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Research Article

From Intention to Practice: An Extended Technology Acceptance Model of Organic Farming Adoption Among Farmers

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Abstract: The transition to organic farming is increasingly recognized as a viable remedy for environmental degradation, health problems and the long-term viability of agricultural systems. However, despite growing awareness, farmers continue to adopt organic farming practices unevenly, creating a gap between intention and practice. This study proposes an enlarged Technology Adoption Model (TAM) to examine the key determinants of farmers' adoption of organic farming. By including components like perceived risk, social influence, perceived economic benefits, perceived environmental concern and institutional support, the model builds upon the traditional TAM concepts of perceived utility and perceived ease of use. Using primary data collected from farmers via a standardized questionnaire, the study employs structural equation modelling to investigate the relationships among these parameters. The findings demonstrate that perceived utility and environmental concern have a significant impact on farmers' opinions on organic farming, which in turn affects their behavioral intentions. Perceived risk also acts as a barrier to adoption, although institutional support and social influence are crucial mediators in turning intention into actual practice. The study contributes to the body of knowledge by highlighting the elements that facilitate the transition from intention to practice and by empirically validating an extended TAM in the context of organic farming. The results offer useful information that agricultural stakeholders, governments and extension agencies may utilize to develop targeted interventions that encourage farmers to adopt organic farming practices more broadly.

Keywords: Intention, Technology Acceptance Model, Organic Farming, Environmental Risk, Actual Usage

INTRODUCTION

The adoption of organic farming has gained significant attention worldwide due to its potential to enhance environmental sustainability, improve soil health and provide safe food products [1]. Despite these benefits, the transition from conventional to organic farming remains slow in many regions, often due to farmers' hesitation, perceived complexity and inadequate support [2]. Understanding the factors that influence farmers' adoption decisions is critical for designing effective policies and extension programs that encourage sustainable agricultural practices. The Technology Acceptance Model (TAM) has been widely employed to explain the adoption of new technologies and innovations in diverse sectors, highlighting the role of perceived usefulness and perceived ease of use in shaping user intention [3]. However, when applied to agriculture, particularly organic farming, TAM requires extension to incorporate socio-environmental and policy-related factors that influence farmers' behavior [4,5]. Studies suggest that constructs such as social influence, environmental awareness, government incentives and perceived economic benefits play a significant role in bridging the gap between intention and actual adoption [6,7]. Despite these insights, limited empirical research has examined the combined effects of technological, social and policy-related factors on the intention and practice of adopting organic farming. This study seeks to fill this gap by developing an extended Technology Acceptance Model that integrates environmental, social and institutional variables to explain farmers' adoption behavior more comprehensively. The findings are expected to provide actionable recommendations for policymakers, extension agencies and agricultural stakeholders aiming to promote organic farming effectively.

Literature Review

Within the frameworks of sustainable agriculture, environmental preservation and rural development, the use of organic farming practices has been thoroughly investigated. Organic farming, according to the literature, is more than just a technological advancement; it's a complicated social, economic and behavioral shift that necessitates new ways of thinking and doing things for farmers [8]. Although organic farming has many acknowledged health and environmental benefits, its acceptance rate is low owing to a number of interconnected factors, according to researchers [1].

Organic Farming Adoption: Determinants and Challenges

A number of studies have looked at what makes organic farming more appealing to farmers. Critical factors cited by Panel *et al*. [9], include anticipated profitability, conversion costs, yield uncertainty and access to premium markets. Because organic farming methods have a longer payoff period and reduce short-term yields, many farmers are unwilling to adopt them. Particularly for small and marginal farmers, there are additional obstacles to adoption, such as a shortage of organic inputs, complicated certification processes and an inadequate market infrastructure [10]. The decisions that are made about adoption are also significantly influenced by issues of knowledge and awareness. Based on the findings of Knowler and Bradshaw [11], it has been discovered that farmers' comprehension of organic techniques and their confidence in putting such techniques into practice are favorably influenced by extension services, training programs and peer learning. According to several studies, farmers with higher levels of education and greater exposure to agricultural advances are more inclined to experiment with and adopt organic farming approaches.

Perceived Ease of Use and Behavioral Intention

Perceived Ease of Use (PEOU) refers to the degree to which farmers believe that organic farming technologies can be learned and implemented without excessive effort. According to the Technology Acceptance Model (TAM), ease of use significantly influences an individual's intention to adopt a new technology, particularly in contexts where users have limited technical exposure [3]. In agricultural settings, farmers are more likely to develop positive intentions toward new technologies when practices are simple, compatible with existing knowledge and require minimal procedural complexity [12]. Empirical studies in sustainable agriculture suggest that complicated organic farming techniques, lack of clarity regarding input preparation and labor-intensive processes often discourage farmers from forming adoption intentions [11]. Conversely, when organic technologies are perceived as manageable and farmer-friendly, behavioral intention increases.

- **H1:** Perceived Ease of Use has a significant positive effect on farmers' behavioral intention to use organic farming technologies

Perceived Usefulness and Behavioral Intention

Perceived Usefulness (PU) is defined as the extent to which farmers believe that organic farming technologies enhance farm performance, productivity, soil health, profitability and long-term sustainability. TAM literature consistently identifies perceived usefulness as the strongest predictor of behavioral intention [3,5].

In the context of organic farming, perceived usefulness includes expectations of reduced chemical input costs, improved soil fertility, better market prices and resilience to climate variability. Studies have shown that farmers are more inclined to adopt organic practices when they perceive tangible agronomic and economic benefits [1,9]. Therefore, perceived usefulness plays a central role in shaping farmers' willingness to engage with organic technologies.

- **H2:** Perceived Usefulness has a significant positive effect on farmers' behavioral intention to use organic farming technologies

Perceived Risk and Behavioral Intention

Perceived Risk refers to farmers' assessment of potential losses or uncertainties associated with adopting organic farming technologies, such as yield reduction during conversion, market instability, certification costs and price volatility. Risk perception is a critical determinant of technology adoption in agriculture, where livelihood security is highly sensitive to production outcomes [13].

Several studies indicate that even when farmers recognise the long-term benefits of organic farming, high perceived risk can significantly weaken their intention to adopt such practices [14]. In particular, uncertainty during the transition period discourages farmers from committing to organic technologies.

- **H3:** Perceived Risk has a significant negative effect on farmers' behavioral intention to use organic farming technologies

Environmental Risk and Behavioral Intention

Environmental Risk reflects farmers' perception of ecological threats arising from conventional farming practices, including soil degradation, declining soil fertility, groundwater contamination, biodiversity loss and climate-related stresses. Farmers who perceive higher environmental risks are more likely to seek alternative, sustainable farming solutions [15].

Prior research suggests that awareness of environmental degradation increases farmers' motivation to adopt environmentally friendly technologies, including organic farming [16]. When environmental risks are perceived as severe, farmers are more inclined to form intentions that favor sustainable agricultural practices.

- **H4:** Environmental Risk has a significant positive effect on farmers' behavioral intention to use organic farming technologies

Behavioral Intention and Actual Usage of Organic Farming Technologies

Behavioral Intention represents the motivational readiness of farmers to adopt organic farming technologies and is widely accepted as the most immediate predictor of actual behavior [3,4]. In agricultural adoption studies, intention serves as a crucial link between perception and real-world practice.

Empirical evidence confirms that farmers with strong behavioral intentions are significantly more likely to implement organic technologies, provided structural constraints do not completely inhibit action [12]. Thus, behavioral intention acts as a mediating mechanism through which perceptual factors influence actual usage.

- **H5:** Behavioral intention to use organic farming technologies has a significant positive effect on the actual usage of organic farming technologies

Extended TAM and Organic Farming Adoption

According to recent research that used extended TAM frameworks to sustainable and organic farming contexts, farmers' views about organic techniques are greatly impacted by their concern for the environment. Both intentions and actions regarding adoption might be influenced by social factors, such as peer farmers, community norms and farmer networks [16]. Government subsidies, extension services and certification assistance are all examples of institutional support that can help lower perceived risk and make the change from intention to practice easier [15]. The number of empirical research that use an expanded TAM framework to examine the intention-to-practice transition in organic farming is still low, despite these advances. Much of the current literature ignores the processes that link intention and adoption outcomes in favor of studying one or the other. To fill this knowledge vacuum and provide a more thorough explanation for organic farming adoption, more all-encompassing models are required. These models should incorporate behavioral, social and institutional components. Economic, behavioral and institutional variables all have a role in organic farming's uptake, according to the research. To capture the complexity of organic farming decisions, it is needed to extend TAM to add context-specific factors, however TAM does provide a good framework for understanding farmers' adoption behavior. To better understand how farmers move from intentions to practice organic farming, this study contributes to the existing literature by presenting and experimentally testing an expanded TAM.

The Technology Acceptance Model (TAM) serves as the foundation for the conceptual framework (Figure 1), which has been expanded to describe the transition from the intention of farmers to the actual practice of organic farming.

At the core of the framework are the traditional TAM constructs:

- **Perceived Ease of Use (PEOU):** The extent to which farmers feel that organic agricultural methods are simple to learn and put into practice
- **Perceived Usefulness (PU):** The degree to which farmers believe that organic farming would be helpful in terms of increasing production, enhancing soil health, maintaining stable income and ensuring long-term sustainability
- According to the hypothesis, both PEOU and PU have a direct impact on the attitude that farmers have toward organic farming. This attitude is a reflection of the farmers' overall opinion of whether or not they are in favor of adopting organic farming techniques.
- Additional context-specific factors that are particularly pertinent to the adoption of organic farming are incorporated into the framework, which results in increased functionality
- **Environmental Concern:** The farmers' knowledge of the destruction of the environment and their concern for the ecological sustainability, which influences their attitude toward organic farming
- **Perceived Risk:** The impression of yield unpredictability, market volatility and conversion concerns among farmers, which has a detrimental impact on both their desire to adopt and their actual choice to do so

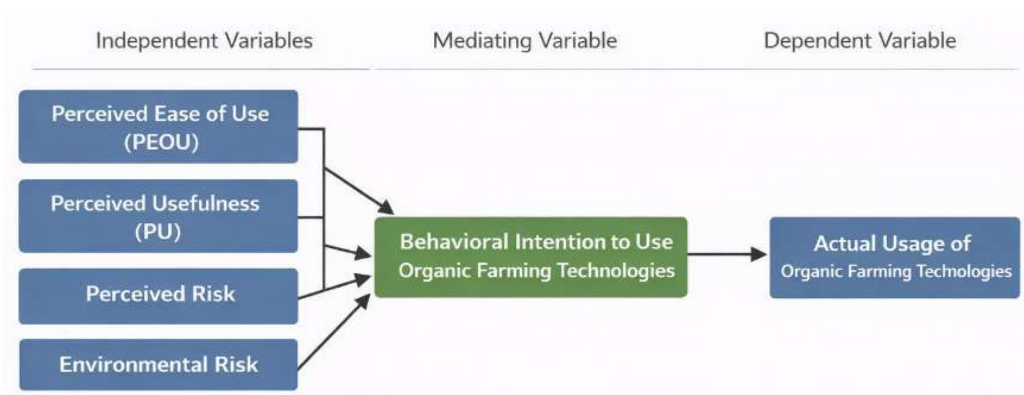

Figure 1: Conceptual Framework

The farmers' preparedness and desire to embrace organic farming techniques is represented by their Behavioral Intention to embrace Organic Farming, which is directly influenced by their attitude toward organic farming. In contrast to the conventional TAM, the paradigm unequivocally acknowledges that intention does not necessarily result in acceptance.

As a result, there is a connection between Behavioral Intention and Actual Adoption of Organic Farming Practices. Institutional Support serves as a factor that facilitates this, while Perceived Risk serves as a factor that constrains this intention–practice relationship.

In conclusion, the conceptual framework demonstrates that the adoption of organic farming is a multi-stage process. This process is characterized by the fact that technological perceptions, environmental ideals, social pressures and institutional processes all work together to influence the migration of farmers from intention to sustained organic farming practice.

Hypotheses

- **H1:** Perceived Ease of Use has a significant positive effect on farmers’ behavioral intention to use organic farming technologies
- **H2:** Perceived Usefulness has a significant positive effect on farmers’ behavioral intention to use organic farming technologies
- **H3:** Perceived Risk has a significant negative effect on farmers’ behavioral intention to use organic farming technologies
- **H4:** Environmental Risk has a significant positive effect on farmers’ behavioral intention to use organic farming technologies
- **H5:** Behavioral intention to use organic farming technologies has a significant positive effect on the actual usage of organic farming technologies

MATERIALS AND METHODS

Population, Sample and Data Collection

The target population of the study comprised farmers residing in the hill regions of Uttarakhand, India. Data were collected using paper-based questionnaires that were distributed during regular farmer meetings across several districts of Uttarakhand between October 2024 and October 2025. A total of 450 questionnaires were administered, of which 287 were returned, resulting in a response rate of 76.22%. Among the returned questionnaires, 37 were excluded from further analysis due to incomplete responses or insufficient respondent engagement. Consequently, the remaining 250 valid questionnaires were administered for data analysis. This sample size was considered adequate for examining the proposed complex path model using Structural Equation Modelling (SEM). According to Kline, a sample size of 200 or more is sufficient for SEM analysis, particularly when the research model involves multiple latent constructs and hypothesized relationships.

Measurement

The instrument that was used for the investigation was broken up into three portions. The first part of the report provided an overview of the goals of the research as well as directions for filling out the questionnaires. Table 1 contains the demographic information that was acquired from the responses gathered in the second section. The primary research questions, which were derived from an earlier study and shown in Table 2, were included in the third part. We then asked the respondents to assess their responses using a Likert scale with five points, ranging from one to five, where one indicated "strongly disagree" and five indicated "strongly agree."

Data Analysis Procedure

For the purpose of analyzing the data and estimating structure equation models, the partial least squares-structural equation models (PLS-SEM) technique was utilized. To do this, the Smart PLS program was utilized and the process was carried out in two steps. According to Hair *et al*. [17], PLS-SEM is an excellent method for analyzing complicated models and it does not require a big sample size or certain assumptions on the distribution of data. According to Hair *et al*. [17], the suggested sample size for PLS-SEM is at least ten times the number of arrows that point to a particular construct. As a result, it is an excellent choice for the ongoing study. In this investigation, 13 arrows point to the structures and the sample size is 225, which exceeds the minimum required.

Table 1: Characteristics of the Respondents' Socioeconomic Backgrounds and Distribution

Variable	Frequency	%
Gender		
Male	160	64
Female	90	36
Age (years)		
18-30years	40	16
31-45years	90	36
46-60years	85	34
60yearsandabove	35	14
Garhwal Region		
Almora: (18%)	45 farmers	18
Bageshwar: (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 (lessthan2acres)	100 farmers	40
Medium farms (2-5acres)	120 farmers	48
Large farms (above5acres)	30 farmers	12

Table 2: Measurement Instruments Used in the Study

Variable	Description	No. of Items	Source
Perceived Ease of Use (PEOU)	Degree to which farmers believe that using organic farming technologies requires minimal effort	4	Davis [3]
Perceived Usefulness (PU)	Degree to which farmers believe that organic farming technologies enhance farming performance and productivity	4	Davis [3]
Perceived Risk (PR)	Farmers' perception of potential economic, production and market risks associated with adopting organic farming technologies	5	Featherman and Pavlou
Environmental Risk (ER)	Perceived environmental uncertainty related to climate variability, soil degradation and pest incidence affecting organic farming	4	adapted from Stone and Grønhaug
Behavioural Intention (BI)	Farmers' intention to adopt and continue using organic farming technologies	4	Davis [3]
Actual Usage (AU)	Extent of actual adoption and application of organic farming technologies in farming practices	3	Venkatesh *et al.*

RESULTS

Common Method Bias

Prior to moving further with analysis, it is advised that common technique bias be evaluated, as suggested by previous research. According to the recommendation made by Kock, a Variance Inflation Factor (VIF) value that is more than 3.3 suggests the presence of possible bias concerns. All of the VIFs in the internal model fell within the range of 1.460 to 2.760, which is significantly lower than the threshold of 3.3. Given that the VIF values of all items are summarized in Table 2, this indicates that there are no worries regarding the common technique bias involved.

Assessment of Measurement Models

Internal consistency (reliability) and validity (convergent and divergent) were the primary foci of the evaluation of the measurement model. The connections between constructs and the indicator variables measuring them were examined to do this. According to Vinzi *et al*. [18], factor loadings should preferably be more than 0.7, with a minimum acceptable threshold of 0.50. Reliability and validity were enhanced by removing items OB3 and CP1 due to low loading. Cronbach's alpha and rho scores between 0.70 and 0.95 are considered good in terms of dependability. In addition, when evaluating convergent validity, we consider AVE values. The validity and reliability are established by the values in Table 3.

Assessment of Discriminant Validity

We then tested the model to see whether it could discriminate correctly. The goal was to exclude any possibility of a correlation between the measurements of different constructs. You can use the Hetero-trait Mono-trait ratio of correlations (HTMT) method, the criteria of Fornell and Larcker [19], or cross-loadings to examine this. We used the HTMT criterion to achieve this objective. According to Henseler *et al*. [20], a cautious cutoff for the HRMT ratio should be 0.90 or lower to assess discriminant validity. As shown in Table 4, discriminant validity was established because no HTMT value exceeded the threshold of 0.90.

Evaluating Structural Models

We followed expert advice and assessed the structural model after confirming the validity and reliability of the measurement model [21]. According to Hair *et al*. [17], the structural model illustrates the interrelationships between the study's constructs. According to Hair *et al*. [21], it is essential to check for collinearity across variables before testing hypotheses. One popular tool for detecting collinearity is the Variance Inflation Factor (VIF), which should be kept below 5 [22]. All VIF values are less than 5 (Table 3), indicating no collinearity among the variables.

Hypothesis Testing

In this study, we examined the direct correlations between the constructs using the bootstrapping method with 5,000 subsamples. After examining beta values, standard errors, t-statistics and p-values, we determined if the direct effects of the exogenous constructions on the endogenous constructs were statistically significant. According to Hair *et al*. crucial t-values for two-tailed tests were 1.65 at the 10% level of significance, 1.96 at the 5% level of significance and 2.58 at the 1% level to follow. Except for one, all of the major hypotheses were accepted according to the study's results. Testing compatibility and intent to use is what H1 is all about. We reject H5 since the findings show that compatibility has a substantial influence on the intention to use ($\omega = 0.401$, $t = 5.223$, $p<0.05$). You may find a summary of the results in Table 5.

Model Explanatory Power

The R-squared statistic is a metric used to assess the extent to which fluctuations in an endogenous variable are explained by exogenous variables or factors. All it does is demonstrate the degree to which differences in one or more independent variables might explain variations in the variable that is being studied (the dependent variable). It is possible to evaluate a model's capacity to explain or predict anything based on a sample by calculating its R Squared value. This number indicates the amount of variation that can be attributed to each endogenous construct. As an illustration of how Cohen [23], suggested determining R-squared values for endogenous latent variables, the following are the values: significant at 0.26, moderate at 0.13 and weak at 0.02.

Table 3: Reliability and Convergent Validity Assessment

Construct	Items	Outer Loadings	Cronbach's Alpha	Composite Reliability	AVE	VIF
Behavioural Intention (BI)	BI1	0.842	0.846	0.897	0.687	1.912
	BI2	0.809	-	-	-	1.634
	BI3	0.858	-	-	-	2.041
	BI4	0.801	-	-	-	1.778
Perceived Ease of Use (PEOU)	PEOU1	0.812	0.829	0.886	0.662	1.521
	PEOU2	0.845	-	-	-	1.873
	PEOU3	0.798	-	-	-	1.694
	PEOU4	0.826	-	-	-	1.604
Perceived Usefulness (PU)	PU1	0.861	0.862	0.905	0.704	2.117
	PU2	0.834	-	-	-	1.942
	PU3	0.872	-	-	-	2.284
	PU4	0.801	-	-	-	1.766
Perceived Risk (PR)	PR1	0.786	0.804	0.872	0.630	1.489
	PR2	0.822	-	-	-	1.753
	PR3	0.791	-	-	-	1.668
	PR4	0.805	-	-	-	1.594
Environmental Risk (ER)	ER1	0.794	0.817	0.879	0.646	1.832
	ER2	0.821	-	-	-	2.006
	ER3	0.835	-	-	-	2.134
	ER4	0.778	-	-	-	1.691
Actual Usage (AU)	AU1	0.865	0.798	0.881	0.712	1.427
	AU2	0.841	-	-	-	1.562
	AU3	0.823	-	-	-	1.489

Table 4: Heterotrait–Monotrait Ratio (HTMT) Values

Constructs	BI	PEOU	PU	PR	ER	AU
Behavioral Intention (BI)	-	-	-	-	-	-
Perceived Ease of Use (PEOU)	0.612	-	-	-	-	-
Perceived Usefulness (PU)	0.684	0.531	-	-	-	-
Perceived Risk (PR)	0.398	0.276	0.344	-	-	-
Environmental Risk (ER)	0.421	0.315	0.362	0.589	-	-
Actual Usage (AU)	0.739	0.602	0.658	0.417	0.439	-

Table 5: Hypothesis Testing Path Coefficients

Hypotheses	Path	β	STDEV	T Statistics	p-value	Result
H1	PEOU → BI	0.312	0.068	4.588	0.000	Supported
H2	PU → BI	0.354	0.071	4.986	0.000	Supported
H3	PR → BI	−0.221	0.064	3.453	0.001	Supported
H4	ER → BI	−0.187	0.059	3.169	0.002	Supported
H5	BI → AU	0.429	0.073	5.877	0.000	Supported

Cohen [23], asserts that the model's capacity to explain phenomena is robust due to the fact that the data (table) show that the R Square value for all of the endogenous components is much higher than zero. It is possible that by calculating the predicted change in R Squared when we remove a particular exogenous construct, we will be able to acquire a more accurate understanding of the extent to which each exogenous variable contributes to the overall explanation provided by the model. We make use of the word "effect size" (f square) in order to measure this factor. The effect size is a measure used to assess the impact of each independent variable on the dependent variable. When an independent variable is removed from the PLS path model, the fluctuation in squared correlation values is assessed. This is done in order to determine the extent of the change. It investigates whether the value of the dependent variable is significantly influenced by the independent variable that was left out of the analysis. At the structural level, an f-square value of 0.35 indicates that the predictor variable has a significant influence, 0.15 indicates a medium influence and 0.02 indicates a moderate influence [23]. The f-square effect size of the model provides insight into the degree to which an external latent variable influences the R-squared value of an internal latent variable. In the process of determining the extent of a connection between latent variables, effect size is a clear approach to express the phenomenon. The information presented in table 1 reveals that the f-square effect shows a substantial difference between the influence of IM on POS (0.930) and the impact of POS on OP (0.001, negligible). Most importantly, endogenous constructs had Q Square values that were larger than zero, which demonstrated the predictive significance of these constructs.

DISCUSSION

This study examined the factors influencing farmers' adoption of organic farming technologies by applying an extended Technology Acceptance Model (TAM). The findings indicate that TAM is effective for understanding technology adoption within sustainable agriculture. Farmers are more likely to adopt organic methods when these technologies are perceived as easy to use, practical and compatible with existing routines. This aligns with previous research emphasizing the significance of usability in technology adoption. The study further demonstrates that perceived usefulness is the most influential factor shaping farmers' intentions. Farmers tend to favor technologies that enhance productivity, improve soil health and promote long-term economic viability, supporting earlier findings that performance benefits are central to adoption decisions. Conversely, perceived risks such as uncertain yields, volatile markets and conversion costs reduce the likelihood of adopting organic methods. However, farmers who recognize the environmental risks associated with conventional farming exhibit greater openness to organic alternatives. Finally, the strong association between intention and actual adoption underscores the pivotal role of intention in translating beliefs into behavior, confirming its importance as an intermediary between attitudes and actions.

Theoretical Implications

Focusing on innovation traits outlined by the Diffusion of Innovations Theory (DIT), this study investigates why organic farmers embrace new technology. According to the research, the main criteria that determine adoption behavior are the perceived innovative qualities, which include relative benefit, compatibility, complexity, trialability and observability. This research sets up a structured methodology to measure these features and see how these views affect the intent to use e-learning. This method does double duty: it adds to the existing body of research on e-learning and provides educational policymakers and providers with helpful pointers on how to enhance their adoption methods. In order to understand how organic farmers adopt new technologies; the study's results confirm the need of DIT. This study adds to what is already known by conducting an in-depth examination of characteristics of innovation adoption that have received little attention. Researchers drew on two foundational theories the Diffusion Innovation Theory (perceived innovation attributes) and the Technology Acceptance Theory (behavioral intention) to shed light on the theoretical and empirical factors that influence organic farmers' behavioral intentions to adopt technological interventions. From a theoretical standpoint, this work makes a substantial addition to the larger area of user adoption research. As antecedents of the adoption process, innovative traits are currently under-explored in most research pertaining to the agricultural industry. Additionally, the study's proposal of the IDT-TAM integrated model fills a crucial knowledge vacuum regarding farmers' adoption of technology. According to this study's findings, farmers are more likely to adopt technological interventions when they take into account the following factors: the relative advantage of using organic input over chemical fertilizer; the compatibility of using such technology with ancient practices; and the observability of others using the same and benefiting from its adoption. However, farmers' behavioral intention towards such technology is significantly impacted when they perceive its complexity. The findings provide credence to the notion that DIT variables might be employed as an independent variable to gauge the extent to which farmers have embraced technology.

Practical Implications

Among the many real-world consequences for the agricultural industry are suggestions for how lawmakers may best invest in farmers' technology adoption. Strategies to increase agricultural production and promote agricultural growth are primarily driven by technological change, which occurs as a result of the adoption of new technology. In addition, by raising people's consciousness, we may encourage the creation of cooperative models in which different groups work together to educate farmers, offer analytical services and promote sustainable farming methods. New developments in organic farming provide workable answers to the problems of increasing harvests while decreasing negative effects on the environment and strengthening long-term economic viability. Organic agricultural technology interventions aim to improve farmers' abilities, provide local resources and increase the availability of organic products for marginal farmers. Organic farmers may benefit from increased technical literacy if policymakers make it a priority. Organic inputs may be more widely used in farming techniques with the help of training. Organic farmers can benefit from more education and understanding of their products (Michael, 2020). The results suggest that encouraging farmers to switch to organic farming practices and providing incentives for organic producers to keep up their organic production should be the primary goals of efforts to increase the use of technology in organic farming,

Limitations and Future Research

The study isn't without its flaws. To begin, it is difficult to take into account other aspects of the theories mentioned since farmers in hilly areas have not yet investigated training and knowledge of organic farming technology. According to Gridis *et al*. and Kapser and Abdelrahman, behavioral intention is the most direct predictor of technology adoption. However, this study just employed behavioral intention. Secondly, further research might expand the scope to include demographic characteristics such as age, gender, education level, agricultural experience, etc., while this one only focuses on examining perceived innovative traits. Additionally, the study used a cross-sectional technique, which may not provide a comprehensive view of how agricultural practitioners embrace new technologies. A more appropriate approach would be to use a longitudinal methodology. Researchers should use this model to experimentally study different types of links, whether they are direct or indirect. Social influence can also serve as an independent variable in subsequent research. Our study laid the groundwork for several new lines of inquiry. Future study can assess farmers' attitude towards these technologies by include perceived simplicity of use and perceived utility instead of relative advantage and complexity, respectively, to understand technology adoption by farmers. It would be interesting to see what factors influence people's openness to using technology on farms in future studies.

CONCLUSION

This study provides a comprehensive understanding of the factors influencing farmers' adoption of organic farming through the lens of an extended Technology Acceptance Model (TAM). By integrating behavioral, cognitive and environmental constructs into the traditional TAM framework, the research bridges the gap between farmers' intentions and their actual adoption practices. The findings reveal that perceived usefulness and perceived ease of use remain significant determinants of farmers' intention to adopt organic farming practices. However, the study also highlights the crucial roles of attitude towards organic farming, social influence, perceived behavioral control and awareness of environmental and health benefits, which collectively shape adoption intentions and eventual practices. Notably, facilitating conditions such as access to training, technical support and financial incentives significantly moderate the intention–practice relationship, indicating that even motivated farmers may face barriers without adequate support systems. From a practical perspective, these insights emphasize the importance of policy interventions and extension services tailored to farmers' needs. Governments and agricultural organizations should focus on enhancing awareness, simplifying organic farming techniques and providing financial and infrastructural support to encourage widespread adoption. Moreover, fostering community-level knowledge sharing and peer learning can further reinforce positive attitudes and social norms toward sustainable agriculture. The study also underscores that intentions alone are insufficient to guarantee adoption; bridging the intention–behavior gap requires addressing both psychological and structural barriers. Future research could explore longitudinal patterns of organic farming adoption, the impact of regional and cultural differences and the integration of emerging technologies such as precision agriculture to facilitate sustainable practices. In conclusion, this research contributes to the theoretical refinement of the TAM in the context of sustainable agriculture while offering actionable insights for policymakers, extension workers and farmer communities. By understanding and addressing the multifaceted drivers of adoption, stakeholders can promote a more resilient, environmentally friendly and economically viable agricultural sector.

REFERENCES

[1] Reganold, J.P. and J.M. Wachter. "Organic agriculture in the twenty-first century." *Nature Plants*, vol. 2, 2016, p. 15221. https://doi.org/10.1038/nplants.2015.221.
[2] Pugliese, P. *et al*. "Understanding farmers' behavior in adopting organic farming: evidence from Europe." *Agricultural Systems*, vol. 164, 2018, pp. 1–12. https://doi.org/10.1016/j.agsy.2018.03.002.
[3] Davis, F.D. "Perceived usefulness, perceived ease of use and user acceptance of information technology." *MIS Quarterly*, vol. 13, no. 3, 1989, pp. 319–340. https://doi.org/10.2307/249008.
[4] Ajzen, I. "The theory of planned behavior." *Organizational Behavior and Human Decision Processes*, vol. 50, no. 2, 1991, pp. 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.
[5] Venkatesh, V. and H. Bala. "Technology acceptance model 3 and a research agenda on interventions." *Decision Sciences*, vol. 39, no. 2, 2008, pp. 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x.
[6] Sharma, S. *et al*. "Role of social influence and incentives in promoting organic farming: Evidence from India." *Sustainable Agriculture Research*, vol. 9, no. 2, 2020, pp. 45–56. https://doi.org/10.5539/sar.v9n2p45.
[7] Bhatia, A. and R. Singh. "Factors influencing farmers' adoption of organic farming practices in India." *Journal of Rural Studies*, vol. 87, 2021, pp. 52–63. https://doi.org/10.1016/j.jrurstud.2021.04.003.
[8] Lampkin, N. *Organic Farming*. Old Pond Publishing, 2002.
[9] Pannell, D.J. *et al*. "Understanding and promoting adoption of conservation practices by rural landholders." *Australian Journal of Experimental Agriculture*, vol. 46, no. 11, 2006, pp. 1407–1424.
[10] Kallas, Z. *et al*. "Farmers' objectives as determinants of organic farming adoption: The case of catalonian vineyard production." *Agricultural Economics*, vol. 41, no. 5, 2010, pp. 409–423.
[11] Knowler, D. and B. Bradshaw. "Farmers' adoption of conservation agriculture: A review and synthesis of recent research." *Food Policy*, vol. 32, no. 1, 2007, pp. 25–48.
[12] Adrian, A.M. *et al*. "Producers' perceptions and attitudes toward precision agriculture technologies." *Computers and Electronics in Agriculture*, vol. 48, no. 3, 2005, pp. 256–271.
[13] Greiner, R. and D. Gregg. "Farmers' intrinsic motivations, barriers to the adoption of conservation practices and effectiveness of policy instruments: empirical evidence from northern Australia." *Land Use Policy*, vol. 28, no. 1, 2011, pp. 257–265.
[14] Burton, R.J.F. "The influence of farmer demographic characteristics on environmental behaviour: A review." *Journal of Environmental Management*, vol. 135, 2014, pp. 19–26.

[15] Meemken, E.M. and M. Qaim. "Organic agriculture, food security and the environment." *Annual Review of Resource Economics*, vol. 10, 2018, pp. 39–63.

[16] Sutherland, L.A. *et al*. "Triggering change: Towards a conceptualisation of major change processes in farm decision-making." *Journal of Environmental Management*, vol. 104, 2012, pp. 142–151.

[17] Hair Jr., J.F. *et al*. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).* Sage Publications, 2016.

[18] Vinzi, V.E. *et al*. *Handbook of Partial Least Squares: Concepts, Methods and Applications.* Springer Science & Business Media, 2010.

[19] Fornell, C. and D.F. Larcker. "Evaluating structural equation models with unobservable variables and measurement error." *Journal of Marketing Research*, vol. 18, no. 1, 1981, pp. 39–50.

[20] Henseler, J. *et al*. "A new criterion for assessing discriminant validity in variance-based structural equation modeling." *Journal of the Academy of Marketing Science*, vol. 43, no. 1, 2015, pp. 115–135.

[21] Hair, J.F. *et al*. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).* 3rd ed., Sage, 2022.

[22] Hair Jr., J.F. *et al*. "Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research." *European Business Review*, 2014.

[23] Cohen, J. *Statistical Power Analysis for the Behavioral Sciences.* 2nd ed., Hillsdale, 1988, pp. 413.