

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

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5
6 **Abstract**

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

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

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19 **1. INTRODUCTION**

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

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

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

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

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

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1 **1.1 Theoretical background**

2 To deepen understanding of innovation adoption, Rogers' Innovation Decision Theory (IDT)
3 elucidates the link between farmers' adoption and their knowledge-based perception of an
4 innovation (Bakkabulindi, 2014). Despite EOE technology being perceived as new among aromatic
5 crop growers due to limited knowledge, its global adoption and economic efficacy from aromatic
6 plants are well-documented (Chhetri et al., 2021). An empirical model integrating TPB (Ajzen,
7 1991), Rogers' IDT (Miller, 2015) , and TAM by Davis (Silva, 2015) (Figure 1) was proposed to
8 study variables' cause-and-effect relationship on adoption behavior. While no universally accepted
9 model exists, TPB and TAM are commonly applied in agricultural technology adoption
10 (Marangunić and Granić, 2015). This study's model explains eucalyptus growers' intention through
11 attitude into perceived usefulness (Pu) and ease of use (Peou) from TAM, and perceived
12 compatibility (Pc) from Rogers' IDT, perceived control into self-efficacy and perceived resources
13 (Pr), and normative concerns, further enriched with elements from social media (Sm), influence
14 (Si), technical training (Tt), and extension services (Es) to capture social pressure and
15 communication source (Momani, 2020).

16 **1.2 Generation of hypotheses for the proposed adoption model**

17 H₁= Attitude, perceived control, and normative concerns have significant and positive effects on
18 the growers' intentions toward EOE practices.

19 H₂= All observed variables (Pu, Peou, Pc, Tt, Si, Sm, Es, Pe, Pr) have significant and positive
20 effects on the growers' Bi concerning EOE practices.

21 H₃= Attitude facilitates the positive effects of perceived usefulness, ease of use, and
22 compatibility on EOE adoption intentions.

23 H₄= Normative concerns mediate the effects of social media, technical training, and extension
24 services on the growers' intentions towards EOE practices.

25 H₅= Perceived control mediates self-efficacy and resources positively on growers' intended
26 behavior towards EOE adoption.

27 H₆= Socioeconomic factors moderate positive relationships between variables towards EOE
28 adoption.

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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

1 measured, are inferred from observed variable responses. However, the variance-based PLS-SEM
 2 approach was chosen to assess the adoption model for several reasons: (i) maximizing explained
 3 variability (R^2) in the criterion variable; (ii) flexibility regarding data structure normality; (iii)
 4 accommodating underlying variables with few items; and (iv) favoring prediction over theory
 5 testing (Leguina, 2015). This methodological choice allows for a comprehensive examination of
 6 relationships in the adoption model, prioritizing practical relevance and prediction accuracy. The
 7 PLS-SEM adoption model underwent evaluation in two steps using SMART-PLS: first, assessing
 8 the relationship between indicators and inferred variables (measurement model), and second,
 9 examining causal relationships among inferred variables (structure model) (Khoi and Van Tuan,
 10 2018). Hence, Each PLS path item is a linear function with errors:

$$11 \quad X_j = \Lambda_j \xi_j + \varepsilon \text{ (exogenous latent variable } \xi_j) \dots \dots \dots (1)$$

$$12 \quad X_l = \Lambda_l \xi_l + \delta \text{ (endogenous latent variable } \xi_l) \dots \dots \dots (2)$$

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

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

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

17 Λ_j and Λ_l = loading coefficient matrices ($\Lambda_1, \dots, \Lambda_m$), k = no. of indicators (items)

18 ε and δ = set of error terms for the items

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

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

$$27 \quad \xi_k = B \xi_k + \Gamma \xi_j + \zeta \dots \dots \dots (3)$$

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

29 Γ = coefficient matrix of the causal effects of the external implied variable ξ_j on the internal
 30 inferred variable ξ_k . In the structural model, an inferred endogenous variable can also act as an
 31 exogenous variable for another endogenous variable, with ζ representing the residuals or error

1 terms. A bootstrapping process with 5,000 subsamples calculated p-values and effect sizes (f^2 -
2 value) (Purwanto, 2021). Furthermore, moderating variables like farm area, farming experience,
3 and farm income were assessed through bootstrap multi-group analysis (Tian et al., 2021).
4 Predictive relevance Q^2 for the endogenous variable (Bi) was also estimated using PLS-Predict
5 (Hossan et al., 2020).

6

7 **3. RESULTS**

8 **3.1 Estimation results of the extended proposed adoption model of the study**

9 **3.1.1 Measurement model**

10 Annex-A results indicate no HTMT ratio surpassing the critical level of 0.9 for each variable
11 under each EOE practice. Table 2 displays mean and factor loading results for each variable. CR
12 values above 0.7 denote favorable internal consistency within the adoption model for each practice.
13 The lowest CR value, 0.724, was observed for extension services in the use of a steam distillation
14 unit for EOE. The highest CR value, 0.895, was found for the implied variable 'Bi' in by-product
15 preparation. Cronbach's alpha (α) for each variable was also assessed, with the highest values
16 (0.863 and 0.798) for 'Bi' in by-product preparation and usage of a steam distillation unit,
17 respectively. Convergent validity, measured by AVE, exceeded 0.5 for each inferred variable. Each
18 variable can account for over 50% of indicator variance. The latent variable "self-efficacy under
19 1st practice" had the lowest AVE (0.512), confirming convergent validity. VIFs below 5 indicate
20 no multicollinearity for these variables (Annex B).

21

22 **3.1.2 Structure model**

23 Table 3 displays SEM outcomes, including path coefficients, p-values, and effect sizes (f^2 -value).
24 Behavioral intention predicts approximately 79% for by-product preparation and 65% for using a
25 steam distillation unit. Attitude, perceived control, and normative concerns are significant
26 predictors of Pothwar growers' EOE adoption intention. Respondents with positive attitudes,
27 indicated by standardized coefficients, tended to show stronger intentions towards adopting by-
28 product preparation ($\beta = 0.48$) and steam distillation usage ($\beta = 0.23$) compared to others. The
29 variance (R^2) of normative concerns extracted by assigned variables was 50% for by-product
30 development and 40% for steam distillation usage. The latent variable 'perceived controls'
31 encompassed both personal efficacy and perceived resources, predicting 84% (by-product

1 preparation) and 40% (steam distillation usage) of available variance. The findings supported the
2 hypotheses (H₁), indicating favorable At, Pc, and Nc significantly influence Pothwar growers'
3 adoption intentions.

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

12

13 3.1.2.1 *Mediation analysis*

14 Table 3 illustrates the mediation results of inner or structure model PLS-SEM for both EOE
15 practices. Attitude explains approximately 64% and 43% of available variance (R^2) in respondents'
16 attitudes towards the 2nd and 1st practices, respectively. Improved attitudes by 19% and 17% for
17 by-products and steam distillation usage, respectively. Thus, the findings support the H₃, indicating
18 attitudes mediate the positive effect of Pu and Peou on growers' intentions for both EOE practices.

19 Normative concerns, reflecting peer groups and external factors, show significant positive effects
20 on each EOE practice, except for extension services. Technical training had a notably higher
21 coefficients ($\beta = 0.83$) for by-product preparation than for the other practice. However, extension
22 services lacked a substantial effect on farmers' normative concerns regarding either practice. Thus,
23 H₄, stating positive and significant mediating effects of technical training and social media
24 influence on growers' intentions through normative concerns, was supported for both practices,
25 while extension services did not demonstrate a positive mediation effect on intentions.

26 Positive and significant indirect effects of perceived resources influence individuals' intention
27 towards EOE practices, mediated by perceived control. Self-efficacy demonstrates positive indirect
28 effects, except for the first practice's non-significant effect. Hypothesis (H₅) proposed perceived
29 control mediates positive effects of personal willingness and resources on intentions, except for
30 self-efficacy's non-significant effect in the 2nd practice. Moreover, large-sized effects were

1 observed for Peou on At ($f^2 = 2.70$) (2nd practice), Tt on Nc ($f^2 = 0.66$) (1st practice), and Nc on
2 Bi ($f^2 = 0.64$) (2nd practice).

3 4 **3.1.2.2 Moderation analysis**

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

16 17 **3.1.3 PLS-SEM model predict**

18 The Q2 value for all predicted measured variable 'Bi' surpassed zero, indicating adequate
19 predictive relevance. Errors in the PLS-SEM_MAE model were fewer than in the linear model
20 (LM_MAE) for all Bi indicators, demonstrating high predictive power for by-product preparation
21 (1st practice), with medium prediction power for steam distillation (1st practice) (Annex C).

22 23 **4. DISCUSSIONS**

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

1 5 indicate significant collinearity in the formative model, requiring evaluation to avoid indicator
2 insignificance (Wong, 2013).

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

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

3
4 **5. CONCLUSIONS, LIMITATIONS, AND SUGGESTIONS**

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

16
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20
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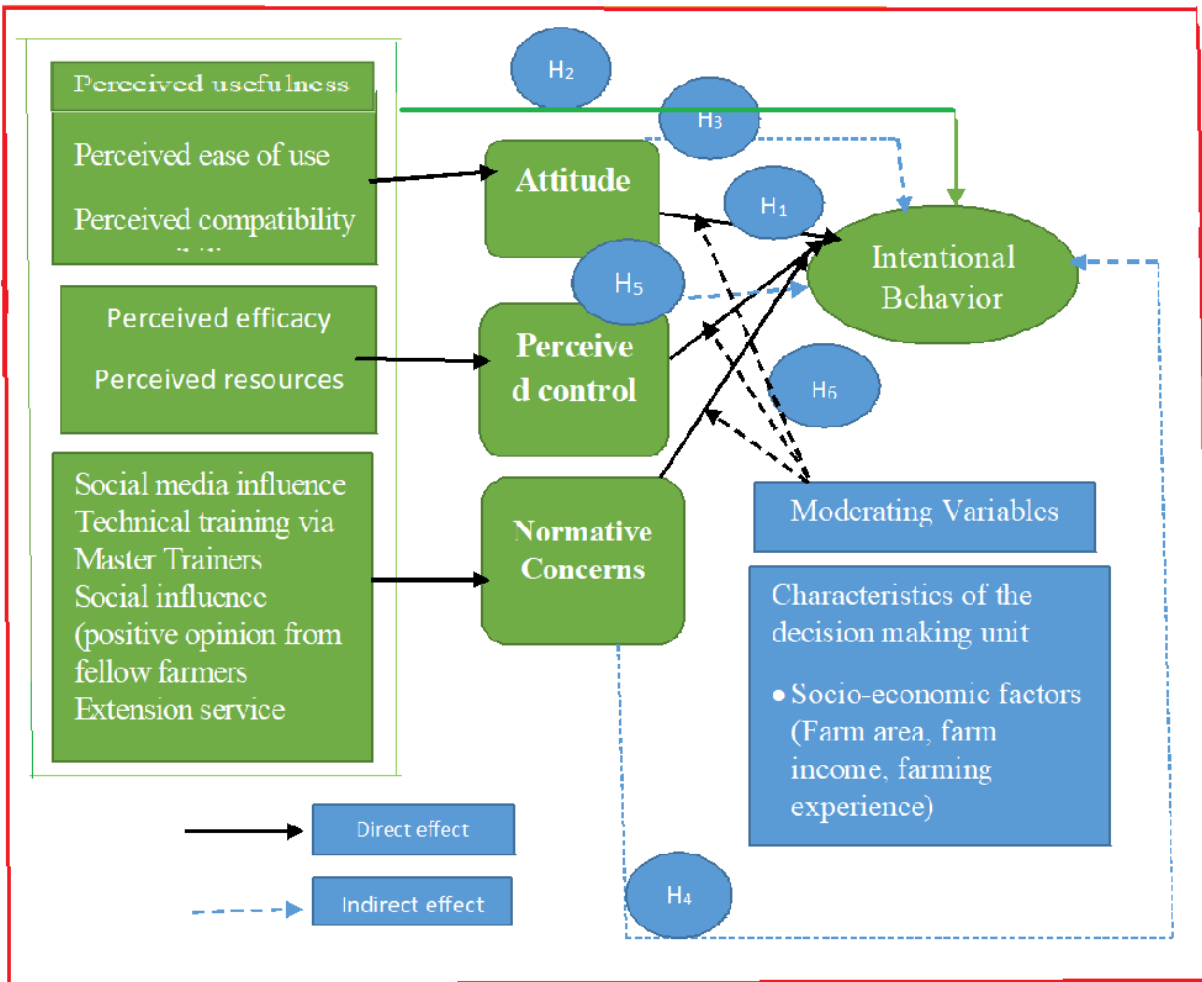
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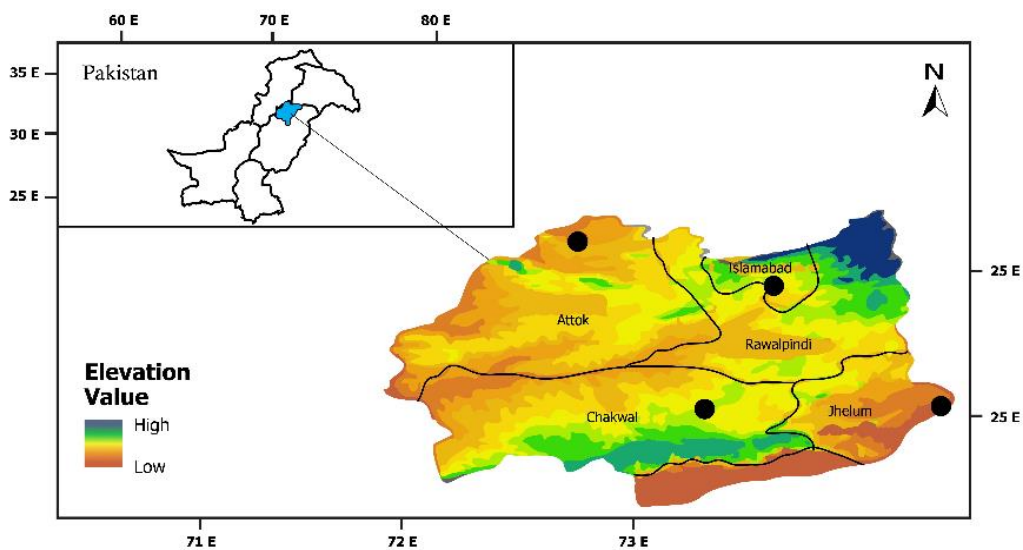
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 2 **Figure 1** Extended proposed adoption model of the study (conceptual framework for behavioral
 3 intention of eucalyptus growers towards EOE practices). The proposed adoption model for EOE
 4 practices is a fusion of three different theories; Theory of Planned Behavior (TPB) by (Ajzen,
 5 1991), Technology Acceptance Model (TAM) by (Davis, 1989) , and Innovation Diffusion Theory
 6 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

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

4 Cut-off level: $\alpha > 0.7$; AFL > 0.7; CR > 0.7; AVE > 0.5; P value < 0.005 "non-normality"

5 α Cronbach- α (reliability) AFL Average factor loading, CR composite reliability AVE average variance extracted.

6 Statements were evaluated utilizing a five-point Likert scale (1= highly disagree; 5= highly agree).
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1 **Table 3.** PLS-SEM results for the structure model for 1st practice (usage of steam distillation unit
 2 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 (<i>Bi</i>)	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 (<i>At</i>)	Perceived usefulness-> Attitudes	0.28	0.009	0.07	0.31	0.006
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 (<i>Nc</i>)	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 (<i>Pct</i>)	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

3 **1st practice:** Bi ($R^2= 0.65$), At ($R^2= 0.43$), Nc ($R^2= 0.44$), Pc ($R^2= 0.40$)

4 **2nd practice:** Bi ($R^2= 0.79$), At ($R^2= 0.64$), Nc ($R^2= 0.77$), Pc ($R^2= 0.37$)

5 *Bi* behavior intention; *At* attitude; *Nc* normative concern; *Pct* perceived control

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1 **Table 4.** PLS-SEM results for the moderation effect for 1st practice (usage of steam distillation
2 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 (<i>kanal</i>)	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 (<i>kanal</i>)	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***

3 *Bi* behavior intention; *At* attitude; *Nc* normative concern; *Pc* perceived control

4 Farm income (PKR) (low=< 40,000/-; medium= 40,001–120,000/-; high= > 120,001 and above)

5 Farm area (*kanal*) (low= 1-8 and 9-24; medium = 25-44; high = > 45)

6 Farm experience (year) (low=< 5 ; medium= 6-10; high= > 11 and above)

7 P< 0.001 (P< 0.01; P< 0.05) is inferred by *** (**; *)