evolving as a valid alternative for unlocking the potential of agriculture education by communicating data and insights to producers and content facilitators both in an intrinsic and extrinsic way (Agarwal and Kumar, 2013). Emerging technologies and the utilization of ICT into classroom instruction have expedited the evolution of e-learning and conceptually revolutionized the way learning occurs. Numerous new instructional technologies, such as e-learning, are now being used as a result of the rapid advancement of ICT and the escalating computer literacy of the populace (Vyas and Nirban, 2014). In the workplace, e-learning, or the digital transmission of data for the purpose of learning and information acquisition, has grown more common (Brown and Charlier, 2013). Institutions across sectors have used e-learning systems to assist professional growth in maintaining operational efficiency since e-learning could transmit ideas and insights to users (Yoo and Huang, 2015). Cultivators can also be benefitted from e-learning. It can benefit farmers/farmwomen of all ages, locations and can link the gaps formed by geographical barriers,

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languages, conflicts and political restrictions. In agriculture, e-learning can amass resources and information from distant places that may otherwise be unattainable. It can connect farmers with far away scientists and consultants. Concomitantly, it can also affectedly surge the numbers of farmers who can be reached by single training programs (Leary and Berge, 2006). E-learning seems to be an effective way of conveying nearly every major concern in the world and it seemed to be an ideal solution to almost every learning and training requirement in early stages (Vigneswaran *et al.,* 2017). Thus it is ideal for providing disseminating information related to climate-smart horticulture to the farmers.

In Arunachal Pradesh, horticulture is an imperative field with excellent prospects for alleviating rural poverty thanks to presence of diverse agro-climatic zone and high adaptableness to undulating landscape of the state. India is the second-largest producer in the world in terms of fruit production (NHB, 2018). The horticulture of the state Arunachal Pradesh is very promising with the production of 212.73 thousand MT and area of 62.71 thousand Ha (NHB, 2018-19). As for Arunachal Pradesh, state is India's second-largest producer of large cardamom. State is the top producer in India in terms of Kiwi (MoFPI, 2017). In Apple's case, the state is India's fourth-largest producer and first among the North Eastern states (NHB, 2018). Thereby having the potential to become one of the leading exporters. The aim of this article was to establish a framework to study the effectiveness of the e-learning module on climate-smart horticulture.

Research model and research hypotheses

This research work studies on acceptance of E-learning module on CSH by the farmers on improved scientific packages of practices (ISPP) by providing right information in right time through asynchronous e-learning module. The study adapts 'Technology Acceptance Model' which was originally proposed by Davis (1989) and a research model called 'E-learning Acceptance Model' as depicted in Fig 1 was propounded by integrating seven constructs *viz.,* Attitude towards 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's specific objective is to assess and validate the model of tribal farmers' acceptance and adoption of an e-learning module using the following hypotheses in relation to the study's constructs.

Research hypotheses

The path diagram of the E-learning Acceptance Model (ELAM) was consolidated in the study, as shown in Fig 1. As a result, nine hypotheses were proposed, as shown in Table 4.

H1: Self efficacy positively influences perceived ease of use.
H2: Perceived ease of use positively affects behavioural intention to use an E-learning module.
H3: Perceived ease of use positively influences perceived usefulness of module.
H4: Perceived usefulness of module positively influences attitude towards E-learning.
H5: Attitude towards E-learning positively influences behavioural intention to use an e-learning module.
H6: Subjective norm positively influences perceived usefulness of module.
H7: Facilitating condition positively influences perceived usefulness of module.
H8: Facilitating condition positively influences behavioural intention to use an E-learning module.
H9: Facilitating condition positively influences perceived ease of use.

MATERIALS AND METHODS

The state of Arunachal Pradesh was deliberately selected as the main area of study. Two districts, namely Lower Subansiri and West Kameng were selected. Then the two most horticulturally relevant community and rural development (C&RD) blocks from each listed district were deliberately selected *i.e.* C&RD blocks Dirang and Kalaktang from the district of West Kameng and C&RD blocks Ziro-I and Ziro-II from the district of Lower Subansiri. Then a cluster of two villages from each established C&RD block was selected, taking into account the significance and contiguity of horticulture. Consequently, villages Rungkhung and Zimthung were selected from the Dirang C&RD block. Similarly, villages *viz*., Shergaon and Rupa were selected from Kalaktang C&RD block. Furthermore, the two villages were considered for study from Ziro-I C&RD, namely Hari and Siro and the Deed and the Yachuli villages were selected for study from the Ziro-II C&RD block. A total of 200 (n_{apple} = 67; n_{kiwi} = 70 and $n_{large\ cardamom}$ = 63) farmers were then finally selected based on probability proportional to size sampling (PPS). Climate-smart horticulture was addressed in an e-learning module that included topics such as climate-smart

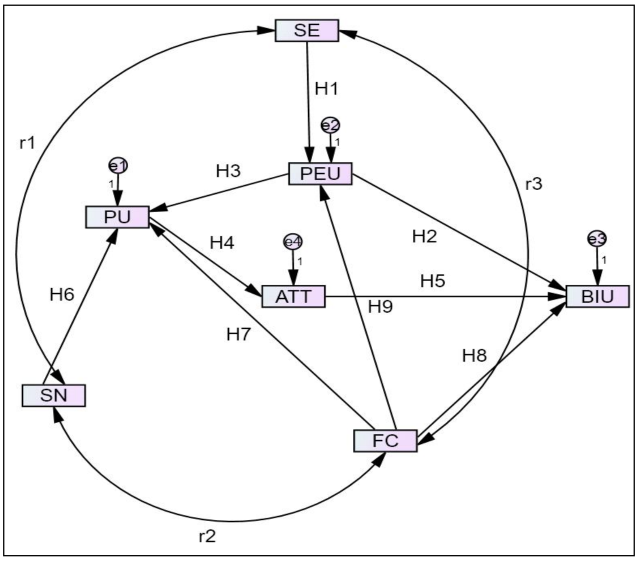

Fig 1: Proposed research model (ELAM).

Table 1: Profile of the respondents.

Characteristics	Categories	Number (n=200)	Percentage
Age	Young	33	16.50
	Middle	90	45
	Old	77	38.50
Education	Primary	34	17
	High School	79	39.50
	Higher Sceondary	58	29
	Graduate	29	14.50
Land holding	Marginal (<1 ha)	26	13
	Small farmers (1-2 ha)	13	6.50
	Semi-medium farmers (2-4 ha)	68	34
	Medium farmers (4-10 ha)	84	42
	Large farmers (>10 ha)	9	4.50
Annual income	Low (< ₹ 33,750)	53	26.50
	Medium (₹ 33,750- ₹ 1,44,000)	94	47
	High (> ₹ 1,44,000)	53	26.50

cultural practices, climate-smart post-harvest techniques and climate-smart plant protection practices, among many others. The data was obtained as a result of a survey that began in 2017 and concluded in 2019. The structural equation model was analysed using SPSS AMOS.

RESULTS AND DISCUSSION

Table 1 shows that a higher percentage of respondents (45.00%) were in the middle age group. In terms of education, a higher percentage of respondents (39.50%) had completed high school. A greater percentage of respondents (42.00%) had a medium-sized agricultural land holding (4-10 ha). By looking into respondents' annual income it could be observed that high percentage (47%) of them were in medium income category (₹ 33,750 - ₹ 1,44,000/-).

Cronbach's α, composite reliability, average variance extracted and correlation coefficient between the exogenous constructs were computed to assess the reliability and validity of the constructs under investigation. Table 2 shows that, with the exception of ATT (0.64), all of the constructs' Cronbach's á match the required requirement of 0.70. The composite reliability of all the constructs exceeds the required value of 0.60. All other constructs meet the recommended value of 0.50 when estimating average variance extracted, with the exception of ATT (0.42) (Fornell and Larcker, 1981).

The three correlation coefficients depicted by a double-headed arrow with respective values of r1=0.25, r2=0.60 and r3=0.16 between the endogenous variables SE and SN, SN and FC and SE and FC indicate that there was no redundancy among the variables studied under ELAM because the value of all three correlation coefficients was less than 0.85 (Kline, 2005), suggesting that multicollinearity was not an issue; indicating a discriminant valid SEM (Fig 2).

Model fit

The model fit indices of ELAM are shown in Table 3. With

Table 2: Reliability and validity of the construct.

Scales	Cronbach's α	Average variance extracted (AVE)	Composite reliability (CR)
PU	0.93	0.68	0.93
FC	0.90	0.57	0.90
SE	0.80	0.50	0.80
ATT	0.64	0.42	0.67
BIU	0.85	0.54	0.85
SN	0.95	0.71	0.94
PEU	0.92	0.62	0.92

Table 3: Model fitting indices of ELAM.

Fit indices	Criterion	Result
χ^2	11.16	-
df	9	-
p-value	> 0.05 (Hayduk, 1987)	0.26
χ^2/ df	< 3.00 (Kline, 2005)	1.24
CFI	=> 0.99 Klem (2000), McDonald and Ho (2002)	0.99
TLI	=> 0.99 Klem (2000), McDonald and Ho (2002)	0.98
SRMR	<0.08 (Hu and Bentler, 1999)	0.04
RMSEA	<0.07 (Steiger, 2007)	0.04

the Chi square value *i.e.* χ^2 =11.16, degrees of freedom *i.e.* df=9 and p=0.26, there was a model fit index of 1.24 that met the requirements of limit for good model fit less than 3.00. The study indicated that CFI and TLI had the respective values of 0.99 and 0.98, which suggested a good fit for the model because the acceptance criteria were >0.90. The study showed a good model fit with SRMR=0.04, because the limit of the testing criterion was <0.08. A thorough analysis on the model's RMSEA indicated that the computed value of 0.04 falls within a reasonable fit range as the acceptance criterion limit was <0.07.

Hypotheses testing

Table 4 shows the outcomes of the hypotheses test as well

Table 4: Results from the hypotheses testing.

Hypotheses	Path	Actual beta values	Standard error (S.E.)	Critical ratio (C.R.)	*p*-value	Significance
H1	SE → PEU	0.56	0.11	4.53	0.001	Significant
H2	PEU → BIU	0.11	0.03	2.12	0.034	Significant
H3	PEU → PU	-0.25	0.08	- 3.56	0.001	Significant
H4	PU → ATT	0.01	0.02	0.09	0.926	Insignificant
H5	ATT → BIU	0.06	0.08	1.16	0.245	Insignificant
H6	SN → PU	-0.13	0.11	- 1.48	0.138	Insignificant
H7	FC → PU	0.02	0.12	0.23	0.816	Insignificant
H8	FC → BIU	0.70	0.03	13.62	0.001	Significant
H9	FC → PEU	0.24	0.08	3.73	0.001	Significant

Table 5: Mediation effect in ELAM.

Hypotheses	Direct Effect	Indirect Effect	Result
FC → PEU → BIU	0.244***	0.030*	Partial Mediation

*** $p<0.001$, * $p<0.05$.

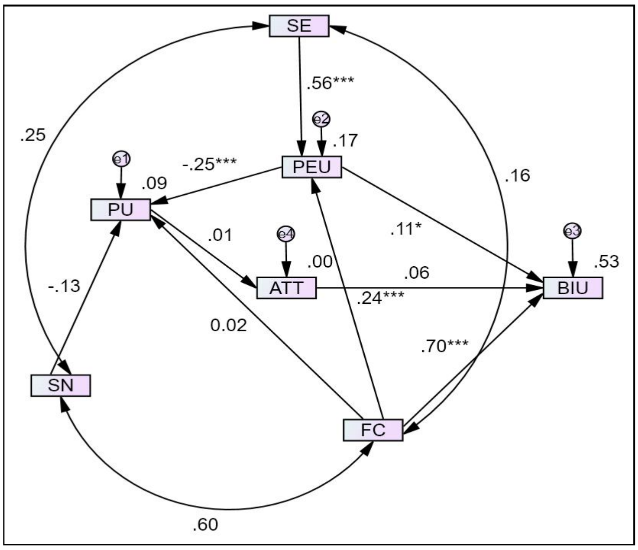

Fig 2: E-Learning acceptance model.

as the path coefficients of the proposed research model. Overall, the findings supported five ELAM hypotheses (H1, H2, H8 and H9). H3, on the other hand, was noted to be significantly negative. SE was found to have significant positive influence on PEU. The result concur with those of Humida *et al.* (2021); Fathema *et al.* (2015); and Punnoose (2012), differed from those of Kimathi and Zhang (2019). PEU was found to have significant positive influence on BIU. Humida *et al.* (2021); Kimathi and Zhang (2019); Budu *et al.* (2018) have reported similar findings. PEU was found to have significant negative on PU. The findings reported were found to be in conflict with Humida *et al.* (2021); Jere (2020); Kimathi and Zhang (2019); Budu *et al.* (2018); Sivo *et al.* (2018). FC was found to have significant positive influence on BIU. Humida *et al.* (2021) have reported a similar finding. The results differed from those of Alshmrany and Wilkinson (2017); Ain *et al.* (2015); Nguyen *et al.* (2014). FC was also found to have significant positive influence on PEU. Similar findings have been reported by Humida *et al.* (2021); Jere (2020); Agarwal *et al.* (2018). Four endogenous variables were tested in the ELAM. SE, PEU FC and ATT all predicted BIU, resulting in a combined R^2 of 0.53. This suggests that the exogenous variables SE, PEU FC and ATT collectively explained and predicted 53.00 percent of the variance in BIU. Similarly, SE and FC predicted PEU, resulting in a combined R^2 of 0.17, showing that SE and FC account for 17% of the precision in predicting PEU. Furthermore, the endogenous variable PU with R^2 of 0.09 stated that exogenous variables such as PEU, SN and FC contributed 9% of the accuracy in the estimation of PU. Also, ATT with R^2 value of 0.00 revealed that the exogenous variable PEU had no role in estimating ATT (Fig 2).

Mediation effect

By referring Table 5, it could be vouched that there was a partial mediation through PEU since both the direct as well as indirect effects between FC and BIU were significant $p<0.001$ and $p<0.05$ respectively. The result clearly indicates that BIU was indirectly predicted by FC and mediated by PEU. FC alone may not have inspired respondents to use the CSH e-learning module.

CONCLUSION

Advances in information and communication technologies (ICTs) have paved the way for farmers to learn at their own pace in ways that improve their rural livelihoods by adapting and mitigating climate change by adopting and integrating recommended climate smart-horticultural methodologies. Farmers have embraced E-learning module-based user experience as a significant medium for content delivery and it offers a range of possibilities. The 'E-learning Acceptance Model' is a valid model for empowering tribal farmers in Arunachal Pradesh by delivering the relevant information at the right time using an E-learning module based information delivery system on climate-smart horticultural strategies.

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REFERENCES

Agarwal, H. and Kumar, A. (2013). E-learning for agriculture education in India. International Journal of Research in Engineering and Technology. 12(2): 101-104.

Aggarwal, D. (2018). Using the Technology Acceptance Model to Understand the Use of Bring Your Own Device (BYOD) to Classroom. Journal on Today's Ideas - Tomorrow's Technologies. 6(2): 83-91.

Ain, N., Kaur, K. and Waheed, M. (2015). The influence of learning value on learning management system use: An extension of UTAUT2. Information Development. https://doi.org/10.1177/0266666915597546.

Ali, J. and Kumar, S. (2011). Information and communication technologies (ICTs) and farmers' decision-making across the agricultural supply chain. International Journal of Information Management. 31(2): 149-159.

Alshmrany, S. and Wilkinson, B. (2017). Factors influencing the adoption of ICT by teachers in primary schools in Saudi Arabia. International Journal of Advanced Computer Science and Applications. 8(12): 143-156.

Brown, K.G. and Charlier, S.D. (2013). An integrative model of e-learning use: Leveraging theory to understand and increase usage. Human Resource Management Review. 23(1): 37-49.

Budu, K.W.A., Yinping, M. and Mireku, K.K. (2018). Investigating the effect of behavioral intention on e-learning systems usage: Empirical study on tertiary education institutions in Ghana. Mediterranean Journal of Social Sciences. 9(3): 201-216.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use and user acceptance of information technology. Management Information Systems Quarterly. 13: 319-340.

FAO (2021). E-learning methodologies and good practices: A guide for designing and delivering e-learning solutions from the FAO elearning Academy, second edition. Rome. https://doi.org/10.4060/i2516e.

Fathema, N., Shannon, D. and Ross, M. (2015). Expanding the technology acceptance model (TAM) to examine faculty use of learning management systems (LMSs) in higher education institutions. MERLOT Journal of Online Learning and Teaching. 11(2): 210-232.

Fornell, C. and Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research. 18(1): 39-50.

Hashim, H. and Tasir, Z. (2014). E-learning readiness: A literature review. Proceedings - 2014 International Conference on Teaching and Learning in Computing and Engineering, LATICE 2014, (April 2014): 267-271.

Hayduk, L.A. (1987). Structural Equation Modeling with LISREL: Essentials and Advances. Baltimore, MD: Johns Hopkins University Press.

Hu, L.T. and Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling. 6(1): 1-55.

Humida, T., Al Mamun, H.A. and Keikhosrokiani, P. (2021). Predicting behavioral intention to use e learning system: A case study in Begum Rokeya University, Rangpur, Bangladesh. Education and Information Technologies. https://doi.org/10.1007/s10639-021-10707-9.

Jere, J.N. (2020). Investigating university academics behavioural intention in the adoption of e-learning in a time of COVID-19. South African Journal of Information Management 22(1): 1-9.

Kimathi, F.A. and Yi Zhang, Y. (2019). Exploring the General Extended Technology Acceptance Model for e-Learning Approach on Student's Usage Intention on e-Learning System in University of Dar es Salaam. Creative Education. 10: 208-223.

Klem, L. (2000). Structural Equation Modeling. In: Reading and Understanding Multivariate Statistics [L. Grimm and P. Yarnold (Eds.)], (Vol. II). Washington, DC: American Psychological Association.

Kline R.B. (2005). Principles and practice of structural equation modeling. Second edition, Guilford, New York.

Leary, J. and Berge, Z.L. (2006). Trends and challenges of e-learning in national and international agricultural development. International Journal of Education and Development using Information and Communication Technology. 2(2): 51-59.

McDonald, R.P. and Ho, R.H. (2002). Principles and practice in reporting structural equation analyses. Psychological Methods. 7: 64-82.

MoFPI (2017). Investment Environment and Opportunities in Food Processing - Arunachal Pradesh. Government of India, New Delhi.

Nguyen, T.D., Nguyen, D.T. and Cao, T.H. (2014). Acceptance and use of information system: E-learning based on cloud computing in Vietnam. 2nd Information and communication technology - EurAsia conference (ICT-EurAsia). Pp.139-149, April 14-17, 2014. Bali, Indonesia.

NHB (2018). Horticulture statistics at a glance. Ministry of Agriculture and Farmers Welfare, Department of Agriculture, Cooperation and Farmers Welfare, Horticulture Statistics Division, Govt. of India, New Delhi.

NHB (2018-19). Area and production of horticulture crops for 2018-19 (3rd Advance Estimates).

Parganiha, O.P., Shrivastava, S.K., Chaubey, A.K. and Nag, J.L. (2012). Impact of Kisan Mobile Advisory (KMA) on Agricultural Technology Dissemination, Indian Research Journal of Extension Education. 2(Special Issue): 157-178.

Punnoose, A.C. (2012). Determinants of intention to use eLearning based on the Technology Acceptance Model. Journal of Information Technology Education: Research. 11: 301-337.

Steiger, J.H. (2007). Understanding the limitations of global fit assessment in structural equation modelling. Personality and Individual Differences. 42(5): 893-98.

Stockley, D. (2003). E-learning definition and explanation. http://derekstockley.com.au/elearning-definition.html.

Vigneswaran, S., Leelamani, A., Divya, S. and Divya, K. (2017). Communicating Climate Change Importance through Interactive Multimedia Frame Work for Promoting Education and Effective Public Awareness on Climate Change. International Journal of Applied Environmental Sciences. 12(3): 409-420.

Vyas, N. and Nirban, V.S. (2014). Students' perception on the effectiveness of mobile learning in an institutional context. ELT Research Journal. 31(1): 26-36.

World Bank. (2017). ICT in Agriculture (Updated Edition): Connecting Smallholders to Knowledge, Networks and Institutions. Washington, DC: World Bank. https://openknowledge.worldbank.org/handle/10986/27526.

Yoo, S.J. and Huang, W.D. (2015). Can e-learning system enhance learning culture in the workplace? A comparison among companies in South Korea. British Journal of Educational Technology. 47(4): 575-591.