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Predicting farmers' behavioral intentions towards adoption of essential oil extraction practices using structural equation modeling

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Abstract

Smallholder farmers in northern Punjab struggle to adopt sustainable practices like essential oil extraction, despite their potential to improve livelihoods. Core elements from theory of planned behavior, technology acceptance model, and innovation diffusion theory are amalgamated to develop an adoption model, which is subsequently analyzed using structural equation model. The results unveil significant mediating effects involving attitudes (perceived usefulness, easiness), normative concerns (social influence), and indicating maximum variation (R^2) regarding by-product preparation (0.76) and steam distillation (0.65). The model successfully accounts moderating effects of socioeconomic variables, indicating a robust association among latent variables. Hence, improving the adoption behavior among smallholders necessitates a focus on socio-psychological and socioeconomic factors.

Key words: Diffusion; adoption, essential-oil extraction, aromatic growers; decision-making.

1. INTRODUCTION

Worldwide demand for essential oils is increasing due to growing interest and commercial importance. Currently, Pakistan heavily relies on imported essential oils, with over 90% of local industry demand being met through imports. Research by (Riaz et al., 2021) shows imports ($9.2 million) exceeding exports ($3.2 million) threefold, indicating a need for local production initiatives. Favorable climatic conditions in Pakistan make it conducive for high-value essential oil production, with potential benefits for both awareness and education (Khalid et al., 2020). Utilizing essential oils alongside herbal and agro-based materials presents an eco-friendly and cost-effective approach to co-composting (Greff et al., 2021). Among many, *Eucalyptus globules*, the most prevalent species used for essential oil extraction (EOE), possesses insect repellent properties,

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offering innovative applications in bio-pesticides and composting (Dhakad et al., 2018). Eucalyptus leaves, often discarded, hold potential for essential oil extraction (EOE), serving domestic and industrial purposes (Barbosa et al., 2016). Steam distillation efficiently extracts oils, preserving their properties to a minimum (Ndiaye et al., 2018). Steam-distilled eucalyptus oil enriches composting and improves soil fertility. Moreover, it acts as a bio-pesticide, against garden pests (Regnault-Roger et al., 2012).

The pace of agricultural technology adoption among end users in developing nations remains sluggish, driven by economic potential but not always profit maximization (Ikram et al., 2021). Analyzing farmers' perceptions aids decision-making (Liu et al., 2018). Socio-psychological factors, often analyzed through the Theory of Planned Behavior (TPB), shape adoption behavior (Dessart et al., 2019). Understanding communication channels improves integration and predicts agricultural technique adoption, including EOE (Mohd Israfi et al., 2022). Hence, this study aims to grasp eucalyptus growers' behavioral intentions to promote EOE practices, focusing on (i) steam distillation and (ii) byproduct preparation like bio-pesticides and bio-compost.

The present study contributes significantly in several ways. Recent research has integrated TPB/ Technology Acceptance Model (TAM) with Structural Equation Modeling (SEM) or combined both methodologies to understand agricultural technology adoption and model farmers' behavior towards implementing good agricultural practices (Dong et al., 2022). However, these studies often overlook the economic potential of cultivating aromatic plants among smallholders. **Firstly,** this study fills this gap by employing a combination of TPB, TAM, Innovation Decision Theory (IDT), and SEM to assess aromatic crop growers' intention towards adopting EOE practices. **Secondly**, besides mediation analysis using Partial Least Square (PLS)-SEM, moderation analysis, incorporating socioeconomic variables, predicts the relationship direction between exogenous and internal variables. **Thirdly**, the study also examines direct effects of latent and observed variables on behavioral intention (Bi), and finally, evaluates predictive efficacy using PLS-SEM to enhance model robustness.

The paper follows this structure: introduction of background, significance, and contributions; theoretical context and hypothesis formulation; data and methodology; results and discussions; conclusion with limitations and suggestions.

1.1 Theoretical background

To deepen understanding of innovation adoption, Rogers' Innovation Decision Theory (IDT) elucidates the link between farmers' adoption and their knowledge-based perception of an innovation (Bakkabulindi, 2014). Despite EOE technology being perceived as new among aromatic crop growers due to limited knowledge, its global adoption and economic efficacy from aromatic plants are well-documented (Chhetri et al., 2021). An empirical model integrating TPB (Ajzen, 1991), Rogers' IDT (Miller, 2015) , and TAM by Davis (Silva, 2015) (Figure 1) was proposed to study variables' cause-and-effect relationship on adoption behavior. While no universally accepted model exists, TPB and TAM are commonly applied in agricultural technology adoption (Marangunić and Granić, 2015). This study's model explains eucalyptus growers' intention through attitude into perceived usefulness (Pu) and ease of use (Peou) from TAM, and perceived compatibility (Pc) from Rogers' IDT, perceived control into self-efficacy and perceived resources (Pr), and normative concerns, further enriched with elements from social media (Sm), influence (Si), technical training (Tt), and extension services (Es) to capture social pressure and communication source (Momani, 2020).

1.2 Generation of hypotheses for the proposed adoption model

H_1= Attitude, perceived control, and normative concerns have significant and positive effects on the growers' intentions toward EOE practices.

H_2= All observed variables (Pu, Peou, Pc, Tt, Si, Sm, Es, Pe, Pr) have significant and positive effects on the growers' Bi concerning EOE practices.

H_3= Attitude facilitates the positive effects of perceived usefulness, ease of use, and compatibility on EOE adoption intentions.

H_4= Normative concerns mediate the effects of social media, technical training, and extension services on the growers' intentions towards EOE practices.

H_5= Perceived control mediates self-efficacy and resources positively on growers' intended behavior towards EOE adoption.

H_6= Socioeconomic factors moderate positive relationships between variables towards EOE adoption.

2. RESEARCH METHODOLOGY

2.1 Universe of Study

The universe of study was Pothwar region of Punjab Pakistan (Northern Punjab) with longitude 73.07° E, latitude 33.6° N and elevation of 517m from mean sea level located between the Indus and Jhelum rivers comprising four main districts namely Chakwal, Attock, Jhelum and Rawalpindi (Figure 2). The study focuses on steam distillation and by-product preparation for essential oil extraction, as they are practical, widely used, and easier to adopt, offering greater benefits to farmers' livelihoods.

2.2 Selection of sample size and data collection

A list of 942 registered eucalyptus growers was obtained from the Director of Agriculture (Extension and Adaptive Research) Rawalpindi and Punjab Forestry Department. A sample size of 274 was obtained by using the table developed by (Krejcie and Morgan, 1970) from a homogenous finite population using simple random sampling from each district (Table 1). Initially, master trainers were used to disseminate the targeted information about EOE practices among the sampled respondents during training sessions. Further, the data were collected through personal (face-to-face) interviews of the respondents using a structured research instrument.

2.3 Implementation of an extended proposed adoption model of study

The proposed adoption model was employed to test the aligned hypotheses. The model was analyzed using PLS-SEM which was further subdivided into measurement and structural model.

2.3.1 Structure of the adoption model (research instrument)

The variables examined were latent (unobserved) and assessed through observable statements. About 84 statements were used in the questionnaire for both EOE practices. The statements were loaded into 13 factors. The factors including Bi, At, Nc, Pct, self-efficacy, and Pr were weighted by six, four, four, three, two, and two recorded statements respectively, while the remaining factors were loaded by three statements under each practice.

2.3.2 Partial least squares-structural equation modeling (assumptions and estimation)

Structural Equation Modeling (SEM), a statistical method blending factor analysis and multiple regression, analyzes cause-effect relationships among latent variables. These variables, not directly measured, are inferred from observed variable responses. However, the variance-based PLS-SEM approach was chosen to assess the adoption model for several reasons: (i) maximizing explained variability (R_2) in the criterion variable; (ii) flexibility regarding data structure normality; (iii) accommodating underlying variables with few items; and (iv) favoring prediction over theory testing (Leguina, 2015). This methodological choice allows for a comprehensive examination of relationships in the adoption model, prioritizing practical relevance and prediction accuracy. The PLS-SEM adoption model underwent evaluation in two steps using SMART-PLS: first, assessing the relationship between indicators and inferred variables (measurement model), and second, examining causal relationships among inferred variables (structure model) (Khoi and Van Tuan, 2018). Hence, Each PLS path item is a linear function with errors:

$$Xj = \Lambda j\xi j + \varepsilon \text{ (exogenuos latent variable } \xi j) \dots\dots\dots (1)$$

$$Xl = \Lambda k\xi l + \delta \text{ (endogenuos latent variable } \xi l) \dots\dots\dots (2)$$

Here, ξ_j = set of the exogenous (external) underlying variables

ξ_l = set of the endogenous (internal) underlying variables.

X_j and X_l = associated set of indicator (X_1,…., X_j ; X_1, …, X_l) of the external variable ξ_j and internal variable ξ_l, respectively.

Λ_j and Λ_l = loading coefficient matrices (λ_1,... λ_m), k = no. of indicators (items)

ε and δ = set of error terms for the items

Furthermore, Indicator reliability, convergent validity, and discriminant validity using Heterotrait-monotrait (HTMT) were assessed for the measurement model. Factor loadings should surpass 0.7, AVE > 0.5, and CR > 0.7 (Annex A).

Before proceeding to the structure model estimation phase, multicollinearity issues were assessed using variation inflation factors (VIF) for each variable (Annex B). An iterative sequence of least square regressions was then utilized to estimate model parameters, maximizing explained variance (R^2) (Monecke and Leisch, 2012). Hence, the structure model links the internal (ξ_k) and external (ξ_j) implied variables and can be expressed as:

$\xi_k = B\,\xi_k + \Gamma\,\xi_j + \zeta$………… (3)

Where, B = coefficient matrix indicating the causal effects between internal implied variables,

Γ = coefficient matrix of the causal effects of the external implied variable ξ_j on the internal inferred variable ξ_k. In the structural model, an inferred endogenous variable can also act as an exogenous variable for another endogenous variable, with ζ representing the residuals or error terms. A bootstrapping process with 5,000 subsamples calculated p-values and effect sizes (f^2-value) (Purwanto, 2021). Furthermore, moderating variables like farm area, farming experience, and farm income were assessed through bootstrap multi-group analysis (Tian et al., 2021). Predictive relevance Q^2 for the endogenous variable (Bi) was also estimated using PLS-Predict (Hossan et al., 2020).

3. RESULTS

3.1 Estimation results of the extended proposed adoption model of the study

3.1.1 Measurement model

Annex-A results indicate no HTMT ratio surpassing the critical level of 0.9 for each variable under each EOE practice. Table 2 displays mean and factor loading results for each variable. CR values above 0.7 denote favorable internal consistency within the adoption model for each practice. The lowest CR value, 0.724, was observed for extension services in the use of a steam distillation unit for EOE. The highest CR value, 0.895, was found for the implied variable 'Bi' in by-product preparation. Cronbach's alpha (α) for each variable was also assessed, with the highest values (0.863 and 0.798) for 'Bi' in by-product preparation and usage of a steam distillation unit, respectively. Convergent validity, measured by AVE, exceeded 0.5 for each inferred variable. Each variable can account for over 50% of indicator variance. The latent variable "self-efficacy under 1st practice" had the lowest AVE (0.512), confirming convergent validity. VIFs below 5 indicate no multicollinearity for these variables (Annex B).

3.1.2 Structure model

Table 3 displays SEM outcomes, including path coefficients, p-values, and effect sizes (f2-value). Behavioral intention predicts approximately 79% for by-product preparation and 65% for using a steam distillation unit. Attitude, perceived control, and normative concerns are significant predictors of Pothwar growers' EOE adoption intention. Respondents with positive attitudes, indicated by standardized coefficients, tended to show stronger intentions towards adopting by-product preparation ($\beta = 0.48$) and steam distillation usage ($\beta = 0.23$) compared to others. The variance (R^2) of normative concerns extracted by assigned variables was 50% for by-product development and 40% for steam distillation usage. The latent variable 'perceived controls' encompassed both personal efficacy and perceived resources, predicting 84% (by-product preparation) and 40% (steam distillation usage) of available variance. The findings supported the hypotheses (H_1), indicating favorable At, Pc, and Nc significantly influence Pothwar growers' adoption intentions.

Results show perceived usefulness and ease of use positively affect farmers' intended behavior, while perceived compatibility negatively impacts intentions for the 2nd practice (-0.248). Normative concerns, including technical training, social media, and social influence, have significant direct effects on growers' intentions for both practices. However, extension services have negative indirect effects on adoption behavior. Perceived controls, like perceived resources and self-efficacy, significantly affect intentions, except for resources in the 1st practice ($p = 0.395$). These findings support H2, suggesting positive direct effects of observed variables on intentions, except for perceived resources and extension services.

3.1.2.1 Mediation analysis

Table 3 illustrates the mediation results of inner or structure model PLS-SEM for both EOE practices. Attitude explains approximately 64% and 43% of available variance (R^2) in respondents' attitudes towards the 2nd and 1st practices, respectively. Improved attitudes by 19% and 17% for by-products and steam distillation usage, respectively. Thus, the findings support the H_3, indicating attitudes mediate the positive effect of Pu and Peou on growers' intentions for both EOE practices.

Normative concerns, reflecting peer groups and external factors, show significant positive effects on each EOE practice, except for extension services. Technical training had a notably higher coefficients ($\beta= 0.83$) for by-product preparation than for the other practice. However, extension services lacked a substantial effect on farmers' normative concerns regarding either practice. Thus, H_4, stating positive and significant mediating effects of technical training and social media influence on growers' intentions through normative concerns, was supported for both practices, while extension services did not demonstrate a positive mediation effect on intentions.

Positive and significant indirect effects of perceived resources influence individuals' intention towards EOE practices, mediated by perceived control. Self-efficacy demonstrates positive indirect effects, except for the first practice's non-significant effect. Hypothesis (H_5) proposed perceived control mediates positive effects of personal willingness and resources on intentions, except for self-efficacy's non-significant effect in the 2nd practice. Moreover, large-sized effects were observed for Peou on At (f2 = 2.70) (2nd practice), Tt on Nc (f2 = 0.66) (1st practice), and Nc on Bi (f2 = 0.64) (2nd practice).

3.1.2.2 Moderation analysis

Table 4 illustrates results from bootstrap multi-group analysis, indicating socio-economic variables' moderation effects for both EOE practices. Notably, normative concerns exhibit the most positive and significant path coefficient (β = 0.545) on intention towards adopting steam distillation usage under medium-level farm income (PKR 40,001-120,000). Similarly, a positive standardized path coefficient (β = 0.389) is observed for normative concerns on intended behavior under high-level farm income (PKR 120,001 & above) in by-product preparation. The model also predicts significant coefficients (β = 0.664) for normative concerns on growers' intentions with medium farm area (9-24 kanal) for steam distillation usage. Additionally, 'β = 0.378' is significant for perceived control on intentions in by-product preparation with high farming experience (11-15 years). These findings support H6, indicating socio-economic variables moderate positive and significant effects between exogenous and endogenous latent variables.

3.1.3 PLS-SEM model predict

The Q2 value for all predicted measured variable 'Bi' surpassed zero, indicating adequate predictive relevance. Errors in the PLS-SEM_MAE model were fewer than in the linear model (LM_MAE) for all Bi indicators, demonstrating high predictive power for by-product preparation (1st practice), with medium prediction power for steam distillation (1st practice) (Annex C).

4. DISCUSSIONS

The estimation results under the measurement scale reflect significant values concerning reliability and validity as supported by Henseler et al. (2015) that the discriminant validity of the model must not exceed a value of 0.9 for all constructs. Furthermore, internal consistency, as measured by CR, indicates the extent to which items effectively measure an underlying variable and should surpass a threshold of 0.7 (Mohd Dzin and Lay, 2021). Further, Cronbach's alpha presents another estimate of internal consistency similar to CR value, but less precise than CR measured under PLS-SEM (Hair et al., 2019). The results are also in line with Cheah et al. (2018) that AVE must surpass a value of 0.5 depicted convergent validity of the model. VIF values over

5 indicate significant collinearity in the formative model, requiring evaluation to avoid indicator insignificance (Wong, 2013).

The proposed adoption model yielded positive and significant results from mediation-moderation analysis among specific variables derived from Rogers' IDT, TAM by Davis, and Ajzens' TPB. The reported R^2 values of 0.67, 0.33, and 0.19 for PLS-SEM indicate substantial, modest, and weak explanatory power, respectively (Kock and Hadaya, 2018). Thus, the R^2 of the proposed model can be characterized as substantial and modest for all inferred variables. Additionally, Hair et al. (2019) reported that f^2-values exceeding 0.02, 0.15, and 0.35 indicate small, medium, and large effects of the external on the internal variable, respectively, while Q^2 values surpassing 0 indicate adequate predictive relevance of the proposed model (Shmueli et al., 2019). Furthermore, a high R^2 in the PLS-SEM indicates the model effectively captures key factors influencing respondents' decisions in adopting EOE practices. Farmers' intentions to adopt EOE practices are shaped by attitudes, perceived control, and normative concerns. These findings align with Riaz et al. (2021), who identified perceived usefulness, ease of understanding, and lack of complexity as influential factors affecting farmers' intentions towards sustainable practices in developed countries, as well as the cultivation of medicinal and aromatic plants in developing countries. The adoption of EOE interventions, such as combining eucalyptus farming and essential oil extraction, is likely influenced by technical training provided to growers through master trainers. Thus, training and social influence, including positive opinions from peers, may alleviate growers' uncertainty about the economic potential of cultivating high-value crops (Roussy et al., 2017). Similarly, this applies to the preparation of by-products like bio-compost and bio-pesticides derived from distillation waste of aromatic plants (Lalthazuali and Mathew, 2017; Zaccardelli et al., 2021). While extension services are often considered significant in improving farmers' perceptions towards adopting innovative practices (Labarthe and Laurent, 2013). However, in this study, they showed a non-significant effect on normative concerns about eucalyptus growers' intentions towards both EOE practices. This could be due to limited access of extension personnel to potential technology users (Gatdet, 2022), preferably during the growing season of the targeted crop, or lack of field expertise within the particular research area. Additionally, an increase in external resources is associated with an increase in perceived behavioral control, suggesting that barriers such as a shortage of economic resources may impede practice adoption. These findings are consistent with those of

(Dessart et al., 2019; Zeweld et al., 2017) who argued that resource conditions perspectives, and compatibility greatly impact technology adoption.

5. CONCLUSIONS, LIMITATIONS, AND SUGGESTIONS

This study examines the adoption of two essential oil extraction (EOE) practices—steam distillation and by-product preparation—for eucalyptus. Key drivers include socio-psychological factors, particularly attitudes and normative concerns, which enhance intentions to adopt these practices. Attitudes improve perceptions of usefulness and ease of use, while normative concerns influence the effects of training and social support. Perceived resources do not significantly affect adoption intentions, and socio-economic factors such as farm size, experience, and income moderate the adoption, as confirmed by the PLS-SEM model. This study has few limitations and recommends future research on alternative extraction methods beyond steam distillation and by-product preparation. Employing covariance-based CB-SEM and exploring similar agro-climatic regions could enhance the model, while broader sampling may improve predictions of the relationship between intention and actual adoption.

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References

Ajzen, I. 1991. The theory of planned behavior. Organizational behavior and human decision processes, 50(2), 179-211. doi:https://doi.org/10.1016/0749-5978(91)90020-T

Bakkabulindi, F. E. K. 2014. A call for return to Rogers' innovation diffusion theory. Mak. J. High. Edu., 6(1), 55–85-55–85. doi:10.4314/majohe.v6i1.4

Barbosa, L. C. A., Filomeno, C. A., and Teixeira, R. R. 2016. Chemical variability and biological activities of Eucalyptus spp. essential oils. Molecules, 21(12), 1671. doi:https://doi.org/10.3390/molecules21121671

Cheah, J.-H., Sarstedt, M., Ringle, C. M., Ramayah, T., and Ting, H. 2018. Convergent validity assessment of formatively measured constructs in PLS-SEM: On using single-item versus multi-item measures in redundancy analyses. Int. J. Cont. Hos. Mgt., 30(11), 3192-3210. doi:https://doi.org/10.1108/IJCHM-10-2017-0649

Chhetri, V. T., Shrestha, S., Thapa, S., and Timilsina, S. 2021. Status and Role of Medicinal and Aromatic Plants (MAPs) in Nepalese Livelihood. Int. J. Environ., 10(1), 112-136. doi:https://doi.org/10.3126/ije.v10i1.38405

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS quarterly, 319-340.

Dessart, F. J., Barreiro-Hurlé, J., and Van Bavel, R. 2019. Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. Europ. Rev. Agric. Econ., 46(3), 417-471. doi:https://doi:10.1093/erae/jbz019

Dhakad, A. K., Pandey, V. V., Beg, S., Rawat, J. M., and Singh, A. 2018. Biological, medicinal and toxicological significance of Eucalyptus leaf essential oil: a review. J. Sci. Food Agric., 98(3), 833-848. doi:https://doi.org/10.1002/jsfa.8600

Dong, H., Wang, H., and Han, J. 2022. Understanding ecological agricultural technology adoption in China using an integrated technology acceptance model—theory of planned behavior model. Frontiers in Environmental Science, 10, 927668. doi:https://doi.org/10.3389/fenvs.2022.927668

Gatdet, C. 2022. The Ethiopian agricultural extension services: A mixed perspective. Cog. Food Agri., 8(1), 2132848. doi:https://doi.org/10.1080/23311932.2022.2132848

Greff, B., Lakatos, E., Szigeti, J., and Varga, L. 2021. Co-composting with herbal wastes: Potential effects of essential oil residues on microbial pathogens during composting. Crit. Rev. Environ. Sci. Technol., 51(5), 457-511. doi:https://doi.org/10.1080/10643389.2020.1732780

Hair, J. F., Risher, J. J., Sarstedt, M., and Ringle, C. M. 2019. When to use and how to report the results of PLS-SEM. Europ. Buis. Rev., 31(1), 2-24.

Henseler, J., Ringle, C. M., and Sarstedt, M. 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Market. Sci., 43, 115-135. doi: 10.1007/s11747-014-0403-8

Hossan, D., Aktar, A., and Zhang, Q. 2020. A Study on Partial Least Squares Structural Equation Modeling (PLS-SEM) as Emerging Tool in Action Research. LC International Journal of STEM (ISSN: 2708-7123), 1(4), 130-146. doi:https://doi.org/10.5281/zenodo.5149796

Ikram, M., Sroufe, R., Awan, U., and Abid, N. 2021. Enabling progress in developing economies: A novel hybrid decision-making model for green technology planning. Sustainability, 14(1), 258. doi:https://doi.org/10.3390/su14010258

Khalid, K. A., Ahmed, A. M., and El-Gohary, A. E. 2020. Effect of growing seasons on the leaf essential oil composition of Citrus species that are cultivated in Egypt. Journal of Essential Oil Research, 32(4), 296-307. doi:https://doi.org/10.1080/10412905.2020.1749947

Khoi, B. H. and Van Tuan, N. (2018). Using SmartPLS 3.0 to analyse internet service quality in Vietnam. Paper presented at the Econometrics for Financial Applications.

Kock, N. and Hadaya, P. 2018. Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. Inf. Sys. J., 28(1), 227-261.

Krejcie, R. V. and Morgan, D. W. 1970. Determining sample size for research activities. Educational and psychological measurement, 30(3), 607-610. doi:10.1177/001316447003000308

Labarthe, P. and Laurent, C. 2013. Privatization of agricultural extension services in the EU: Towards a lack of adequate knowledge for small-scale farms? Food Policy, 38, 240-252.

Lalthazuali and Mathew, N. 2017. Mosquito repellent activity of volatile oils from selected aromatic plants. Parasitol. Res., 116(2), 821-825. doi:10.1007/s00436-016-5351-4

Leguina, A. 2015. A primer on partial least squares structural equation modeling (PLS-SEM). Int. J. Res. Meth. Edu., 38(2), 220-221. doi:10.1080/1743727X.2015.1005806

Liu, T., Bruins, R. J., and Heberling, M. T. 2018. Factors influencing farmers' adoption of best management practices: A review and synthesis. Sustainability, 10(2), 432. doi:https://doi.org/10.3390/su10020432

Marangunić, N. and Granić, A. 2015. Technology acceptance model: a literature review from 1986 to 2013. Universal access in the information society, 14, 81-95. doi:10.1007/s10209-014-0348-1

Miller, R. L. 2015. Rogers' innovation diffusion theory (1962, 1995). In Information seeking behavior and technology adoption: Theories and trends (pp. 261-274): IGI Global.

Mohd Dzin, N. H. and Lay, Y. F. 2021. Validity and reliability of adapted self-efficacy scales in Malaysian context using PLS-SEM approach. Education Sciences, 11(11), 676. doi:https://doi.org/10.3390/educsci11110676

Mohd Israfi, N. A., Mohd Ali, M. I. A., Manickam, S., Sun, X., Goh, B. H., Tang, S. Y., Ismail, N., Abdull Razis, A. F., Ch'ng, S. E., and Chan, K. W. 2022. Essential oils and plant extracts for tropical fruits protection: From farm to table. Front. Plant Sci., 13, 999270. doi:https://doi.org/10.3389/fpls.2022.999270

Momani, A. M. 2020. The unified theory of acceptance and use of technology: A new approach in technology acceptance. Int. J. Sociotechnol. Know. Develop., 12(3), 79-98. doi:10.4018/IJSKD.2020070105

Monecke, A. and Leisch, F. 2012. semPLS: structural equation modeling using partial least squares. Retrieved from https://ro.uow.edu.au/commpapers/3138

Ndiaye, E. H. B., Diop, M. B., Gueye, M. T., Ndiaye, I., Diop, S. M., Fauconnier, M.-L., and Lognay, G. 2018. Characterization of essential oils and hydrosols from senegalese Eucalyptus camaldulensis Dehnh. J. Essent. Oil Res., 30(2), 131-141. doi:https://doi.org/10.1080/10412905.2017.1420554

Purwanto, A. 2021. Partial least squares structural squation modeling (PLS-SEM) analysis for social and management research: a literature review. J. Ind. Eng. Mgt. Res. doi:https://doi.org/10.7777/jiemar.v2i4

Regnault-Roger, C., Vincent, C., and Arnason, J. T. 2012. Essential oils in insect control: low-risk products in a high-stakes world. Annu. Rev. Entomol., 57, 405-424. doi:https://doi.org/10.1146/annurev-ento-120710-100554

Riaz, U., Iqbal, S., Sohail, M., Samreen, T., Ashraf, M., Akmal, F., Siddiqui, A., Ahmad, I., Naveed, M., and Khan, N. 2021. A comprehensive review on emerging importance and economical potential of medicinal and aromatic plants (MAPs) in current scenario. Pak. J. Agric. Res., 34(2), 381-392. doi:https://dx.doi.org/10.17582/journal.pjar/2021/34.2.381.392

Rogers, E. 2003. Diffusion of Innovations fifth Ed Free Press. New York. Rezvani, Z., Jansson, J. & Bodin.

Roussy, C., Ridier, A., and Chaib, K. 2017. Farmers' innovation adoption behaviour: role of perceptions and preferences. Int. J. Agric. Resour. Govn. Ecol., 13(2), 138-161. doi:https://doi.org/10.1504/IJARGE.2017.086439

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., and Ringle, C. M. 2019. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. Europ. J. Mar., 53(11), 2322-2347.

Silva, P. 2015. Davis' technology acceptance model (TAM)(1989). Information seeking behavior and technology adoption: Theories and trends, 205-219. doi:10.4018/978-1-4666-8156-9.ch013

Tian, H., Iqbal, S., Anwar, F., Akhtar, S., Khan, M. A. S., and Wang, W. 2021. Network embeddedness and innovation performance: a mediation moderation analysis using PLS-SEM. Buis. Proc. Mgt. J., 27(5), 1590-1609. doi:https://doi.org/10.1108/BPMJ-08-2020-0377

Wong, K. K.-K. 2013. Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. Market. Bulletin, 24(1), 1-32. doi:http://www.researchgate.net/publication/268449353

Zaccardelli, M., Roscigno, G., Pane, C., Celano, G., Di Matteo, M., Mainente, M., Vuotto, A., Mencherini, T., Esposito, T., and Vitti, A. 2021. Essential oils and quality composts sourced by recycling vegetable residues from the aromatic plant supply chain. Ind. Crops. Prod., 162, 113255. doi:https://doi.org/10.1016/j.indcrop.2021.113255

Zeweld, W., Van Huylenbroeck, G., Tesfay, G., and Speelman, S. 2017. Smallholder farmers' behavioural intentions towards sustainable agricultural practices. J. Environ. Manage., 187, 71-81.

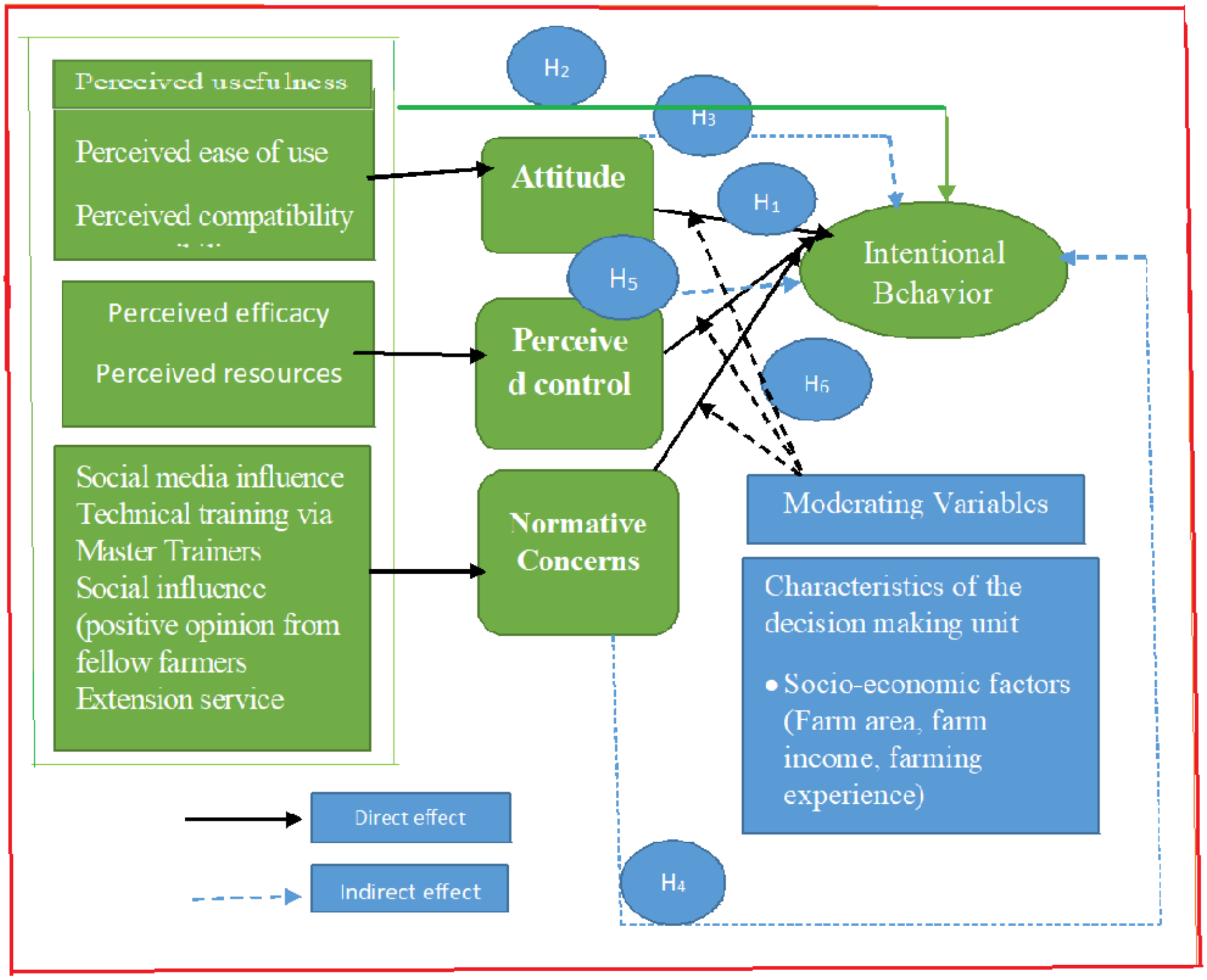
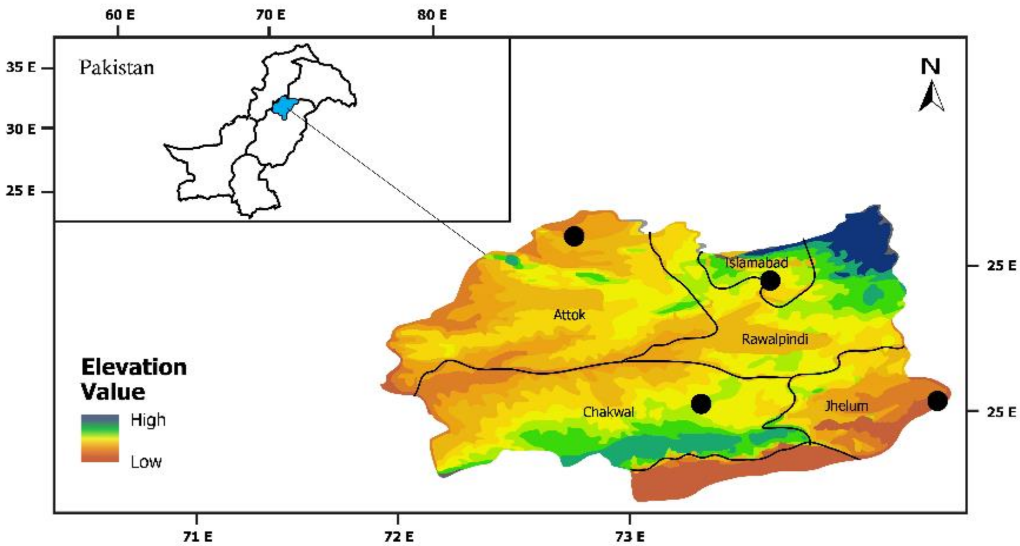


Figure 1 Extended proposed adoption model of the study (conceptual framework for behavioral intention of eucalyptus growers towards EOE practices). The proposed adoption model for EOE practices is a fusion of three different theories; Theory of Planned Behavior (TPB) by (Ajzen, 1991), Technology Acceptance Model (TAM) by (Davis, 1989) , and Innovation Diffusion Theory by (Rogers, 2003).



Map of Pothwar Plateau, Pakistan

Figure 2. Map of study area.

Table 1. Estimation of sample size from each selected district of the study area.

District	Population	Percentage	Sample size (n)
Attock	349	36.81	101
Chakwal	277	29.22	80
Jhelum	210	22.15	61
Rawalpindi	112	11.81	32
Total	948	100.00	274

Table 2. Results for the measurement model concerning 1st practice (Usage of steam distillation unit for essential oil extraction) and 2nd practice (By-products preparation) in the study.

Variable	**Statements (Indicator)**			**1st practice**			
		Mean	α	AFL	CR	AVE	Cramer-von Mises p value
Behavioral intentions	6	3.525	0.772	0.769	0.887	0.579	0.000
Attitudes	4	3.511	0.772	0.756	0.843	0.607	0.000
Perceived controls	4	3.240	0.779	0.841	0.879	0.602	0.000
Normative concerns	4	3.324	0.794	0.782	0.859	0.640	0.000
Perceived usefulness	3	3.136	0.725	0.715	0.779	0.574	0.000
Perceived ease of use	3	3.229	0.750	0.794	0.837	0.710	0.000
Perceived compatibility	3	3.949	0.745	0.730	0.783	0.614	0.000
Perceived efficacy	2	2.934	0.777	0.701	0.776	0.550	0.000
Perceived resources	3	2.951	0.760	0.734	0.779	0.508	0.000
Social influence	3	3.128	0.787	0.755	0.799	0.512	0.000
Social media	3	3.897	0.756	0.732	0.779	0.508	0.000
Technical training	3	3.694	0.798	0.778	0.861	0.675	0.000
Extension service	3	2.656	0.795	0.796	0.724	0.513	0.000
Variable	**Statements (Indicator)**	**2nd practice**					
		Mean	α	AFL	CR	AVE	Cramer-von Mises p value
Behavioral intentions	6	3.725	0.863	0.770	0.895	0.695	0.000
Attitudes	4	3.446	0.756	0.756	0.843	0.673	0.000
Perceived controls	4	3.582	0.793	0.841	0.879	0.707	0.000
Normative concerns	4	3.556	0.783	0.726	0.859	0.606	0.000
Perceived usefulness	3	3.305	0.775	0.734	0.779	0.543	0.000
Perceived ease of use	3	4.066	0.708	0.845	0.837	0.632	0.000
Perceived compatibility	3	4.176	0.709	0.856	0.783	0.656	0.000
Perceived efficacy	2	4.130	0.701	0.705	0.774	0.677	0.000
Perceived resources	3	2.044	0.796	0.838	0.708	0.626	0.000
Social influence	3	3.882	0.723	0.746	0.799	0.570	0.000
Social media	3	4.024	0.794	0.803	0.779	0.545	0.000
Technical training	3	3.997	0.804	0.878	0.826	0.618	0.000
Extension service	3	2.848	0.704	0.685	0.776	0.575	0.000

Cut-off level: α> 0.7; AFL> 0.7; CR> 0.7; AVE> 0.5; P value< 0.005 "non-normality"
α Cronbach- α (reliability) *AFL* Average factor loading, *CR* composite reliability *AVE* average variance extracted.
Statements were evaluated utilizing a five-point Likert scale (1= highly disagree; 5= highly agree).

Table 3. PLS-SEM results for the structure model for 1st practice (usage of steam distillation unit for essential oil extraction) and 2nd practice (by- product preparatory methods) (n= 274).

Model	Variable's path	Path-coefficient β	P-value	f-square [a]	Path-coefficient β	P-value	f-square [a]
		1st practice			**2nd practice**		
Behavior intention (*Bi*)	At -> Bi	0.23	0.000	0.15	0.48	0.000	0.34
	Nc-> Bi	0.53	0.003	0.24	0.55	0.004	0.64
	Pct-> Bi	0.17	0.000	0.17	0.21	0.000	0.15
	Perceived usefulness	0.224	0.000		0.721	0.000	
	Perceived ease of use	0.258	0.000		0.34	0.031	
	Perceived compatibility	0.097	0.015		-0.248	0.228	
	Technical training	0.256	0.000		1.709	0.006	
	Social media	0.314	0.000		0.319	0.037	
	Social influence	0.229	0.001		0.031	0.017	
	Extension service	-0.029	0.663		-0.272	0.070	
	Personal efficacy	0.177	0.009		0.168	0.048	
	Perceived resources	0.105	0.395		0.302	0.000	
Attitude (*At*)	Perceived usefulness-> Attitudes	0.28	0.009	0.07	0.31	0.006	0.24
	Perceived ease of use-> Attitudes	0.17	0.048	0.13	0.19	0.003	2.70
	Perceived compatibility-> Attitudes	0.22	0.008	0.15	0.20	0.035	0.11
Normative concerns (*Nc*)	Technical training -> Nc	0.34	0.000	0.66	0.83	0.027	2.17
	Social media-> Nc	0.28	0.046	0.20	0.13	0.049	0.06
	Social influence-> Nc	0.15	0.244	0.02	0.12	0.040	0.18
	Extension service-> Nc	0.04	0.695	0.03	-0.10	0.308	0.04
Perceived controls (*Pct*)	Personal efficacy-> Pct	0.14	0.071	0.12	0.17	0.009	0.02
	Perceived resources-> Pct	0.19	0.039	0.28	0.22	0.001	0.03

1st practice: Bi (R^2= 0.65), At (R^2= 0.43), Nc (R^2= 0.44), Pc (R^2= 0.40)
2nd practice: Bi (R^2= 0.79), At (R^2= 0.64), Nc (R^2= 0.77), Pc (R^2= 0.37)
Bi behavior intention; *At* attitude; *Nc* normative concern; *Pct* perceived control

Table 4. PLS-SEM results for the moderation effect for 1st practice (usage of steam distillation unit for essential oil extraction) and for 2nd practice (By-products preparation) (n= 274).

Moderating Variable	Path	Coefficient β (low)	Coefficient β (Medium)	Coefficient β (high)	P-value (Low)	P-value Medium	P-value (High)
		1st practice					
Income (PKR)	At -> Bi	0.197	0.189	0.339	0.060	0.045*	0.001***
	Nc -> Bi	0.467	0.545	0.485	0.000***	0.000***	0.000***
	Pc-> Bi	-0.002	0.220	0.313	0.988	0.028*	0.002***
Farm area (*kanal*)	At -> Bi	0.067	0.276	0.133	0.716	0.000***	0.196
	Nc -> Bi	0.454	0.664	0.483	0.032*	0.000	0.000***
	Pc-> Bi	0.085	0.236	0.212	0.467	0.002	0.149
Farm experience (year)	At -> Bi	0.109	0.220	0.367	0.131	0.003	0.001***
	Nc -> Bi	0.429	0.491	0.453	0.000***	0.000***	0.001***
	Pc-> Bi	0.148	0.214	0.327	0.266	0.011***	0.001***
		2nd practice					
Income (PKR)	At -> Bi	0.181	0.397	0.233	0.008	0.001***	0.000***
	Nc -> Bi	-0.031	0.156	0.381	0.882	0.226	0.000***
	Pc-> Bi	0.348	0.593	0.622	0.001	0.000***	0.000***
Farm area (*kanal*)	At -> Bi	0.162	0.223	0.293	0.303	0.005***	0.000***
	Nc -> Bi	0.372	0.251	0.292	0.149	0.199	0.003***
	Pc-> Bi	0.240	0.359	0.440	0.297	0.016**	0.001***
Farm experience (year)	At -> Bi	0.311	0.246	0.458	0.000	0.000***	0.001***
	Nc -> Bi	0.120	0.101	0.543	0.199	0.120	0.000***
	Pc-> Bi	0.125	0.367	0.378	0.678	0.035*	0.007***

Bi behavior intention; *At* attitude; *Nc* normative concern; *Pc* perceived control
Farm income (PKR) (low=< 40,000/-; medium= 40,001–120,000/-; high= > 120,001 and above)
Farm area (*kanal*) (low= 1-8 and 9-24; medium = 25-44; high = > 45)
Farm experience (year) (low=< 5 ; medium= 6-10; high= > 11 and above)
P< 0.001 (P< 0.01; P< 0.05) is inferred by *** (**; *)