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Intention to Adopt Sustainable Farming Practices: Evidence from Selected Indian Villages

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Digital technologies can help farmers adopt sustainable farming practices. This study addresses the urgent need for sustainable agriculture in India by examining how science communication, as an interpretive lens, may influence farmers' awareness and perceived ease of use, while considering the role of government support in shaping their adoption decisions. A field-based case study in Bharuch district, Gujarat, conducted under the Lal Bahadur Shastri Institute of Management Rural Immersion Program, analysed a final sample of 248 farmers using item-level Confirmatory Factor Analysis (CFA), Structural Equation Modelling (SEM), and moderation analysis. Perceived ease of use ($\beta = 0.238$, $p = 0.005$) and awareness ($\beta = 0.289$, $p < 0.001$) were positively associated with intention to adopt sustainable farming practices, and the structural model explained 39.3% of the variance in intention. Government support significantly moderated the awareness-intention relationship, with intention being attenuated ($\beta = -0.124$, $p = 0.014$; bootstrap 95% CI for B: −0.173 to −0.020). Awareness was strongly associated with intention when government support was low. The association weakened and became non-significant at high government support. Samples were geographically restricted and non-probability in nature; thus, findings cannot be statistically generalised beyond the selected villages. However, the study suggests that clear, locally relevant communication, combined with credible institutional support, may enhance awareness and perceived manageability of sustainable farming practices.

Keywords: Digital literacy, Farmers, Government support, Institutional practices, Science communication

Introduction

India, one of the world's largest agricultural countries, has witnessed a major shift in farming techniques. Following the announcement of Digital Public Infrastructure (DPI) for agriculture in the Union Budget for 2023–24 and 2024–25, the Government of India approved the Digital Agriculture Mission in September 2024. Digital platforms provide information in local languages, making it more accessible and relevant to farmers, thereby creating pathways for their development.[1]

With the global population expected to reach 9.7 billion by 20504, pressure on agricultural systems to meet rising food demand and environmental challenges has never been greater. Sustainable agricultural practices have therefore become important for efficient pest management and food security while promoting environmental conservation and fiscal resilience of farmers worldwide.[2,3]

Agriculture constitutes the backbone of the Indian economy, supporting over half the labour force and contributing significantly to national GDP.[4] Major changes in agricultural practices are required to address climate change, biodiversity loss, and degradation of natural resources.[5] So far, Indian agricultural policies have failed to bring about the necessary changes; meanwhile, public demands for new regulations have sparked massive farmer protests.[6] Given this, there is a pressing need to better understand the factors that influence farmers' uptake of sustainable agricultural practices.[7]

Sustainable farming practices, including diversified crop rotations, agroforestry, organic farming, and integrated pest management, offer a viable opportunity to address environmental degradation caused by chemical-based agriculture.[8] However, these alternatives should be critically analysed through the socio-economic and behavioural barriers that can impede their widespread acceptance. Studies suggest that external factors such as supportive policies, farm size, and farmers' personal characteristics, such as gender, age, and livelihood capital, affect their pro-environmental behaviour. The literature indicates that the complexity of these practices contributes to lower acceptance rates of

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sustainable farming practices.[9] There is a strong need to create a favourable market and regulatory environment that supports sustainable practices without compromising farmers' interests.

Digital decision-support tools can also help farmers. For instance, AI-based systems have been developed to recommend season-specific crops to be grown on farm.[10] Researchers have extensively studied sustainable farming practices, especially in the European context. Several previous studies have uncovered the myriad internal and external influences on farmers' decision-making processes.[11–13] Nevertheless, important knowledge gaps remain in understanding sustainable farming adoption, particularly in contexts of developing economies. One Indian-context study identified disparities in internet access and the affordability of user-friendly technologies as hindrances to ICT adoption.[14]

Although digital tools promise to ease environmental challenges, many conventional farmers remain hesitant because they do not fully understand how these technologies work in real-world farming settings or the advantages they may offer over time. Scientific and technical information is often difficult to translate into day-to-day farm decisions; consequently, science communication and extension activities that use familiar language, local examples, and practical demonstrations can improve the accessibility and relevance of such information.[15]

The present study therefore focuses on behavioural mechanisms pertinent to science communication, particularly awareness, perceived ease of use, and institutional support, rather than whether access to technology alone drives adoption. It examines awareness and perceived ease of use, the outcomes that communication and extension efforts aim to change. The study uses science communication as a lens for interpreting the results. The analysis uses responses from the final analytical sample of 248 farmers to examine these relationships using CFA, SEM, and moderation analysis.

Research Objectives

The present study's key objectives are:

- To examine the association of farmers' perceived ease of use and awareness of sustainable farming practices with their intention to adopt these practices.
- To examine whether perceived government support moderates the relationship between farmers' awareness of sustainable farming practices and their intention to adopt these practices.
- To assess the role of perceived relative advantage and social influence in farmers' intention to adopt sustainable farming practices.

While the adoption of sustainable farming has been studied extensively in European and Chinese contexts,[16,17] the Indian literature remains limited in three key respects. First, existing studies tend to focus either on technical barriers[18] or on broad policy analysis,[3] without integrating the socio-psychological antecedents of adoption intent. Second, science communication as a mechanism bridging awareness and adoption has received minimal empirical attention in the Indian agricultural context. Third, the moderating influence of government support on the awareness–intention relationship remains untested among Indian smallholders. The present study addresses these gaps by applying a TPB-informed framework to examine how perceived ease of use, awareness, and government support relate to the intention to adopt sustainable practices.

Accordingly, the study addresses three research questions, each corresponding to one of the hypotheses:

1. Is farmers' perceived ease of use of sustainable farming practices associated with their intention to adopt these practices (H1)?
2. Is farmers' awareness of the benefits of sustainable farming associated with their intention to adopt these practices (H2)?
3. Does government support moderate the relationship between awareness and intention to adopt (H3)?

Farmers' adoption decisions depend on motivation and feasible alternatives under prevailing conditions. Regulations, weather variability, and price systems can narrow a farmer's options even when the intention to change already exists. Gütschow *et al.*[7] capture this idea through the concept of action space, which separates intention formation from the later stages of identifying, implementing, and maintaining a new practice. The present study focuses on the first stage by asking whether awareness and perceived ease of use, the two mechanisms science communication most directly seeks to influence, are associated with intention, and whether government support, as an external institutional condition, alters the awareness–intention relationship.

Conceptual Framework

Conceptualising the Action Space

The capability of a farmer to alter farming practices is conceptualised as the action space: the degree of autonomy farmers perceive when experimenting with new practices, especially when forces beyond their control constrain them.[7] Beyond focusing solely on individual motivation, the concept emphasises contexts in which real-life conditions constrain the array of choices and shape what seems feasible.[15,16,19] Change unfolds in four stages: recognising a problem, identifying a solution, implementing it and maintaining it over time. Once an intention has formed, the action space shapes the last three stages, so what follows depends heavily on constraints and opportunities that may not be visible when the intention forms. Gütschow *et al.* identified the five main types of obstacles which define the limits of action space.[7]

Smallholder farmers frequently face depressed commodity prices that fail to cover production costs, while limited access to local processing and marketing infrastructure compounds their economic vulnerability. A small number of large agribusiness intermediaries concentrate market power, leaving primary producers with weak bargaining positions in supply chains. The asymmetric power distribution between smallholders and downstream processors and retailers creates a structural economic barrier to adopting sustainable practices, as many farmers lack the financial stability to invest in new methods.

Frequent and unpredictable policy changes discourage farmers from investing in new practices. Policies in different domains sometimes conflict, so measures intended to benefit one area can impede sustainable solutions in another.

Education and advisory systems tend to support standard single-crop systems. They offer few opportunities to learn about alternatives and place little value on local knowledge, which is often central to sustainable solutions. Variable climatic conditions and recurrent droughts can hinder agricultural activities. For instance, cover crops may establish poorly in dry seasons and then compete with the main crop for scarce soil moisture instead of benefiting it.

Prior investments in conventional equipment, established cropping routines, and entrenched notions of "correct" agricultural practice create self-reinforcing patterns that constrain farmers' willingness to experiment with alternatives. These path dependencies are not merely habitual; they reflect rational risk aversion in contexts where the farming household bears the direct costs of failed experimentation. As a result, practices that may be environmentally suboptimal persist not because farmers are unaware of alternatives, but because they perceive switching costs- financial, cognitive, and social- as outweighing the anticipated benefits.

These barriers are deeply interconnected. For instance, the absence of local supply chains constrains opportunities for crop diversification, while narrow profit margins prevent farm-level reinvestment in sustainable alternatives.[7]Expanding farmers' action space therefore requires systemic intervention by external actors, including policymakers and market regulators, to create enabling conditions under which sustainable practices are both legally supported and economically viable.[10]

Conceptualising the Intention to Adopt

Drawing on Ajzen's Theory of Planned Behaviour (TPB),[16] the present study treats intention as the proximal behavioural outcome. The framework is TPB-informed rather than a complete test of all canonical TPB paths. Perceived ease of use is conceptually aligned with perceived behavioural control because greater manageability and compatibility should increase farmers' perceived capability to act. This study treated awareness as an informational antecedent that can shape a favourable evaluation of sustainable practices, rather than as a direct substitute for the TPB attitude construct. The broader questionnaire captured subjective-norm processes through Social Influence items concerning other farmers and community leaders and included them in the measurement-validation model, while the focal structural hypotheses focus on Ease of Use, Awareness, and Government Support. Government Support is conceptualised as an external institutional context rather than a core TPB construct and is tested as a moderator of the Awareness-Intention relationship. This mapping prevents the present model from being interpreted as a full TPB replication while retaining TPB as the theoretical lens for understanding intention formation.[16,19]

Ease of Use and Awareness are engaged as focal predictors, while science communication and extension activities aim to inform farmers about the potential benefits of these practices. The Awareness items (AW1-AW3) and Ease of Use items (EOU1-

EOU2) represent message-level outcomes through which communication can shape intentions.

Subjective norms are the perceived social pressure to perform or refrain from a given behaviour and play a significant role in shaping farmers' adoption decisions. Social influence operates through trusted referents, including neighbours, community leaders, and agricultural extension workers; where these networks endorse new practices, farmers are more likely to form favourable intentions. Perceived behavioural control, the third TPB antecedent, reflects farmers' assessments of their ability to perform an intended behaviour given the resources and constraints available to them. Access to appropriate equipment, technical knowledge, financial capital, and institutional support shapes this perception. When any of these enabling resources is absent, perceived control diminishes, and intention is less likely to translate into action. Factors such as tool ownership, credit access, and extension service availability are therefore relevant not merely as logistical considerations, but as determinants of perceived behavioural capacity.

Conceptualizing the Awareness

Awareness refers to farmers' knowledge of environmental challenges and the practices they use to respond. The factor provides a cognitive basis for later decisions. Sustainability challenges include recognising unusual weather patterns and their visible effects on crops and land (Appendix Table A1).[20]

Farmer's knowledge and beliefs influence how farmers view adoption, motivation, and resilience. Prevailing narratives may portray farmers as victims and may discourage proactive measures.[17,20]

Conceptualising the Ease of Use

Perceived ease of use measures farmers' judgement of whether a new practice fits their routines, and it shapes how much control they feel over adopting it. The literature shows that clear explanations of procedures and steps lead to higher adoption rates.[7,20] Relevance of suggested techniques to everyday practices makes information clear to users.[17,20] The present study measure ease of use by perceived ease of learning sustainable farming techniques and the perceived clarity of those techniques.

Conceptualising the Government Support

Government support refers to the institutional context, including policies, programmes and training to help and motivate farmers.[7,17] Institutional strength, including actor diversity, learning capacity, and leadership, strengthens government support.[23] In the present study, government support is measured through farmer's perception of the adequacy of government training and of the extent to which government policies encourage sustainable farming practice adoption. Research indicates that trust is essential to promote adoption; a lack of trust disrupts collaborative engagement and reduces compliance with policy directives.[17]

Hypotheses

This study is based on three hypotheses related to its objectives. Ease of use is expected to strengthen farmers' perceived capability to act and thus positively influence intentions. Government support is treated as an institutional condition altering the strength of awareness-intention relations (Fig. 1).

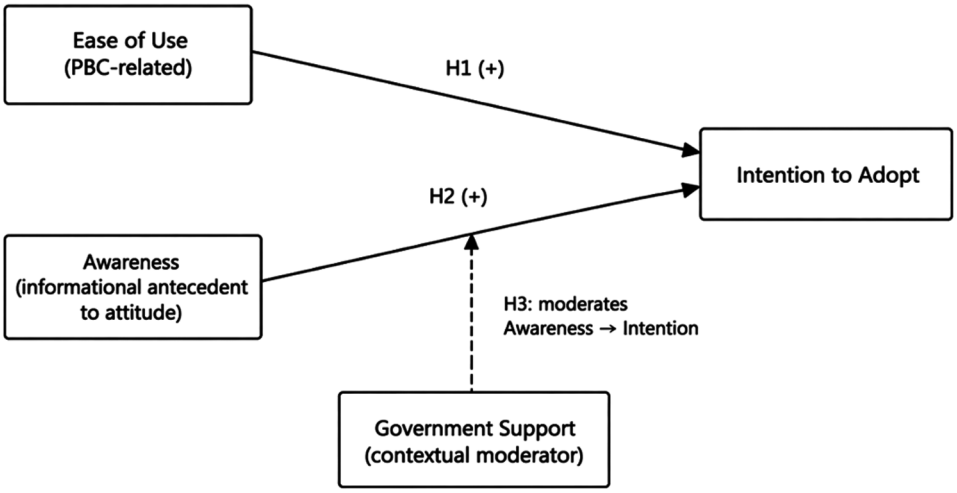

Fig. 1 — TPB-informed focal conceptual model tested in the study

Thus, the third hypothesis, H3, is stated as a non-directional moderation hypothesis.

H1: Ease of use positively influences intention to adopt (RQ1).

H2: Awareness positively influences intention to adopt (RQ2).

H3: Government support moderates the relationship between awareness and intention to adopt (RQ3).

Research Methodology

The data come from 248 farmers in Bharuch district, Gujarat. The wider survey gathered responses from several field sites, but only those from Bharuch were kept to match the study's geographical focus. The local network and connections built through LBSIM's regular annual rural immersion program were used to collect responses from farmers through a combination of snowball and convenience sampling.

No complete list of farming households existed for these remote communities, so a probability sample was not an option. Access also depended on people the farmers already trusted, such as panchayat representatives, self-help groups, and partner NGOs. The authors found this approach reasonable enough for an exploratory field study, though it did not allow them to generalise to the entire farming population of Bharuch. Therefore the results were interpreted as sample-specific only, and do not claim representativeness of the district. Selected demographic characteristics of the analytical sample are reported in Appendix Table A2. The questionnaire covered six constructs: Ease of Use, Awareness, Relative Advantage, Government Support, Social Influence, and Intention to Adopt. Each item was rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The full wording of every item appears in Appendix Table A1.

All multi-item constructs were validated through CFA to assess their measurement properties, and the focal structural model tested Ease of Use and Awareness as predictors of Intention to Adopt, with Government Support as the moderator. Intention to Adopt was measured with a single item and was therefore treated as an observed endogenous variable, as internal-consistency measures such as Cronbach's alpha, CR, and AVE do not apply to single-item measures.

Using a single item to measure intention to adopt follows methods used by previous researchers. One item can be adequate when the construct is concrete, i.e., when the object being rated and the attribute being judged are clear and easily understood.[21,22] In the present study, intention was modelled as an observed variable; any random measurement error is absorbed in its residual variance. Such error lowers the explained variance and the standardised coefficients. However, as some studies have shown that single items often predict less well than multi-item scales,[23] this is acknowledged as one of the limitations.

Data Preparation and Model Estimation

The Likert responses were coded from 1 to 5 and analysed them on their original scale; min-max normalisation was not used. Item-level CFA and the focal structural model were estimated in Python using semopy 2.3.11 with Maximum Likelihood Wishart (MLW) estimation. Model fit was evaluated using chi-square (χ^2), degrees of freedom, χ^2/df, CFI, TLI, RMSEA with its 90% confidence interval, and SRMR. The focal structural model estimated direct paths from Ease of Use, Awareness, and Government Support to Intention to Adopt. Stability of the direct paths was examined using 1,000 bootstrap resamples; all 1,000 models converged.

Moderation was assessed separately using mean composite scores for Ease of Use, Awareness, and Government Support. The mean-centred Ease of Use, Awareness, and Government support were taken into account before creating the Awareness × Government Support interaction. The regression contained all constituent main effects and the interaction term. To evaluate the interaction, the study used heteroscedasticity-consistent HC3 standard errors, 5,000 bootstrap resamples, change in R^2, variance inflation factors (VIF), and simple slopes at low (−1 SD), mean, and high (+1 SD) Government Support.

Measurement Validation

An item-level CFA was conducted before estimating the structural model. The five multi-item constructs showed standardized factor loadings from 0.794 to 0.918. The measurement model demonstrated acceptable overall fit: $\chi^2(34) = 97.21$, $p < 0.001$; $\chi^2/df = 2.86$; CFI = 0.965; TLI = 0.944; RMSEA = 0.087 (90% CI: 0.067–0.107); and SRMR = 0.044. The measurement-model reliability and convergent validity are given in Table 1.

These findings follow studies,[24] which recommend assessing fit using a combination of indices, with CFI and TLI at or above 0.95 and SRMR at or below 0.09.

Table 1 — Measurement-model reliability and convergent validity

Construct	Items	Loading range	Cronbach α	CR	AVE
Ease of Use	2	0.885–0.918	0.896	0.897	0.813
Awareness	3	0.833–0.910	0.908	0.910	0.770
Relative Advantage	2	0.836–0.892	0.855	0.855	0.748
Government Support	2	0.826–0.873	0.838	0.839	0.723
Social Influence	2	0.794–0.830	0.795	0.795	0.660

Note: Intention to Adopt was a single-item observed outcome; multi-item reliability statistics are therefore not applicable

Table 2 — Fit indices for the measurement and structural models

Fit index	CFA	Structural model
χ^2 (df)	97.21 (34)	19.68 (15)
χ^2 p-value	<0.001	0.185
χ^2/df	2.86	1.31
CFI	0.965	0.996
TLI	0.944	0.993
RMSEA (90% CI)	0.087 (0.067–0.107)	0.036 (0.000–0.074)
SRMR	0.044	0.022

The results of this study meet these thresholds for the CFI (0.965) and SRMR (0.044). The weaker result is the RMSEA. Its point estimate of 0.087 falls in the 0.08-0.10 band that MacCallum *et al.*[25] associate with mediocre fit, and the upper bound of its confidence interval is above 0.10. The significant χ^2 was not weighed heavily as the test is known to be sample size dependent.[24] Together, the indices suggest an acceptable but not necessarily close fit, and the RMSEA should be interpreted with caution. By contrast, the structural model met all these criteria (Table 2).

The scales showed good internal consistency and convergent validity. Cronbach's α ranged from 0.795 to 0.908, composite reliability (CR) from 0.795 to 0.910, and average variance extracted (AVE) from 0.660 to 0.813. Discriminant validity also held. For every construct, the square root of the AVE was larger than its correlations with the other constructs, which satisfies the Fornell–Larcker criterion.[29] The highest HTMT value (0.747) was also well under the 0.85 threshold.[26] No Heywood cases or negative residual variances were found.

Ethical Considerations and Data Handling

The study incorporated ethical safeguards in field data collection. Participants were briefed on the purpose of the study, the voluntary nature of participation and their right to decline or withdraw. Before participation, the study obtained informed consent; sought verbal or written confirmation, as appropriate for respondent literacy. Identifiable personal data was separated from survey responses and analyzed only de-identified data and aggregate findings. The team worked with local panchayat and NGO partners to coordinate field procedures, facilitating culturally appropriate engagement and community trust. The team coordinated field procedures with local panchayat and NGO partners, which helped keep engagement culturally appropriate and build trust within the community.

Results and Analysis

The analysis proceeded in two steps, viz. assessment of the measurement model at the item level and then estimation of the structural relationships of interest. The CFA confirmed that the scales had adequate reliability and convergent and discriminant validity. The main fit indices for the CFA and structural models' are provided in Table 2 side by side.

The structural model showed very good fit, $\chi^2(15) = 19.68$, $p = 0.185$; $\chi^2/df = 1.31$; CFI = 0.996; TLI = 0.993; RMSEA = 0.036 (90% CI: 0.000-0.074); and SRMR = 0.022.Ease of Use and Awareness showed positive and statistically significant relationships with Intention to Adopt. Government Support also had a positive direct effect on Intention to Adopt in the structural model. The structural model explained 39.3% of the variance in Intention to Adopt (R^2 = .393). Bootstrap estimates closely reproduced the MLW estimates, and the 95% bootstrap confidence intervals for all direct effects excluded zero. The structural model path estimates are given in Table 3.

H3 was examined separately using composite-score moderation analysis with mean-centred constituent terms and the Awareness × Government Support interaction (Table 4). In this moderation analysis, the main-effects regression explained 37.1% of the variance in Intention to Adopt ($R^2 = 0.371$). Adding the interaction term increased explained variance to 38.2% ($R^2 = 0.382$), a modest but statistically significant incremental contribution ($\Delta R^2 = 0.012$, F-change = 4.61, $p = 0.033$). The interaction was significant and negative ($B = -0.097$, robust SE = 0.040, $\beta = -0.124$, $p = 0.014$; 5,000-resample bootstrap 95% CI [−0.173, −0.020]). Thus, H3 was supported as a non-directional moderation hypothesis, although Government Support attenuated rather than strengthened the positive Awareness–Intention relationship.

Simple-slope analysis clarifies the interaction. Awareness was strongly and positively associated with Intention at low Government Support (B =

Table 3 — Structural-model path estimates

Hypothesis/effect	Path	B	Robust SE	β	p	Bootstrap 95% CI (B)	Decision
H1	Ease → Intention	0.245	0.087	0.238	0.005	0.074 to 0.430	Supported
H2	Awareness → Intention	0.347	0.098	0.289	<0.001	0.169 to 0.517	Supported
Direct effect	Govt. Support → Intention	0.234	0.073	0.219	0.001	0.089 to 0.407	—

Table 4 — Moderation and simple-slope results

Effect / level	B	Robust SE	β	p	95% CI
Awareness × Govt. Support	-0.097	0.040	−0.124	0.014	−0.173 to −0.020*
Awareness slope: low support (−1 SD)	0.351	0.064	—	<0.001	0.225 to 0.478
Awareness slope: mean support	0.234	0.075	—	0.002	0.086 to 0.382
Awareness slope: high support (+1 SD)	0.116	0.108	—	0.285	−0.097 to 0.329

**Bootstrap 95% CI for the interaction; simple-slope intervals are HC3-based 95% confidence intervals.*

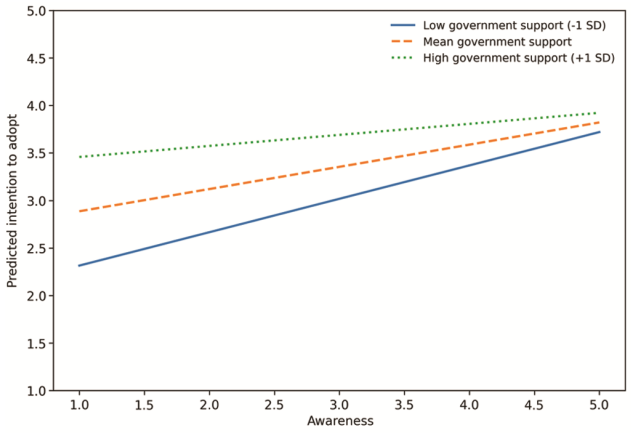

Fig. 2 — Moderating effect of government support on the awareness–intentionrelationship (Ease of use held at its mean)

0.351, p < 0.001) and remained significant at mean support (B = 0.234, p = 0.002), whereas at high Government Support the association was smaller and non-significant (B = 0.116, p = 0.285). The attenuation pattern can be seen in Fig. 2.

Policy Level Recommendations

The study yields three major policy-level implications. First, awareness and perceived ease of use were both positively associated with intention. Outreach programs should clearly and concisely explain the benefits of sustainable practices. The negative interaction between awareness and government support shows that awareness matters most when perceived government support is low. Awareness-building is especially valuable among farmers who view government training and policy support as weak. Also, when perceived support was high, intention was less dependent on individual awareness. Communication efforts should be paired with credible, accessible support, such as adequate training programs and consistent policy encouragement. Additionally, during field immersion in Bharuch villages, some farmers described using digital technologies while cultivating dragon fruit and kiwi in the field. These interactions indicated that farmers perceived practical benefits from digital technologies. Households commonly used smartphones for digital payments.

In India, the government has launched several initiatives to promote sustainable agriculture. The National Mission for Sustainable Agriculture (NMSA), initiated in 2014-15, aims to enhance agricultural productivity, especially in rainfed areas, by promoting integrated farming, water-use efficiency, soil health management, and the synergisation of resource conservation.[27] Additionally, the Pradhan Mantri Krishi Sinchayee Yojana (PMKSY) focuses on improving water use efficiency through the concept of “Per Drop More Crop”.[28]

Research institutions and non-governmental organisations also help develop and disseminate sustainable farming techniques. Nevertheless, India's adoption of sustainable agriculture practices remains modest. According to a 2020 report by the Centre for Science and Environment, organic farming in India covers only about 2.8 million hectares, which accounts for barely two per cent of the net sown area.[29] Such limited adoption underscores the need to better understand the determinants of farmers' intention to adopt sustainable farming practices.

Despite these policy initiatives, deep-rooted obstacles limit the spread of sustainable farming methods in India. Many farmers remain hesitant because they are uncertain about the long-term ecological benefits, and clearer evidence-based explanations could reduce that uncertainty. Peer learning is valuable, but structured training can address the skill gaps it leaves.

Policy intentions, however, often fail to translate into farm-level practice. Previous studies identify financial incentives, risk perception, peer influence, trust in institutions and local cooperation as factors that determine whether sustainable techniques spread.[16,23] Because these factors combine differently across India's cultural, economic, and climatic settings, further research is needed on how they interact.

Discussion

Ease of Use and Awareness

The SEM results confirm that both Ease of Use ($\beta = 0.238$, $p = 0.005$) and Awareness ($\beta = 0.289$, $p < 0.001$) are positively associated with farmers' Intention to Adopt. These findings are consistent with evidence that practical usability, knowledge, and perceived capability matter for technology and sustainable-practice uptake. In the Indian context, Samadder *et al.*[14] similarly identify access and user-friendliness as key constraints on ICT adoption, while Nguyen and Drakou,[20] highlight the role of awareness in sustainable agricultural intention. The results also align with Dessart *et al*.,[13] who emphasise behavioural factors in farmers' adoption decisions. Within this TPB-informed interpretation, Ease of Use is most closely related to perceived behavioural control, whereas Awareness is treated as an informational antecedent that can support favourable adoption evaluations.

Government Support as an Attenuating Moderator

The moderation analysis changes how Government Support is interpreted. The Awareness × Government Support interaction was significant but negative ($\beta = -0.124$, $p = 0.014$; bootstrap 95% CI for B: −0.173 to −0.020). Awareness was strongly associated with Intention when Government Support was low, less so when Support was average, and not statistically significant when Support was high. This pattern is consistent with a compensatory interpretation: where institutional support is limited, individual awareness may be particularly important for intention formation; where support is stronger, intention may depend less on differences in individual awareness. Government Support also had a positive direct effect in the structural model ($\beta = 0.219$, $p = 0.001$), so the negative interaction does not mean that support lowers intentions. Rather, the interaction indicates that institutional support and individual awareness may partly substitute for one another in explaining intention.

Implications for Science Communication and the TPB-Informed Framework

The findings support the role of science communication in making complex information understandable and locally relevant for farmers. The SEM results provide evidence of adoption-related mechanisms, especially Awareness and Ease of Use. The results suggest that communication strategies aimed at improving awareness and perceived manageability are likely most useful when aligned with credible institutional support. The broader questionnaire also captured Social Influence as a subjective-norm-related construct, while the focal H1-H3 model intentionally concentrated on the communication- and support-related mechanisms specified in the study objectives.

Limitations and Future Research

The sample was non-probability based and drawn from one district, so the study cannot claim statistical representativeness of the wider farmer population. The design was cross-sectional and relied on self-reported intention rather than observed adoption behaviour; intention was measured with a single item.

In addition, science communication was not estimated as a separate latent or experimental exposure variable. The measurement model's RMSEA was mediocre, although the remaining fit indices were satisfactory. Social Influence and Relative Advantage were validated in the measurement model but were not specified as predictors, so their contribution relative to the focal constructs was not estimated.

Future studies should use probability-based multi-district samples where feasible, multi-item measures of intention, longitudinal tracking of actual adoption, and experimental or quasi-experimental designs that directly compare communication formats.

Conclusions

This study analysed the adoption intentions of 248 farmers in Bharuch district using an item-level measurement model and structural equation modelling. Ease of Use and Awareness were significant positive predictors of Intention to Adopt, and the focal structural model explained 39.3% of the variance in Intention to Adopt. Government Support also had a positive direct effect.

The moderation result provides an important policy implication compared with the original analysis. Government Support significantly moderated the Awareness-Intention relationship, but the interaction was negative: Awareness was most strongly associated with Intention when Government Support was low and became non-significant at high support. This suggests that strong institutional support may reduce the extent to which adoption intention depends on individual awareness alone. Given the non-probability, single-district, cross-sectional design and the use of a single-item intention measure, generalise the findings cautiously and do not interpret them as evidence of actual adoption or as a direct causal effect of science communication. Future multi-district, longitudinal, and communication-intervention studies can test whether these intention pathways translate into sustained behavioural change.

AI Declaration Statement

The authors conceptualised the study, its methodology, data collection, and data analyses, including confirmatory factor analysis (CFA), structural equation modelling (SEM), and moderation analysis. In addition, the authors coded in Python. The authors used ChatGPT(OpenAI, GPT-5.2) only to improve the language and make certain parts of the manuscript more understandable. This tool was not used for data or statistical analyses of any kind. The authors have independently confirmed all results, conclusions, and interpretations presented hereafter.

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Conflict of Interest

The authors have no relevant financial or non-financial conflicts of interest to disclose.

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Appendix

Table A1 — Questionnaire items used in the analysis

Construct	Code	Item wording
Ease of Use	EOU1	Learning sustainable farming techniques is easy for me.
Ease of Use	EOU2	Sustainable farming techniques are clear and understandable.
Awareness	AW1	I am aware of the benefits of sustainable farming practices.
Awareness	AW2	I understand how sustainable farming can impact the environment positively.
Awareness	AW3	I am aware of the long-term benefits of adopting sustainable farming practices.
Relative Advantage	RA1	Sustainable farming is more advantageous than conventional farming.
Relative Advantage	RA2	Sustainable farming improves the quality of my produce compared to traditional methods.
Government Support	GS1	The government provides adequate training on sustainable farming.
Government Support	GS2	Government policies encourage the adoption of sustainable farming.
Social Influence	SI1	I am influenced by other farmers in my community who practice sustainable farming.
Social Influence	SI2	Community leaders promote sustainable farming practices.
Intention to Adopt	INT1	Intention to Adopt Sustainable Farming.

Table A2 — Selected demographic characteristics of the analytical sample (N = 248)

Characteristic	Category	n	%
Gender	Male	160	64.5
Gender	Female	88	35.5
Age (years)	15 to 20	2	0.8
Age (years)	21 to 25	13	5.2
Age (years)	26 to 30	21	8.5
Age (years)	31 to 35	31	12.5
Age (years)	36 to 40	40	16.1
Age (years)	41 to 45	21	8.5
Age (years)	45 to 50	29	11.7
Age (years)	51 to 55	22	8.9
Age (years)	56 to 60	22	8.9
Age (years)	61 and above	43	17.3
Age (years)	Multiple categories selected / not classifiable	4	1.6
Education	No formal education	145	58.5
Education	Under graduate	66	26.6
Education	Graduate	34	13.7
Education	Post graduate	3	1.2
Mobile access	Smart phone	122	49.2
Mobile access	Basic phone	86	34.7
Mobile access	No	40	16.1

Note: Percentages are based on the final analytical sample. Four age responses contained more than one selected age category and were not reassigned.