INNOVATION AS A CATALYST: DRIVERS OF TECHNOLOGICAL ADVANCEMENT IN ORGANIC FARMING

Anshi Aswal
School of Management, Doon University

Vivek Dabral
School of Management, Graphic Era Hill University

H.C. Purohit
School of Management, Doon University

"The future of India lies in its villages" – Mahatma Gandhi

ABSTRACT

Purpose: The paper aims to examine innovation attributes and their influence on farmers' behavioural intention to adopt technological interventions in organic farming.

Design/methodology/approach: To achieve research objectives, a combination of E.M. Rogers' (1962) Diffusion of Innovation (DOI) and Fred Davis's (1986) TAM was employed. Research hypotheses were established based on a literature review. Five innovation adoption attributes suggested by Rogers were modified in the context of organic farming and were used in the survey questionnaire design and data analysis.

Findings: The findings revealed that perceived innovation attributes have a significant relationship with behavioural intention to adopt technological intervention in organic farming. where Relative Advantage, Compatibility, and observability exhibit positive relations, whereas complexity and trialability demonstrate a negative relationship.

Practical implication: Policymakers can enhance farmers' understanding of organic farming techniques, leading to greater adoption of organic inputs. By providing training and information, policymakers can improve the knowledge and attitudes of organic farmers. Governmental initiatives and support programs must be thorough, addressing not just incentives for promoting organic practices but also overcoming implementation challenges and barriers.

Originality/value: The significance of this research stems from the scarcity of studies that integrate the Innovation Diffusion Theory (IDT) and the Technology Acceptance Model (TAM) within the context of

organic farming. Furthermore, it contributes to the limited body of literature addressing the factors influencing the adoption of biological input technologies.

Paper Type: Research paper

Keywords: Farmers, Organic Farming, Technology Intervention, diffusion of innovation, technology acceptance model.

Introduction:

A nation's economy majorly depends on its three sectors, i.e., primary, secondary, and tertiary. As per the Economic Survey report (2022-23), the service sector has the highest growth rate, 9.1%, followed by the industry sector at 4.1% and the agriculture sector at 3.5% in terms of GDP contribution. Though the agriculture sector contributes less to GDP, it employs the largest share of the population, 43.96%, and the largest share of the women workforce, 71% (PIB,2022). India is still primarily a rural economy, and agriculture remains a mainstay of the majority population (World Bank,2019). Our population is expected to increase further, reaching 1.6 billion by 2050 (UN, 2017). The growing population will intensify the challenges of achieving food security and reducing environmental impacts (Jha et al., 2022). The Green Revolution's focus on chemical-based technological advancements significantly increased production potential and ensured food security for the nation (Swami, 2020). This transformation of agriculture from "farming for subsistence" to "farming for profits" led to excessive use of chemical fertilizers and pesticides, which had severe effects on the environment (Bhargava,2022). Lack of proper choice and continuous use of these high-energy inputs leads to a drop in the growth in crop production and productivity, which comes at the cost of environmental degradation and declining soil health (Behera, 2012). To mitigate this challenge, the urgent need for environmentally friendly and socially equitable technologies and scientific farming methods should be promoted in a shrinking arable land base (Altieri et al., 2011). In the wake of an ecological imbalance created using chemical fertilizers and pesticides post-green revolution, organic farming is not just an option, but a necessity to bring back sustainability in the farming sector. The unsustainability of conventional agriculture has promoted interest in sustainable farming systems (Reganold et al., 2016). The time to act is now, as the challenges of food security and environmental degradation are becoming more pressing. In pursuing safer food options, there has been a growing demand for organically produced foods over the past few decades. This increased interest in organic food is driven by its potential health advantages and concerns about food safety (Das et al., 2020). the organic farming system has been in practice for centuries, and its roots can be traced back in available ancient texts like the Rigveda, Ramayana, Mahabharata, and Kautilya Arthasashthra (Swami, 2020). With this Indigenous knowledge, the society was self-reliant, and they did not face any problem of large-scale economic crises or pest outbreaks (Eagan et al., 2018).

India occupies the sixth position globally regarding the extent of Organic Agricultural land and ranks first regarding the cumulative number of producers, according to data from the year 2021 (FIBL & IFOAM Year Book, 2023India possesses a substantial agricultural land area across various states, which is significantly susceptible to climatic variability, particularly in topographically diverse regions such as Uttarakhand, which is mainly dryland and rainfed (Panwar et al, 2019). Uttarakhand represents the inaugural state within the nation to have developed a comprehensive organic farming policy, which was instituted in the year 2000. (Jangyukala et al., 2020). The total area covered under organic cultivation in the state accounts for 215483 hectares, involving 465350 registered organic farmers (UOCB, 2023). The Indian economy is shifting towards the modern and mechanized farming system, but this shift is slow and happening only in some regions of the country (Joshi et al,2018). However, the future of agriculture is not just about technological advancements, but also about the farmers who are at the forefront of these changes.

Improving the educational level of the farming community is a long-term goal. However, there is an immediate need to enhance the capacity of farmers to tackle the challenges faced by the agricultural sector efficiently. This study seeks to explore the factors influencing farmers' behavioural intention to adopt such innovations by examining the attributes of these technologies through the lens of Rogers' Diffusion of Innovations (DOI) theory. DOI theory, established by Everett M. Rogers in 1962, represents a well-established theoretical construct that elucidates how, why, and at what rate new ideas and technological innovations disseminate across various cultural contexts. Within this framework, the key attributes, i.e., relative advantage, observability, complexity, compatibility, and trialability, are critical determinants influencing the adoption process.

Innovative agricultural technologies have been developed to promote sustainability and explore more efficient farming methods (Javed et al., 2022). Advances in science and technology have empowered farmers to use their resources more effectively, helping them to maximize crop yields (Meena et al., 2022). The organic farming system focuses on utilizing organic matter to improve soil quality, reduce health hazards related to the food chain, and accomplish closed nutrient cycles (Bisoyi et al., 2017). Literature highlights vermicomposting as a sustainable practice in organic farming, enriching compost with nutrients and microorganisms via earthworms, enhancing soil health, recycling biowaste, and supporting eco-friendly agriculture (Filipović et al., 2023). Additionally, precision farming is increasingly recognized as an effective method for crop production, contributing to environmentally sustainable agriculture (Mandal, 2013). Precision farming requires an integration of various technologies (Uniyal et al., 2018). The pace at which precision farming is mainly adopted depends on the commitment of politicians, scientists, and technocrats, as farmers are significantly influenced by their support and decisions (Javed Ali, 2013). In Ukhimath, Rudraprayag (Uttarakhand), a multistage random sampling identified key factors influencing technology adoption: household head's education, income, and extension contact. The study highlights opportunities and challenges in technology transfer and suggests that practices like protected cultivation, organic composting, GM crops, and precision farming support rural development (Rekha et al., 2019). Adoption of sustainable technology is essential for the future of agriculture and ensuring food security (Joshi et al., 2023). Addressing these challenges requires supportive policies and investments in education and infrastructure to ensure all stakeholders benefit from technological advancements (Pandey et al., 2024). There is also significant potential to enhance the role of agricultural technology in organic farming, which could significantly increase productivity (Sultana, Solaiman, and Salaheen, 2019). This technology helps boost productivity and protects crops and fruit from being lost, even in tough terrain like in Uttarakhand (Gupta et al., 2023).

2. Literature Review:

In 1962, Everett Rogers introduced the "Diffusion of Innovations" theory (Sahar, 2008). The diffusion of innovation elicits scholarly inquiries from a diverse array of academic disciplines (Shahrina, 2018). Innovation is a practice or idea that is new to an individual (Rogers, 2003). This comprehensive social and psychological theory seeks to predict how individuals adopt an innovation by identifying their adoption patterns and analyzing the underlying structure. (S. Min et al., 2018). This study integrates innovation attributes and TAM’s Behavioural intention to adopt. It posits that the Technology Acceptance Model (TAM) may serve as a framework for elucidating the adoption process concerning novel technological innovations. Research on the Technology Acceptance Model (TAM) emphasizes users' subjective attitudes and behaviors toward technology adoption, often neglecting product features and social influences, a limitation that can be addressed by integrating the Innovation Diffusion Theory (Yuen et al., 2020).

Most studies using Rogers' DOI theory are associated with technological innovations (Okour et al., 2020). Agricultural innovation is essential and necessary in developing agricultural activities (Shahrina, 2018). The evolution of technology serves as the foremost catalyst for the formulation of strategies aimed at enhancing agricultural productivity and fostering agricultural development (Witono, 2022). Organic agriculture is an innovation among the agricultural production systems, having unique characteristics, thus making it distinct from traditional and conventional agricultural production systems (Subrahmanyeswari et al., 2022). Y. Duan studied relationships between perceived attributes and the intentional or actual adoption (Y. Duan et al., 2010). Rogers' theory posits that compatibility, relative advantage, complexity, observability, and trialability are the core technological characteristics for technology adoption and usage (Okour M K et al., 2020). The literature suggests that the five attributes of innovation proposed by Rogers account for approximately 87% of the variance observed in the rate of adoption of innovations. Characteristics of technology or attributes of innovation are preconditions for adoption (Witono and Adiyoga, 2022).

2.1 Relative advantage and Behavioural intention

In the past literature, relative advantage is considered one of the best predictors of innovation's adoption rate (Shahrina, 2018; Sahar, 2019). It is characterized as the extent to which a novel innovation offers advantages that surpass those of its predecessor (Mehra et al., 2020; Sahar, 2019 & Y Duan et al.,2010).In their research, (S. Min et al., 2018) found that individuals are likely to adopt innovations when they present a distinct advantage. (Slyke, 2002) Also reported that perceptions of relative advantage are significantly related to the Intention to use.

(Zhang et al., 2010) explored the E-learning adoption intention and found a positive relationship between relative advantage and adoption intention. Kapoor et. al (2014) proved a positive relationship between relative advantage and behavioral intention by testing consumers' intention to adopt mobile banking. In their research, (Lawson-Body et al., 2016) found that relative advantage positively impacts the intention to adopt. (Hameed and Counsell, 2014) explored the IT innovation adoption in organizations and found that relative advantage significantly impacts the intention to adopt. (Duan et al., 2010) examined an innovation adoption perspective of Chinese students' attitudes toward e-learning and concluded that perceived observability did not significantly influence the intention to adopt. (Joo et al., 2014) found that relative advantage significantly influenced learners' intention to use mobile learning.

H1: Relative Advantage positively influences behavioral intention.

2.2 Complexity and Behavioural Intention

Higher complexity means that it is more challenging to understand and use a particular innovation; complexity has a negative association with the intention to use the innovation (Kapoor et al., 2013). Rogers (1995) complexity is delineated as the extent to which a novel innovation is regarded as difficult to comprehend and utilize, highlighting that the rate of adoption diminishes as the perceived level of complexity escalates. (Mehra et al., 2020) asserted a direct impact of complexity on the purchase intention. He found that complexity exerts a significant influence on the intention to use. Similarly, a study reveals that the more complex end-users perceive an innovation, the lower the user's intention to use any innovation (Lin, 2006).

(Joo et al., 2014), found that complexity significantly influenced learners' intention to use mobile learning. (Arts et al., 2011), Their research indicated that innovation characteristics significantly influence both

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adoption intention and behavior, where Complexity positively affects intention to adopt. (Zhang et al., 2010) explored the E-learning adoption intention and found a positive relationship between complexity and adoption intention. (Lee and Kang, 2013) Empirically tested the adoption of sustainable facilities management and confirmed that complexity does not significantly affect the intention to adopt. (Hameed And Counsell, 2014) explored the IT innovation adoption in organizations and concluded that Complexity was determined to have no impact on the adoption intention. (Duan et al., 2010) examined an innovation adoption perspective of Chinese students toward e-learning and concluded that perceived complexity did not significantly influence the intention to adopt.

H2: There is a relationship between complexity and behavioural intention.

2.3 Compatibility and Behavioural Intention

(Min et al., 2018) reported that the concept of compatibility is of paramount importance in examining the extent to which users' prior encounters with analogous technologies affect their willingness to embrace and integrate new innovations. Compatibility is the degree to which innovation is regarded as consistent with the potential end-users existing values, prior experiences, and needs (Rogers, 1995). Compatibility refers to the extent to which an innovation aligns with the values, past experiences, and needs of potential end-users (Rogers, 1995).

(Kapoor et al., 2014) proved a positive relationship between compatibility and behavioral intention by testing consumers' intention to adopt mobile banking. (VOLLINK et al., 2002) explored the concept of energy conservation interventions and confirmed that perceived compatibility is a significant predictor of the intention to adopt. Hameed and Counsell (2014) explored the IT innovation adoption in organizations and found that compatibility significantly impacts the intention to adopt. Zhang et. al (2010) explored the

E-learning adoption intention and found a positive relationship between compatibility and adoption intention. (Duan et. al., 2010) examined an innovation adoption perspective of Chinese students' attitudes toward e-learning and concluded that perceived compatibility significantly influences the intention to adopt.

H3: There is a relationship between compatibility and behavioural intention.

2.4 Observability and Behavioural Intention

Observability refers to the degree to which the outcomes or advantages derived from the implementation of an innovation are perceptible to prospective users (Roger, 1983). (Hanji et al., 2023) reported that when potential users can see chatbots' benefits and successful use cases, their intention to adopt these technologies increases. (Al Breiki et al., 2022) conducted a study that synthesized the Diffusion of Innovation (DOI) theory alongside the Theory of Planned Behavior (TPB) and determined that the discernibility of outcomes (observability) exerts a significant influence on the propensity to embrace virtual reality within the educational sector.

(Moghaddam and Salehi, 2010), observability positively influences the intention to adopt precision agriculture technologies among agricultural specialists in Iran. (Zhang et al., 2010) explored the E-learning adoption intention and found a positive relationship between observability and adoption intention. Lee and Kang (2013) found that observability is positively related to the intention to adopt Sustainable facilities management, suggesting that visible benefits encourage adoption. (Hameed and Counsell, 2014) explored the IT innovation adoption in organizations and found that observability significantly impacts the intention to adopt. (Duan et al., 2010) examined an innovation adoption perspective of Chinese students toward e-learning and concluded that perceived observability did not significantly influence the intention to adopt.

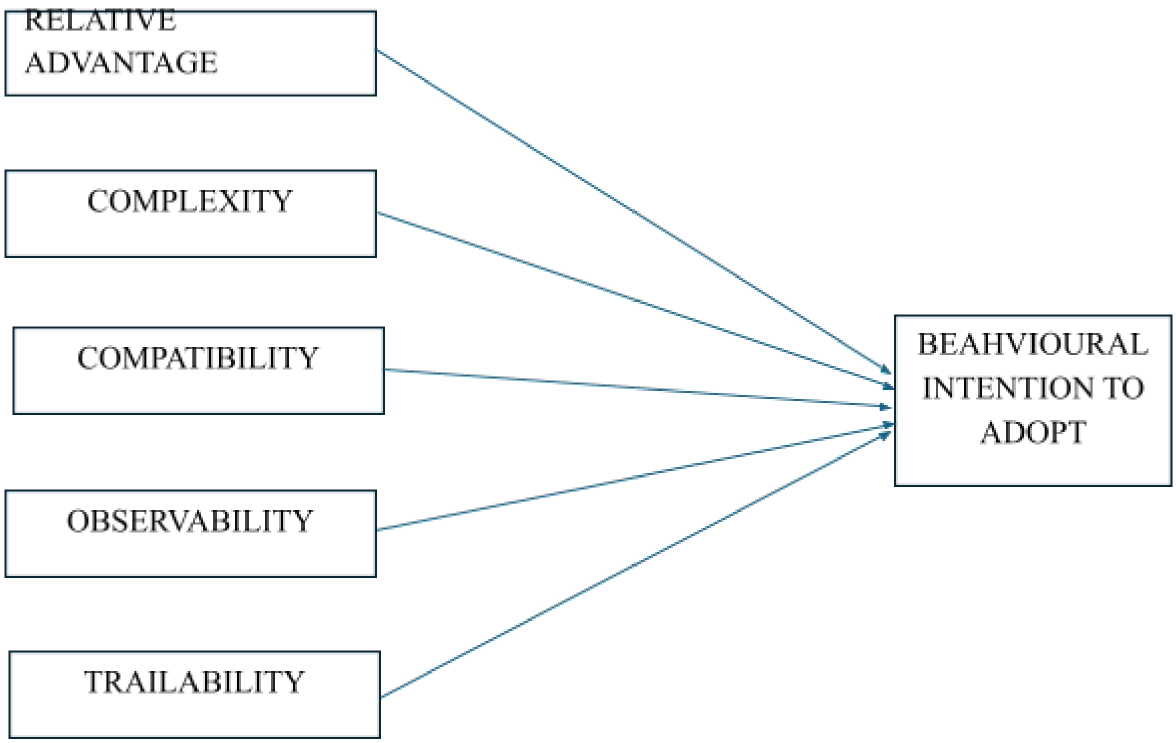
(Joo et al., 2014) found that observability does not significantly influence learners' intention to use mobile learning.

H4: There is a relationship between observability and behavioural intention.

2.5 Trialability and Behavioural Intention

Trialability is important as users aim to minimize the potential loss or risk associated with non-adoption or enhance their confidence (Choshaly, 2019). Trialability refers to the extent to which an innovation can be tested on a limited scale (Rogers, 1995). (Anwar, 2020) In his study explored the influence of trialability and found it to be significantly influencing the intention to adopt, highlighting the importance of perceived benefits and compatibility with existing practices for successful implementation. (Moghaddam and Salehi, 2010), Trialability positively influences the intention to adopt precision agriculture technologies among agricultural specialists in Iran. Zhang et. al (2010) explored the E-learning adoption intention and found a positive relationship between trialability and adoption intention. (Hameed and Counsell, 2014) explored the IT innovation adoption in organizations and found that trialability is a significant determinant of intention to adopt. (Duan et al., 2010) examined an innovation adoption perspective of Chinese students toward e-learning and concluded that perceived trialability significantly influences the intention to adopt. (Joo et al., 2014) found that trialability does not influence learners' intention to use mobile learning significantly.

H5: Trialability positively influences the behavioural intention.



Proposed model is based on the Literature Review

Materials and Methods:

Population, Sample, and Data Collection

The study focused on farmers in the hilly regions of Uttarakhand. Data was gathered using pen-and-paper surveys distributed during farmers' periodic meetings across various districts of Uttarakhand from October 2024 to April 2025. Out of 450 distributed questionnaires, 287 were returned (a response rate of 76.22%), but 37 were discarded due to incomplete or unengaged responses. This left 250 usable questionnaires. Given the complexity of the research model, this sample size is adequate for using Structural Equation Modelling (SEM) to analyze the intricate path model, as Kline (2010) recommended.

Measurement

The study's instrument was divided into three sections. The first section outlined the study's objectives and gave instructions for completing the questionnaires. The second section gathered demographic information about the respondents (Table I). The third section contained the main research questions, adapted from a previous study (Table II). and asked respondents to rate their answers on a five-point (1–5) Likert scale, where 1 meant "strongly disagree" and 5 meant "strongly agree.

Table I: Distribution of respondents, socio-economic characteristics:

Variable	Frequency	Percentage
Gender		
Male	160	64
Female	90	36
Age (years)		
18-30 years	40	16
31-45 years	90	36
46-60 years	85	34
60 years and above	35	14
Garhwal Region		
Dehradun: (18%)	45 farmers	18
Haridwar: (14%)	35 farmers	14
Rudraprayag: (12%)	30 farmers	12
Kumaon Region		
Nainital: (16%)	40 farmers	16
Haldwani: (12%)	30 farmers	12
Uddham Singh Nagar: (16%)	40 farmers	16
Jaunsar Region		
Uttarkashi: (12%)	30 farmers	12
Farm Size		
Small farms (less than 2 acres)	100 farmers	40
Medium farms (2-5 acres)	120 farmers	48
Large farms (above 5 acres)	30 farmers	12

Table II: Source of Measurement Instruments

Variable	Description	No. of Items	Source
RA	Relative Advantage	5	Al-Jabri and Social (2012)
	Complexity	5	Ntemana and olatokum (2012)
	Compatibility	5	Al-Jabri and Social (2012)
	Tribality	5	Ntemana and olatokum (2012)
	Observability	4	Ntemana and olatokum (2012)
	Behavioural Intention	4	Ahmadi Firouzjaie et. al. (2023)

Data Analysis Procedure

The partial least squares-structural equation models (PLS-SEM) approach was employed to analyze the data and estimate structure equation models. Smart PLS software was used for this purpose, and it was done in two stages. PLS-SEM is effective for complex models and does not need a large sample size or specific data distribution assumptions (Hair et al., 2016). The recommended sample size for PLS-SEM is 10 times the number of arrows pointing to a construct (Hair et al., 2016). This makes it ideal for the current research. In this study, 13 arrows point to the constructs, and the sample size is 225, which exceeds the required amount.

Result:

Common Method Bias

Previous research has recommended assessing common method bias before proceeding with analysis. Following Kock's (2015) guideline, a Variance Inflation Factor (VIF) value above 3.3 indicates potential bias issues. In the internal model, all VIFs ranged from 1.460 to 2.760, remaining well below the 3.3 threshold. This suggests no concerns regarding common method bias, with the VIF values of all items summarized in Table 2.

Measurement Model Assessment

The assessment of the measurement model concentrated on evaluating its internal consistency (reliability) and validity (both convergent and divergent). This was achieved by examining the relationships between constructs and their corresponding indicator variables. Factor loadings should ideally be above 0.7, with 0.50 being the minimum acceptable threshold (Vinzi et al., 2010). Items OB3 and CP1 were deleted because of low loading, thus improving the reliability and validity. For reliability, we consider both Cronbach's alpha and rho c values between 0.70 and .95 acceptable. Further, we consider the values of AVE for the assessment of convergent validity. Values in Table III establish the reliability and validity.

Table III: reliability and validity

Construct	Items	Outer loadings	Cronbach's alpha	Composite Reliability	AVE	VIF
BI	BI1	0.881	0.827	0.884	0.657	2.631
	BI2	0.709				1.480
	BI3	0.796				2.107
	BI4	0.845				1.820
CP	CP2	0.791	0.821	0.882	0.652	1.855
	CP3	0.874				2.526
	CP4	0.797				1.901
	CP5	0.762				1.537
CX	CX1	0.783	0.876	0.906	0.660	2.070
	CX2	0.882				2.264
	CX3	0.884				2.983
	CX4	0.756				2.433
	CX5	0.744				1.805
OB	OB1	0.803	0.702	0.834	0.627	1.386
	OB2	0.788				1.405
	OB4	0.784				1.327
RA	RA1	0.699	0.809	0.867	0.569	1.621
	RA2	0.692				1.559
	RA3	0.844				2.220

	RA4	0.842				2.197
	RA5	0.676				1.721
TR	TR1	0.860	0.801	0.856	0.552	2.528
	TR2	0.899				2.582
	TR3	0.525				1.235
	TR4	0.672				1.655
	TR5	0.698				1.713

Assessment of Discriminant Validity

Next, we assessed the model for discriminant validity to ensure that the measures of one construct do not correlate with those of other constructs. This can be evaluated using cross-loadings, Fornell and Larcker's (1981) criterion, and the Heterotrait–Monotrait ratio of correlations (HTMT) method. We employed the HTMT criterion for this purpose. Henseler et al. (2015) recommended a conservative threshold of 0.90 or lower for the HTMT ratio when assessing discriminant validity. Table IV shows that all HTMT values were below the threshold of 0.90, confirming that discriminant validity was achieved.

Table IV: HTMT values

	BI	CP	CX	OB	RA	TR
BI						
CP	0.578					
CX	0.204	0.116				
OB	0.433	0.465	0.091			
RA	0.413	0.616	0.275	0.314		
TR	0.357	0.749	0.216	0.611	0.688	

Structural Model Assessment

After confirming the measurement model's reliability and validity, we evaluated the structural model, following expert recommendations (Hair et al., 2022). The structural model depicts the direct relationships among the constructs in the proposed study (Hair et al., 2016). However, before conducting hypothesis testing, it is crucial to examine collinearity among variables, as advised by Hair et al. (2022). The Variance Inflation Factor (VIF) is commonly used to detect collinearity, with a recommended threshold of five or less (Hair Jr et al., 2014). The results in Table 3 show that all VIF values are below 5, indicating no collinearity among the variables.

Hypothesis Testing

The present study employed the bootstrapping technique with 5000 subsamples to examine the direct relationships among the constructs. The significance of the direct effects of the exogenous constructs on the endogenous constructs was evaluated by analyzing beta values, standard errors, t-statistics, and p-values. Following Hair et al. (2011), critical t-values for two-tailed tests were considered: 1.65 for a significance level of 10%, 1.96 for 5%, and 2.58 for 1%. The result of the study indicates that significant hypotheses were accepted except one. H1 examines whether compatibility and intention to use. The results revealed that compatibility significantly impacts the intention to use (β= 0.401, t=5.223, p<0.01). Hence, H1 was supported. The relationship between complexity and intention to use was negative and significant (β= -0.249, t=4.196, p<0.01), thus confirming H2. Results of the study further revealed that intention to use is being directly impacted by observability (β= 0.177, t=2.571, p<0.05) and relative advantage (β= 0.232, t=3.552, p<0.01), supporting H3 and H4 respectively. However, the relationship between trialability and intention to use was insignificant (β= -0.112, t=1.195, p>0.05), thus rejecting H5. Hypotheses results are summarized in Table V.

Table V: Path Coefficients for Hypothesis Testing

Hypotheses	Beta Coefficient (β)	(STDEV)	T statistics	p-values	Result
H_1: CP □BI	0.401	0.077	5.223	0.000	Supported
H_2:CX □BI	-0.249	0.059	4.196	0.000	Supported

H_3: OB □BI	0.177	0.069	2.571	0.010	Supported
H_4:RA □BI	0.232	0.065	3.552	0.000	Supported
H_5:TR □BI	-0.112	0.094	1.195	0.232	Not Supported
Note:					

Model Explanatory Power

R Square statistics explains the variance in the endogenous variable explained by the exogenous variable(s). Simply, it means how much change in the dependent variable can be accounted for by one or more independent variable(s). The R Square represents the variance explained in each endogenous construct and is a model's explanatory power (Shumeli & Koppius, 2011), also referred to as in-sample predictive power. As a general guideline, Cohen (1988) suggested that R Square values for endogenous latent variables are assessed as follows: 0.26(substantial), 0.13 (moderate), and 0.02 (weak). The results (table) show that R Square for all the endogenous constructs is over; this shows that the model explanatory power is substantial (Cohen, 1998).

To better estimate the explanatory value of each exogenous variable in the model, the change in R Square is estimated if a given exogenous construct is omitted from the model. This measure is referred to as effect size (f square). The effect size measures the influence of each independent variable on the dependent variable. In the PLS path model, when an independent variable is excluded from the model, it measures the variation in squared correlation values. It ascertains whether the excluded independent variable strongly affects the value of a dependent variable. The impact of the predictor variable is high at the structural level if the f-square is 0.35, medium if the f-square is 0.15, and small if the f-square is 0.02 (Cohen, 1998). The model's f square effect size shows how much an exogenous latent variable contributes to an endogenous latent variable's R Square value. In simple terms, effect size assesses the magnitude or strength of the relationship between the latent variables. The results (table 1) revealed that the f-square effect ranged from

0.001 (negligible) for POS on OP to 0.930(high) for IM on POS. Finally, the Q Square values for endogenous constructs were over 0; hence, predictive relevance was established.

Discussion:

This study explored how different innovation attributes affect farmers' intentions to adopt technological interventions in organic farming. The interventions examined included organic fertilizers, protected farming, Azolla culture, and vermicomposting—practices that align with organic farming principles and promote sustainable agriculture. The focus was on five key attributes, i.e., relative advantage, compatibility, complexity, observability, and trialability—to understand how they impact farmers' willingness to adopt innovative technologies in organic farming. By applying the Diffusion of Innovations Theory (Rogers, 2003), the study provides valuable insights into the factors that encourage or discourage adoption in this context.

In line with the first hypothesis (H1), the relative advantage significantly positively affected farmers' intentions to adopt technological innovations. This aligns with the previous studies by Jabri et al. (2012) and Hsiu-Fen Lin (2011), suggesting that farmers are more likely to adopt new technologies if they believe they will enhance productivity, reduce costs, or promote long-term sustainability. Complexity had a significantly positive relationship with farmers' intentions, wherein the complexity of specific interventions, such as protected farming, which involves complicated installation and maintenance, may deter some farmers. This result aligns with previous studies showing that farmers are less likely to adopt technologies perceived as complex to use (Kapoor et al. (2013).

The study indicated that the more these technologies align with current farming practices, the stronger the farmers' willingness to adopt them. In line with the hypothesis (H3), compatibility significantly influences farmer's intentions. Observability emerged as particularly influential in farming communities, where farmers are guided by peer influence and social validation. The study found that when the benefits of a technology are visible, farmers are more inclined to adopt it. This was consistent with past research showing similar outcomes, Moghaddam and Salehi (2010) and Zhang et al. (2010). The hypothesis of trialability (H5) positively impacting behavioural intentions was rejected. It was hypothesized to have a positive relationship, as also found in past research by Jabri et al. (2012) and Jilani et al. (2022).

Technologies like protected farming often require significant upfront investments in infrastructure, making it difficult for farmers to conduct trials. Many farmers may need more financial resources for such trials, mainly when the technology involves high initial costs. The result that trialability negatively influences behavioural intention to adopt is consistent with past research by SLYKE et al. (2002) and Kolodinsky et al. (2004). This research contributes to the existing body of knowledge by providing a comprehensive analysis of less-explored innovation adoption attributes. Theoretically, this study significantly contributes to the broader field of user adoption research. Currently, most studies do not incorporate innovation attributes as antecedents of the adoption process in the farming sector. Another significant contribution of this study addresses a critical research gap in technology adoption by farmers by proposing the IDT-TAM integrated model. Technological interventions in organic farming include enhancing farmers' skills, providing local resources, and improving organic product availability for Marginal farmers. Policymakers can increase technological awareness among farmers of organic farming practices. Training can enhance the adoption of organic inputs in farming practices. Information provision and training can increase the knowledge and perception of organic farmers (Gattinger).

Theoretical Implications:

This research delves into the motivations behind farmers' adoption of new technologies in organic farming, emphasizing the characteristics of innovation identified in the Diffusion of Innovations Theory (DIT). The study emphasizes the importance of perceived innovative characteristics—such as relative advantage, compatibility, complexity, trialability, and observability—as primary factors that influence adoption behavior. By measuring these attributes, the research establishes a structured model to assess how these perceptions shape the intent to adopt e-learning. This approach not only expands current e-learning literature but also offers valuable guidance for educational policymakers and providers to improve adoption strategies. The outcomes of the study validate the significance of DIT in explaining technology uptake in organic farming. This research contributes to the existing body of knowledge by providing a comprehensive analysis of less explored innovation adoption attributes. This study employed factors from two base theories, namely, the Diffusion Innovation Theory (Perceived innovation attributes) and the Technology Acceptance Theory (behavioral intention), to provide an empirical and theoretical understanding of the influence of the proposed technological antecedents on the behavioral intention of farmers to adopt technological interventions in organic farming. Theoretically, this study significantly contributes to the broader field of user adoption research. Currently, most studies do not incorporate innovation attributes as antecedents of the adoption process in the farming sector. Another significant contribution of this study addresses a critical research gap in technology adoption by farmers by proposing the IDT-TAM integrated model. The findings of this study indicate that when farmers notice - the relative advantage of using organic input over chemical fertilizer, compatibility of using such technology as used in ancient times, and observability of others using the same and having a benefit in adopting technological interventions, it positively affects their behavioral intension towards adoption. On the other hand, when farmers feel the complexity of using such technology, it negatively influences their behavioral intention towards the same. Results supported the idea that DIT factors can be used to measure farmers' technology adoption as an independent variable.

Practical Implications:

Several practical implications for the agriculture sector can be identified, including recommendations for policymakers regarding the efficient allocation of resources to enhance technology adoption among farmers. Technological change from the adoption of new technologies is the main driver of the strategies for increasing agricultural productivity and promoting agricultural development.

Furthermore, this awareness can foster the development of collaborative models that involve various stakeholders in providing analytical services, educating farmers, and promoting sustainable agricultural practices. Innovations in organic farming offer practical solutions to improve crop yields, reduce environmental impact, and enhance economic sustainability.

Technological interventions in organic farming include enhancing farmers' skills, providing local resources, and improving organic product availability for Marginal farmers. Policymakers can increase technological awareness among farmers of organic farming practices. Training can enhance the adoption of organic inputs in farming practices. Information provision and training can increase the knowledge and perception of organic farmers(Michael, 2020). A significant inference drawn from the findings is that efforts to enhance and broaden the adoption of technology in organic farming should not only focus on persuading farmers to transition their land to organic farming methods but also on incentivizing organic producers to sustain organic farming as a consistent production system.

Limitations and Future Research:

This study has several limitations. Firstly, training and awareness of technologies used in organic farming are not yet explored by farmers in hilly areas, it is challenging to consider other factors of the theories implied. This study only used behavioral intention as the most direct predictor of technology adoption also widely used by other researchers (Gridis et al. 2020; Kapser and Abdelrahman 2020). Secondly, this study is limited to testing perceived innovation attributes, other studies could be carried out to include factors like demographical variables (age, gender, education, farming experience, etc). thirdly, this study deploys cross-sectional methodology, whereas longitudinal methodology may offer a more holistic perspective on the technological adoption behaviors exhibited by agricultural practitioners. Subsequent research endeavours are advised to implement this model to empirically investigate various direct or indirect relationships. A future study can also focus on Social Influence to act as the independent variable. Our findings proved a basis for several research avenues. To understand the adoption of technology by farmers, future research can encompass perceived ease of use in place of relative advantage and perceived usefulness in place of complexity to measure the attitude of farmers towards these technologies. Future research could also investigate individual characteristics in their readiness to use technology at farms.

Conclusion:

Relative advantage, compatibility, and observability are positively related to behavioural intention. At the same time, Trialability and complexity are adversely connected to the behavioural intention of farmers to adopt technological interventions such as Vermicompost, Azolla culture, Protected farming, mushroom cultivation, vermiwash, etc. Agricultural innovation is seen as a crucial aspect of advancing farming practices. Innovation encompasses introducing new seed varieties, novel pesticides, or fertilizers to improve crop yields in future situations. For example, introducing technologies like the rice dryer reduces grain loss and boosts rice production. Farmers have poor access to such technologies due to poor training and extension programs. The investigation results substantiate the efficacy of the integrated theoretical frameworks concerning the technological adoption behaviours of agricultural practitioners. This research enriches the theoretical discourse by presenting a synthesized model underpinned by empirical evidence. This study has several limitations. Firstly, training and awareness of technologies used in organic farming are not yet explored by farmers in hilly areas; it is challenging to consider other factors of the theories implied. This study only used behavioural intention as the most direct predictor of technology adoption, which is also widely used by other researchers Gridis et al. 2020; Kapser and Abdelrahman 2020. Secondly, this study is limited to testing perceived innovation attributes; other studies could be conducted to include factors like demographical variables (age, gender, education, farming experience, etc). Subsequent research endeavours are advised to implement this model to investigate various direct or indirect relationships empirically. A future study can also focus on Social Influence to act as the independent variable. Our findings proved a basis for several research avenues. To understand the adoption of technology by farmers, future research can encompass perceived ease of use in place of relative advantage and perceived usefulness in place of complexity to measure the attitude of farmers towards these technologies.

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