

Farmers' Smart Agricultural Perception and Technology Adoption: The Mediating Role of Social Media

P M Ramesh Kumar¹., J Satish²., G Nandini^{3*}., P Balaji⁴., R Indumathi⁵

¹ Assistant Professor, PG Department of Commerce,

Dwaraka Doss Goverdhan Doss Vaishnav College (Autonomous), Chennai, TN, India,

ORCID: <http://orcid.org/0000-0003-0346-9229>

² Associate Professor & Head, PG & Research Department of Commerce,

Dwaraka Doss Goverdhan Doss Vaishnav College (Autonomous), Chennai, TN, India

³ Post Graduate Student, PG Department of Commerce,

Dwaraka Doss Goverdhan Doss Vaishnav College (Autonomous), Chennai, TN, India, Email ID:
nandiniyadav1729@gmail.com

⁴ Assistant Professor, PG & Research Department of Commerce, Guru Nanak College (Autonomous),
Chennai, TN, India

⁵ Assistant Professor, PG Department of Commerce,

Dwaraka Doss Goverdhan Doss Vaishnav College (Autonomous), Chennai, TN, India

ABSTRACT

Smart agricultural technologies such as mobile advisory applications, Internet of Things (IoT) sensors, and unmanned aerial vehicles (UAVs) hold considerable promise for improving farm productivity and resource efficiency, yet their adoption among farmers remains uneven. Drawing on an integrated Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT2) framework, this study examines the influence of farmers' perception, perceived usefulness, perceived benefit, effort expectancy, performance expectancy, social influence, and facilitating conditions on the adoption of smart agricultural technologies, and evaluates the mediating role of social media engagement in this relationship. Primary data were collected from 102 farmers using a structured Likert-scale questionnaire and analysed using descriptive statistics, Pearson correlation, and multiple linear regression. The results indicate that facilitating conditions and social influence are the strongest direct predictors of technology adoption, that perceived benefit and facilitating conditions most strongly predict social media engagement, and that effort expectancy and prior technology adoption significantly predict farmers' intention to use smart technologies. Social media, while strongly and positively correlated with adoption, did not emerge as a statistically significant independent predictor once facilitating conditions and social influence were accounted for, suggesting its role operates largely through its shared variance with these enabling conditions rather than as an independent driver. The findings offer practical guidance for policymakers, agricultural extension agencies, and agri-tech firms seeking to design infrastructure-linked, socially embedded interventions that accelerate the adoption of smart agricultural technologies.

Keywords: Smart agriculture, technology adoption, social media, UTAUT2, farmers' perception, digital agriculture

INTRODUCTION

Agriculture is the backbone of the Indian economy, supporting the livelihoods of millions. Over the years, the sector has evolved from traditional methods to modern, technology-driven approaches. Advancements such as precision farming, smart irrigation systems, drones, artificial intelligence (AI), the Internet of Things (IoT), mobile applications, and digital marketplaces have transformed farming. These smart technologies help farmers improve productivity, reduce production costs, and make informed decisions.

Despite the numerous benefits of smart agricultural technologies, their adoption remains uneven. While some farmers are willing to implement them, many continue to use traditional methods due to a lack of awareness, limited technical knowledge, insufficient infrastructure, and resistance to change. Analysing the factors that influence farmers' adoption decisions is crucial for promoting digital transformation in agriculture. In recent years, social media has emerged as a powerful platform for sharing agricultural knowledge. Platforms such as YouTube, Twitter (X), Facebook, WhatsApp, and Instagram enable farmers to access expert advice, weather updates, market prices, and government schemes. Social media allows farmers to share their own experiences, learn from one another, and build confidence in using new technologies, playing a vital role in encouraging the adoption of smart agricultural technologies.

This study examines the factors influencing the adoption of smart agricultural technologies by considering perceived usefulness, perceived benefits, effort expectancy, performance expectancy, social influence, and facilitating conditions. It also investigates the mediating role of social media in strengthening the relationship between these factors and technology adoption. By identifying key drivers, this research aims to provide valuable insights for policymakers, agricultural extension agencies, researchers, and technology developers to promote the effective use of smart technologies and contribute to sustainable agricultural development.

REVIEW OF LITERATURE

To understand the landscape of current research on agricultural technology adoption, it is essential to synthesize existing empirical findings. Table 1 provides a consolidated overview of twenty key studies conducted between 2018 and 2024, summarizing their objectives, methodologies, key variables, and outcomes. These studies offer a foundation for identifying both the established determinants of technology adoption and the critical gaps in current literature.

Table 1: Previous Studies

Author	Year	Overview of introduction	Objectives	Methodology	variables	Findings	conclusions	Results	implication
jitendra yadav, et al.	2023	The researcher discussed that traditional technology adoption studies mainly used surveys and models. With the growth of social media, Twitter plays a vital role	the role of social media in technology adoption was studied, Twitter data were analysed, public sentiment was understood, and its influence on adoption practices was observed.	the researcher says that a quantitative and analytical approach was followed in the study using Twitter Analytics . Secondary data in the form of tweets was collected	Social media interactions were treated as independent variables and technology adoption as the dependent variable	The researcher found that the Social media discussions and significantly influence technology adoption	The researcher concluded that Twitter played a significant role in shaping technology adoption practices. Social media analytics provided valuable real-time insights	the study showed a strong relationship between Twitter activity and technology adoption behaviour. Higher engagement led to higher adoption interest.	The research was useful for business, marketers, and researchers to understand customer behaviour and promote new technologies effectively.

		for sharing opinions about new technologies.		and analysed.					
Jingjin Li, et al.	2023	The researcher discussed that the importance of smart agriculture in modernising agriculture and improving productivity	The factors influencing cotton farmers' adoption of smart agriculture technologies were examined	A quantitative approach using Structural Equation Modelling based on DTPB was adopted	Behavioural beliefs, normative beliefs, control beliefs, willingness, and adoption behaviour were studied	Perceived usefulness and superior influence were found to strongly affect adoption willingness	The study concluded that smart agriculture adoption was found to be driven by behavioural willingness and supportive policies	The research showed the adoption behaviour was positively influenced by willingness, attitudes, and policy satisfaction	The implications are used Policy support, cost reduction, training, and technology improvement were recommended to enhance adoption
Nitesh mishra, et al.	2024	The researcher discussed that the need to adopt Agriculture 5.0 was explained by highlighting technological advancements and low adoption among Nepalese farmers.	The factors influencing farmers' intention to adopt Agriculture 5.0 was observed and implementation challenges were identified.	An explanatory and quantitative research design was adopted using survey data.	Technology anxiety, self-efficacy, social influence, innovativeness, perceived usefulness, perceived ease of use, attitude, and behavioural intention were studied.	Perceived usefulness and ease of use were found to significantly influence farmers' attitudes and intentions to adopt Agriculture 5.0.	The study concluded that The adoption of Agriculture 5.0 mainly depends on psychological, social, and technological factors.	The study showed the Behavioural intention to adopt Agriculture 5.0 was strongly influenced by attitude toward technology use.	The study contribute empirical evidence on technology adoption behaviour in agriculture within developing country contexts.

Sirkka Schukat and Heinke Heise.	2021	the researcher discussed that the importance of smart products in sustainable agriculture with emphasis on farmers' acceptance and use	The study determinants influencing farmers' behavioural intention and actual use of smart products were observed.	A quantitative research design using an extended UTAUT-2 model was adopted.	Performance expectancy, social influence, facilitating conditions, hedonic motivation, trust, technology readiness, behavioural intention, and use behaviour were analysed.	Technology readiness, hedonic motivation, and social influence were found to significantly affect behavioural intention.	Adoption of smart products was concluded to depend mainly on readiness, motivation, and support conditions.	Behavioural intention was shown to significantly influence the actual use of smart products.	The study was, to provide strong empirical support for technology adoption models in smart farming contexts.
Kumar and Singh.	2022	The study discussed that the role of digital technologies in improving agricultural productivity was introduced along with adoption challenges.	The key factors influencing farmers' adoption of digital agricultural technologies were examined.	A quantitative research approach using survey data was adopted.	Perceived usefulness, ease of use, cost, awareness, and adoption intention were analysed.	Perceived usefulness and awareness were found to significantly influence adoption intention.	The researcher concluded that Digital technology adoption was on perceived benefits and accessibility.	The results are shown Adoption intention was positively related to actual technology usage.	The study was found to strengthen empirical understanding of digital adoption behaviour in agriculture
Patel and Verma.	2023	The researcher discussed that need for smart farming technologies to achieve	The factors influencing smart farming technology adoption were examined.	A quantitative and descriptive research design was adopted.	Awareness, cost, perceived usefulness, ease of use, and adoption were analysed.	Awareness and perceived usefulness were found to significantly influence adoption.	Smart farming adoption was concluded to improve agricultural	Adoption of smart technologies was positively related to sustainable	The study was found to provide empirical support for smart technology adoption in agriculture.

		sustainable agriculture					sustainability.	farming practices	
Sharma and Reddy.	2024	The researcher says that importance of precision agriculture for productivity and sustainability was introduced.	The factors influencing farmers' adoption of precision agriculture technologies were examined.	A quantitative cross-sectional survey design was adopted.	Perceived usefulness, cost, technical knowledge, attitude, and adoption were analysed	Perceived usefulness and technical knowledge were found to significantly affect adoption	Precision agriculture adoption was concluded to depend on knowledge, cost, and perceived benefits.	Adoption levels were shown to increase with higher awareness and skill levels.	The study was found to strengthen understanding of technology adoption behaviour in agriculture.
Adeola and Ayodade.	2020	The researcher discussed that the Role of ICT in improving agricultural efficiency and decision-making.	The factors affecting farmers' adoption of ICT tools were examined.	A quantitative survey-based research design was adopted.	Awareness, accessibility, cost, skill level, and ICT adoption were analysed.	Awareness and accessibility were found to significantly influence ICT adoption.	ICT adoption was concluded to depend mainly on access, skills, and affordability.	The study showed the higher ICT usage was associated with improved farming practices.	The study was found to support technology adoption theories in agricultural contexts.
Alalwan, et al	2018	The study discussed that growing importance of digital technologies for improving farm efficiency was introduced.	The factors affecting farmers' adoption of digital agricultural technologies were examined.	A quantitative research approach using survey data was adopted	Perceived usefulness, ease of use, trust, attitude, and adoption were analysed.	Perceived usefulness and trust were found to significantly influence adoption.	Digital adoption was concluded to enhance productivity and decision-making in farming.	The study resulted that Digital technology adoption was positively associated with farm performance.	The study was found to support technology adoption models in agricultural contexts.

Khan, et al	2021	The role of e-agriculture in improving farm efficiency and information access was discussed.	The determinants influencing farmers' adoption of e-agriculture technologies were examined.	A quantitative survey-based research design was adopted.	Awareness, perceived usefulness, ease of use, infrastructure, and adoption were analysed.	Awareness and perceived usefulness were found to significantly influence adoption.	E-agriculture adoption was concluded to depend on awareness, access, and perceived benefits.	Higher e-agriculture usage was associated with improved farm decision-making.	The study was found to strengthen understanding of digital agriculture adoption behaviour.
Leshan Yu, et al	2024	The study discussed that need to promote sustainable agriculture under climate change.	The impact of climate change perceptions on conservation tillage adoption was assessed.	A quantitative approach using an ordered Probit model was employed.	Climate change perception, technology adoption, and control variables were analysed.	Higher climate change perception was found to reduce technology adoption.	Climate perceptions were concluded to hinder conservation tillage adoption.	Climate perception showed a significant negative effect on adoption behaviour.	Improving farmers' awareness and competitiveness was suggested for policy design.
Chen, et al	2022	The researcher discussed that the problem of pesticide overuse and the need for green control techniques.	The effect of pest and disease risk perception on adoption intention was assessed.	A quantitative approach using PLS-SEM was employed.	Risk perception, performance expectancy, effort expectancy, social influence, and usage behaviour were analysed.	Risk perception was found to negatively affect behavioural intention.	Adoption of green control techniques was concluded to depend on perceived risk and expected benefits.	Performance expectancy and facilitating conditions were shown to significantly influence adoption.	Policy support and technical training were suggested to improve green technique adoption.
Jui-Hsiung Chuan, et al	2020	The study discussed the issue of aging farmers and labour shortages in Taiwan.	The factors affecting young farmers' intention to accept IoT technology.	A quantitative research design using the Technology Acceptance	Perceived usefulness, perceived ease of use, organizational support, trust,	Organizational support was found to be the strongest factor influencing IoT	IoT adoption was concluded to depend mainly on support, income	Perceived usefulness, ease of use, trust, and annual turnover were	Policy makers and technology providers were advised to focus on support systems

		agriculture was highlighted, and IoT was presented as a solution.	They were examined.	Technology Model (TAM) was adopted	turnover, and demographic factors were considered.	adoption intention.	level, and technology perception.	shown to significantly affect intention.	and user-friendly design.
Li-Chun Chang and Ming-Hua Lee	2021	The researcher discussed that the importance of smart agriculture technologies in improving farm productivity and sustainability	The perceptions and factors influencing farmers' adoption of smart technologies were examined.	A quantitative research design based on survey analysis was adopted.	Perceived usefulness, perceived ease of use, government support, and social influence were considered.	Perceived usefulness and government support were found to significantly influence adoption intention.	Smart agriculture adoption was concluded to depend largely on awareness, support, and perceived benefits.	A positive relationship between perception factors and technology adoption was established.	Policymakers were advised to strengthen training programs and financial support for farmers.
Md. Abdul Alim	2022	The researcher discussed that the need for precision agriculture to improve productivity and reduce resource wastage	The factors influencing farmers' adoption of precision agriculture technologies were analysed.	A quantitative research design using survey analysis was adopted.	Awareness, perceived usefulness, cost, training, and government support were considered.	Awareness and perceived usefulness were found to significantly influence adoption intention.	Adoption of precision agriculture was concluded to depend mainly on awareness, cost, and institutional support.	A positive relationship between support factors and technology adoption was established.	Policymakers were advised to enhance training programs and financial assistance for farmers.
R. K. Singh and P. Sharma	2023	The importance of digital agriculture in improving	The determinants influencing farmers' adoption of digital technology	A quantitative research design using structured survey	Perceived usefulness, perceived ease of use, awareness, training, and	Awareness and institutional support were found to significantly	Digital agriculture adoption was concluded to depend	A positive relationship between perception factors and	Policymakers were advised to strengthen training, awareness programs, and

		productivity and sustainability was discussed.	es were examined.	analysis was adopted.	government support were considered.	influence adoption intention.	largely on awareness, support, and perceived benefits.	technology adoption was established.	financial assistance.
S. K. Patel and A. R. Deshmukh	2023	The role of smart farming technologies in improving productivity and addressing farming challenges was highlighted.	The factors influencing adoption of smart farming technologies among farmers were examined.	A quantitative research design using survey analysis was adopted.	Awareness, perceived usefulness, cost, training, and institutional support were considered.	Awareness and institutional support were found to significantly influence adoption decisions.	Smart farming adoption was concluded to depend mainly on awareness, cost, and support systems.	A positive relationship between perception factors and adoption intention was established.	Policymakers were advised to enhance training programs and financial support for farmers.
Anjali Verma and R. S. Mehta	2022	The significance of digital technologies in improving agricultural productivity and sustainability was discussed.	The factors influencing farmers' adoption of digital agricultural technologies were examined.	A quantitative research design using survey analysis was adopted.	Awareness, perceived usefulness, cost, training, and government support were considered.	Awareness and training support were found to significantly influence adoption intention.	Digital agriculture adoption was concluded to depend largely on awareness, cost, and institutional support.	A positive relationship between support factors and technology adoption was established.	Policymakers were advised to strengthen digital training programs and financial assistance schemes.
M. Rahman and S. K. Das	2023	The researcher discussed the importance of agricultural technology in improving	The factors influencing farmers' adoption of agricultural technology were examined.	A quantitative research design using survey analysis was adopted.	Awareness, perceived usefulness, cost, training, and institutional support were considered.	Awareness and institutional support were found to significantly influence adoption intention.	Technology adoption was concluded to depend largely on awareness, cost, and	A positive relationship between perception factors and adoption behaviour was	Policymakers were advised to enhance training programs and provide financial assistance to farmers.

		g productiv ity and rural developm ent					support systems.	establish ed.	
Janet Molina - Matura no , et al	20 21	The researche r says that the need to understan d farmers' acceptanc e of mobile app technolog y for agricultur al innovatio n	Farmers' intention to adopt and use a mobile- phone agricultura l applicatio n was examined.	A quantitati ve cross- sectional survey design was adopted.	Performan ce expectanc y, mastery- approach goals, facilitat ing conditions , and connect edness to innovation hubs were considered .	Performan ce expectanc y and intrinsic motivatio n were found to significan tly influence adoption intention.	Mobile app adoption was conclude d to depend on perceived usefulness, motivatio n, and institutional support.	A positive relations hip between perceive d benefits and adoption intention was establish ed.	A positive relationshi p between perceived benefits and adoption intention was established .

The above studies on agricultural technology adoption reveals a consistent pattern: regardless of the specific technology be it smart farming, precision agriculture, ICT, or IoT adoption is primarily driven by perceived usefulness, ease of use, awareness, cost-effectiveness, and institutional or governmental support. Methodologically, most research employs quantitative surveys based on established frameworks such as TAM, UTAUT, and DTPB, utilizing structural equation modeling (SEM) for data analysis. However, significant research gaps persist. Existing studies are largely focused on single-country or single-technology contexts, with a notable absence of longitudinal or comparative research. Critically, many studies measure only the intention to adopt rather than actual, sustained usage and its subsequent impact on farm performance and sustainability. This study seeks to address these gaps by examining the transition from intention to real-world application.

RESEARCH GAP

Existing research on the adoption of smart agricultural technologies has primarily utilized cross-sectional surveys guided by behavioural frameworks such as TAM, UTAUT, and DTPB, with data analysed through SPSS and PLS-SEM. While these studies identify key determinants like perceived usefulness, cost, and institutional support, they often focus on adoption intentions rather than actual, long-term implementation. Furthermore, the specific influence of social media engagement on the decision-making process remains largely unexplored. The integration of behavioural factors with real-time digital insights from social media represents a significant research gap. Additionally, the real-world outcomes of adoption—such as productivity gains, income improvement, and sustainable development—require further investigation. This study aims to bridge these gaps by evaluating the mediating role of social media in the adoption process and its broader implications for agricultural sustainability.

RESEARCH QUESTIONS

1. How does farmers' perception of smart agricultural technology influence their technology adoption ?
2. How does social media use mediate the relationship between farmers' perception and technology adoption ?
3. How do farmer characteristics affect this perception- social media- adoption relationship ?

RESEARCH OBJECTIVES

1. To examine the effect of farmers' perception on smart agricultural technology adoption.
2. To assess the mediating role of social media between perception and technology adoption
3. To determine the influence of farmer characteristics on the perception-social media-adoption relationship.

NEED AND SIGNIFICANCE OF THE STUDY

The agricultural sector is undergoing rapid transformation with the increasing integration of smart technologies, including precision farming, Internet of Things (IoT) sensors, drones, and mobile advisory applications. These technologies facilitate enhanced crop production and resource optimization, reduce operational costs, and support sustainable practices. However, despite these advantages, the implementation of smart agricultural technologies remains limited, particularly among smallholder farmers. Adoption is largely contingent upon farmers' perceptions; they are more inclined to utilize these tools if they perceive them as useful, accessible, affordable, and reliable. A positive perception significantly correlates with interest in modern farming practices. Currently, many farmers leverage social media to acquire critical agricultural information, including learning about new technologies, receiving technical guidance, sharing experiences, and engaging with experts. These factors contribute to knowledge acquisition and enhanced confidence, thereby increasing the propensity to adopt smart agricultural technologies. However, empirical research examining whether social media engagement specifically strengthens the relationship between perception and actual adoption remains limited.

Therefore, this study investigates the mediating role of social media in the relationship between farmers' perceptions and the adoption of smart agricultural technologies. The findings are expected to support policymakers, extension agencies, and agri-tech firms in developing effective communication strategies that encourage digital agriculture, promote sustainable farming, and strengthen food security.

RESEARCH METHODOLOGY

This study employs a formal survey-based research design to obtain primary data from agricultural practitioners. A sample size of 102 farmers with exposure to smart agricultural technologies (e.g., mobile applications, IoT sensors, UAVs) collected via purposive sampling from selected rural clusters based on participation feasibility. A structured Likert-scale survey instrument was administered through both digital and physical channels. The instrument evaluates three primary constructs: technological perception (perceived usefulness, ease of use, and risk), social media engagement (frequency and utility of platforms like WhatsApp, YouTube, and Facebook for agricultural information), and actual adoption behaviour. Relevant demographic variables including age, educational attainment, and farm size will also be recorded. In addition to this survey, information from existing research papers, articles, and government reports will be used to support the study. Collected data processed by using statistical software such as JAMOV to conduct descriptive and inferential analyses. Specifically, the study will test the mediating effect of social media use on the correlation between farmers' perceptions and their technological adoption rates.

RESULTS AND DISCUSSION

Table 1

Demographic Profile	Frequency	Percentage%
Age of the Respondents (In Years)		
Below 25 years	78	76.50%
26–35 years	12	11.80%
36–45 years	3	2.90%
46–55 years	6	5.90%
Above 55 years	3	2.90%
Gender		
Female	48	47.10%
Male	54	52.90%
Educational Qualification		
No formal education	2	2.00%
Primary School	2	2.00%
Secondary School	3	2.90%
Higher Secondary	9	8.80%
Graduate	45	44.10%
Postgraduate and above	41	40.20%
No. of Years of Farming Experiences (In Years)		
Less than 5 years	73	71.60%
5–10 years	16	15.70%
11–20 years	5	4.90%
More than 20 years	8	7.80%
Size of Agricultural Land Holding (In Hct)		
Less than 1 hectare	50	49.00%
1–2 hectares	25	24.50%
2–5 hectares	17	16.70%
More than 5 hectares	10	9.80%

The demographic profile shows a sample skewed toward younger respondents, with the majority reporting fewer than five years of farming experience and holding graduate-level or higher education. This profile is consistent with the study's focus on smart agricultural technologies, which tend to be adopted earlier by younger, more educated farmers who are more comfortable with digital tools. Most respondents operate smallholdings of less than two hectares, which is broadly representative of the fragmented land-holding pattern typical of the Indian agricultural sector and underscores the relevance of low-cost, scalable digital solutions for this segment.

Descriptive Statistics

All measurement items returned Cronbach's alpha coefficients above the conventional 0.70 threshold (ranging from approximately 0.81 for Performance Expectancy to 0.89 for Perceived Benefit), indicating strong internal consistency reliability for every construct. Item-level skewness and kurtosis values fall within acceptable ranges for social science data, although Shapiro-Wilk tests were significant ($p < .001$) for all items, indicating that the item distributions depart from strict normality. Given the sample size and the robustness of ordinary least squares regression to moderate non-normality, this does not materially threaten the validity of the regression results reported below, though it is noted as a limitation of the analysis.

Table 2

Items and Variables	Descriptive Statistics									Test of Normality		Cronbach's Alpha Reliability Statistics
	Mean	Std. error mean	Median	Standard deviation	Variance	Skewness	Std. error skewness	Kurtosis	Std. error kurtosis	Shapiro-Wilk W	Shapiro-Wilk p	
FARMERS PERCEPTION												
FPSAT 1	4.34	0.079	4.5	0.802	0.643	-1.41	0.239	2.61	0.474	0.748	<.001	0.862
FPSAT 2	4.17	0.073	4	0.732	0.536	-1.04	0.239	2.71	0.474	0.778	<.001	
FPSAT 3	4.25	0.082	4	0.829	0.687	-1.15	0.239	1.6	0.474	0.784	<.001	
FPSAT 4	4.04	0.092	4	0.933	0.87	-1.05	0.239	1.14	0.474	0.821	<.001	
FPSAT 5	4.16	0.095	4	0.962	0.926	-1.55	0.239	2.79	0.474	0.755	<.001	
PERCEIVED USEFULNESS												
PERUL 1	4.25	0.084	4	0.849	0.722	-1.68	0.239	4.35	0.474	0.732	<.001	0.814
PERUL 2	4.19	0.076	4	0.767	0.589	-1.14	0.239	2.5	0.474	0.78	<.001	
PERUL 3	4.16	0.079	4	0.793	0.629	-0.897	0.239	1.38	0.474	0.808	<.001	
PERUL 4	4.14	0.078	4	0.784	0.615	-1	0.239	1.89	0.474	0.8	<.001	
PERCEIVED BENEFIT												
PERBN 1	4.28	0.086	4	0.872	0.76	-1.41	0.239	2.52	0.474	0.756	<.001	0.888
PERBN 2	4.13	0.081	4	0.817	0.667	-1.13	0.239	2.52	0.474	0.792	<.001	
PERBN 3	4.13	0.087	4	0.875	0.766	-1.07	0.239	1.63	0.474	0.806	<.001	
PERBN 4	4.16	0.086	4	0.865	0.747	-1.25	0.239	2.27	0.474	0.79	<.001	
EFFORT EXPECTENCY												
EFEX1	4.23	0.089	4	0.9	0.81	-1.3	0.239	1.94	0.474	0.777	<.001	0.862
EFEX2	3.91	0.093	4	0.935	0.873	-0.935	0.239	1.18	0.474	0.838	<.001	
EFEX3	4.14	0.083	4	0.833	0.694	-1.21	0.239	2.54	0.474	0.79	<.001	
EFEX4	4.09	0.087	4	0.88	0.774	-1.06	0.239	1.62	0.474	0.813	<.001	
PERFORMANCE EXPECTANCY												
PEREX 1	4.27	0.084	4	0.846	0.716	-1.36	0.239	2.66	0.474	0.761	<.001	0.842

PEREX 2	4.06	0.0 77	4	0.781	0.61	-1.25	0.239	3.41	0.474	0.772	<.001	
PEREX 3	4.12	0.0 9	4	0.904	0.818	-1.06	0.239	1.33	0.474	0.811	<.001	
PEREX 4	3.96	0.0 91	4	0.922	0.85	-1.08	0.239	1.62	0.474	0.821	<.001	
SOCIAL INFLUENCE												
SOCIN 1	4.12	0.0 87	4	0.882	0.778	-1.38	0.239	2.91	0.474	0.777	<.001	0.835
SOCIN 2	4	0.0 8	4	0.808	0.653	-1.03	0.239	2.37	0.474	0.804	<.001	
SOCIN 3	4.18	0.0 85	4	0.861	0.741	-1.11	0.239	1.84	0.474	0.792	<.001	
SOCIN 4	3.96	0.0 92	4	0.933	0.87	-1.12	0.239	1.59	0.474	0.817	<.001	
FACILITATING CONDITION												
FCCO N1	4.2	0.0 85	4	0.856	0.733	-1.36	0.239	2.67	0.474	0.775	<.001	0.861
FCCO N2	3.95	0.0 97	4	0.979	0.958	-0.999	0.239	0.955	0.474	0.834	<.001	
FCCO N3	4.12	0.0 88	4	0.893	0.798	-1.09	0.239	1.52	0.474	0.809	<.001	
FCCO N4	4.02	0.0 89	4	0.901	0.811	-1.2	0.239	2.15	0.474	0.804	<.001	
SOCIAL MEDIA												
SOCM D1	4.31	0.0 84	4	0.844	0.712	-1.66	0.239	3.75	0.474	0.729	<.001	0.872
SOCM D2	4.01	0.0 94	4	0.949	0.901	-1.15	0.239	1.55	0.474	0.813	<.001	
SOCM D3	3.96	0.0 98	4	0.984	0.969	-0.937	0.239	0.796	0.474	0.838	<.001	
SOCM D4	3.98	0.0 9	4	0.912	0.831	-0.92	0.239	1.02	0.474	0.836	<.001	
TECHNOLOGY ADOPTION												
TECH AD1	4.12	0.0 93	4	0.937	0.877	-1.27	0.239	1.98	0.474	0.793	<.001	0.848
TECH AD2	3.96	0.0 9	4	0.911	0.83	-0.883	0.239	0.947	0.474	0.84	<.001	
TECH AD3	4.03	0.0 86	4	0.873	0.762	-0.969	0.239	1.48	0.474	0.824	<.001	
TECH AD4	3.98	0.0 84	4	0.844	0.712	-0.769	0.239	0.805	0.474	0.839	<.001	
INTENTION TO USE												
INTUS 1	4.23	0.0 82	4	0.831	0.691	-1.29	0.239	2.71	0.474	0.774	<.001	0.836
INTUS 2	4.11	0.0 85	4	0.855	0.731	-1.47	0.239	3.54	0.474	0.76	<.001	
INTUS 3	4.16	0.0 82	4	0.829	0.688	-1.15	0.239	2.38	0.474	0.791	<.001	

INTUS 4	4.19	0.0 89	4	0.898	0.807	-1.47	0.239	2.95	0.474	0.765	<.001	
------------	------	-----------	---	-------	-------	-------	-------	------	-------	-------	-------	--

Table 3

Correlation Matrix											
		1	2	3	4	5	6	7	8	9	10
FARMERS PERCEPTION	1	—									
PERCEIVED USEFULNESS	2	0.745 ***	—								
PERCEIVED BENEFIT	3	0.580 ***	0.665 ***	—							
EFFORT EXPECTANCY	4	0.492 ***	0.559 ***	0.795 ***	—						
PERFORMANCE EXPECTANCY	5	0.569 ***	0.679 ***	0.885 ***	0.831 ***	—					
SOCIAL INFLUENCE	6	0.502 ***	0.631 ***	0.746 ***	0.798 ***	0.819 ***	—				
FACILITATING CONDITION	7	0.443 ***	0.566 ***	0.716 ***	0.851 ***	0.760 ***	0.810 ***	—			
SOCIAL MEDIA	8	0.418 ***	0.567 ***	0.761 ***	0.780 ***	0.723 ***	0.762 ***	0.859 ***	—		
TECHNOLOGY ADOPTION	9	0.490 ***	0.601 ***	0.668 ***	0.771 ***	0.720 ***	0.818 ***	0.825 ***	0.723 ***	—	
INTENTION TO USE	10	0.601 ***	0.702 ***	0.779 ***	0.837 ***	0.813 ***	0.809 ***	0.822 ***	0.777 ***	0.818 ***	—

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Linear Regression Results

Model fit, ANOVA, coefficients, and assumption checks for three regression models.

Model 1: Technology Adoption Intention to Use (M_T_INTUS)

Model Fit Measures

Model	R	R ²
1	0.913	0.833

Note. Model estimated using sample size of $N = 102$.

Omnibus ANOVA Test

Predictor	Sum Squares	df	Mean Square	F	p
Farmers Perception	0.15984	1	0.15984	1.785	.185
Perceived Usefulness	0.32551	1	0.32551	3.635	.060
Perceived Benefit	0.00217	1	0.00217	0.024	.877

Predictor	Sum Squares	df	Mean Square	F	p
Effort Expectancy	0.56442	1	0.56442	6.302	.014
Performance Expectancy	0.07259	1	0.07259	0.811	.370
Social Influence	0.01258	1	0.01258	0.140	.709
Facilitating Condition	0.04367	1	0.04367	0.488	.487
Social Media	0.12458	1	0.12458	1.391	.241
Technology Adoption	0.65410	1	0.65410	7.303	.008
Residuals	8.23967	92	0.08956		

Note. Type III sum of squares.

Model Coefficients — M_T_INTUS

Predictor	Estimate	SE	t	p	Standardized Estimate
Intercept	-0.0405	0.2144	-0.189	.850	—
Farmers Perception	0.0897	0.0672	1.336	.185	0.0882
Perceived Usefulness	0.1572	0.0824	1.906	.060	0.1439
Perceived Benefit	0.0153	0.0983	0.156	.877	0.0162
Effort Expectancy	0.2365	0.0942	2.510	.014	0.2523
Performance Expectancy	0.1009	0.1120	0.900	.370	0.1028
Social Influence	0.0348	0.0929	0.375	.709	0.0355
Facilitating Condition	0.0728	0.1043	0.698	.487	0.0795
Social Media	0.0991	0.0840	1.179	.241	0.1112
Technology Adoption	0.2214	0.0819	2.702	.008	0.2339

Assumption Checks

Normality Tests

Test	Statistic	p
Shapiro-Wilk	0.973	.037
Kolmogorov-Smirnov	0.0943	.324
Anderson-Darling	1.300	.002

Note. Additional results provided by moretests.

Heteroskedasticity Tests

Test	Statistic	p
Breusch-Pagan	16.1	.064
Goldfeld-Quandt	0.771	.796
Harrison-McCabe	0.584	.878

Note. Additional results provided by more tests.

Collinearity Statistics

Predictor	VIF	Tolerance
Farmers Perception	2.40	0.416
Perceived Usefulness	3.14	0.318
Perceived Benefit	6.00	0.167
Effort Expectancy	5.57	0.180
Performance Expectancy	7.19	0.139
Social Influence	4.94	0.202
Facilitating Condition	7.14	0.140
Social Media	4.91	0.204
Technology Adoption	4.13	0.242

Model 2: Technology Adoption (M_T_TECHAD)

Model Fit Measures

Model	R	R ²
1	0.871	0.758

Note. Model estimated using sample size of $N = 102$.

Omnibus ANOVA Test

Predictor	Sum Squares	df	Mean Square	F	p
Farmers Perception	0.03046	1	0.03046	0.212	.646
Perceived Usefulness	0.18165	1	0.18165	1.266	.263
Perceived Benefit	0.00579	1	0.00579	0.040	.841
Effort Expectancy	0.17252	1	0.17252	1.202	.276
Performance Expectancy	0.04875	1	0.04875	0.340	.561
Social Influence	2.10076	1	2.10076	14.639	<.001
Facilitating Condition	1.81086	1	1.81086	12.619	<.001
Social Media	0.05986	1	0.05986	0.417	.520
Residuals	13.34574	93	0.1435		

Note. Type III sum of squares.

Model Coefficients — M_T_TECHAD

Predictor	Estimate	SE	t	p	Standardized Estimate
Intercept	0.0704	0.2713	0.259	.796	—
Farmers Perception	0.0391	0.0849	0.461	.646	0.0364
Perceived Usefulness	0.1166	0.1036	1.125	.263	0.1010
Perceived Benefit	-0.0250	0.1244	-0.201	.841	-0.0251
Effort Expectancy	0.1299	0.1185	1.096	.276	0.1312
Performance Expectancy	-0.0825	0.1416	-0.583	.561	-0.0796
Social Influence	0.4180	0.1093	3.826	<.001	0.4033
Facilitating Condition	0.4401	0.1239	3.552	<.001	0.4544
Social Media	-0.0685	0.1061	-0.646	.520	-0.0728

Assumption Checks

Normality Tests

Test	Statistic	p
Shapiro-Wilk	0.954	.001
Kolmogorov-Smirnov	0.129	.066
Anderson-Darling	1.900	<.001

Note. Additional results provided by moretests.

Heteroskedasticity Tests

Test	Statistic	p
Breusch-Pagan	20.2	.010
Goldfeld-Quandt	0.507	.985
Harrison-McCabe	0.612	.946

Note. Additional results provided by moretests.

Collinearity Statistics

Predictor	VIF	Tolerance
Farmers Perception	2.40	0.417
Perceived Usefulness	3.10	0.323
Perceived Benefit	6.00	0.167
Effort Expectancy	5.50	0.182
Performance Expectancy	7.16	0.140
Social Influence	4.27	0.234
Facilitating Condition	6.29	0.159

Predictor	VIF	Tolerance
Social Media	4.88	0.205

Model 3: Social Media (M_T_SOCMD)

Model Fit Measures

Model	R	R ²
1	0.892	0.795

Note. Model estimated using sample size of $N = 102$.

Omnibus ANOVA Test

Predictor	Sum Squares	df	Mean Square	F	p
Farmers Perception	0.25998	1	0.25998	1.918	.169
Perceived Usefulness	0.13522	1	0.13522	0.998	.320
Perceived Benefit	2.21722	1	2.21722	16.357	<.001
Effort Expectancy	0.00487	1	0.00487	0.036	.850
Performance Expectancy	0.51559	1	0.51559	3.804	.054
Social Influence	0.21985	1	0.21985	1.622	.206
Facilitating Condition	5.33897	1	5.33897	39.388	<.001
Residuals	12.74157	94	0.13555		

Note. Type III sum of squares.

Model Coefficients — M_T_SOCMD

Predictor	Estimate	SE	t	p	Standardized Estimate
Intercept	0.1008	0.2634	0.383	.703	—
Farmers Perception	-0.1132	0.0817	-1.385	.169	-0.0990
Perceived Usefulness	0.1001	0.1002	0.999	.320	0.0816
Perceived Benefit	0.4514	0.1116	4.044	<.001	0.4266
Effort Expectancy	0.0218	0.1151	0.189	.850	0.0207
Performance Expectancy	-0.2631	0.1349	-1.950	.054	-0.2388
Social Influence	0.1341	0.1053	1.274	.206	0.1218
Facilitating Condition	0.6343	0.1011	6.276	<.001	0.6165

Assumption Checks

Normality Tests

Test	Statistic	p
Shapiro-Wilk	0.941	<.001
Kolmogorov-Smirnov	0.112	.154
Anderson-Darling	1.570	<.001

Note. Additional results provided by moretests.

Heteroskedasticity Tests

Test	Statistic	p
Breusch-Pagan	13.2	.068
Goldfeld-Quandt	0.272	1.000
Harrison-McCabe	0.749	1.000

Note. Additional results provided by moretests.

Collinearity Statistics

Predictor	VIF	Tolerance
Farmers Perception	2.35	0.426
Perceived Usefulness	3.07	0.326
Perceived Benefit	5.11	0.196
Effort Expectancy	5.50	0.182
Performance Expectancy	6.88	0.145
Social Influence	4.20	0.238
Facilitating Condition	4.43	0.226

The correlation matrix reveals that all ten constructs are positively and significantly inter-correlated ($p < .001$), with coefficients ranging from a moderate $r = .418$ (Farmers' Perception with Social Media) to a very strong $r = .885$ (Perceived Benefit with Performance Expectancy). Facilitating Conditions shows the strongest association with Social Media ($r = .859$) and with Intention to Use ($r = .822$), while Technology Adoption correlates most strongly with Facilitating Conditions ($r = .825$) and Social Influence ($r = .818$). These uniformly high correlations, together with the elevated Variance Inflation Factors (VIF) observed in the regression models (several exceeding 5, with Performance Expectancy peaking at approximately 7.2), indicate a meaningful degree of multicollinearity among the UTAUT2-based constructs. This is discussed further under Limitations, as it means individual regression coefficients should be interpreted with some caution even though the overall models remain statistically sound.

Three multiple linear regression models were estimated to examine the drivers of Technology Adoption, Social Media engagement, and Intention to Use. In the model predicting Technology Adoption ($R = .871$, $R^2 = .758$), Social Influence ($\beta = .403$, $p < .001$) and Facilitating Conditions ($\beta = .454$, $p < .001$) emerged as the only statistically significant predictors, while Farmers' Perception, Perceived Usefulness, Perceived Benefit, Effort Expectancy, Performance Expectancy, and Social Media were not significant once the other predictors were controlled for. This pattern suggests that farmers' actual adoption behaviour is driven less by individual attitudinal beliefs and more by the social pressure

exerted by peers, extension workers, and community networks, combined with the practical availability of infrastructure, credit, and technical support.

In the model predicting Social Media engagement ($R = .892$, $R^2 = .795$), Perceived Benefit ($\beta = .427$, $p < .001$) and Facilitating Conditions ($\beta = .617$, $p < .001$) were the significant predictors. This indicates that farmers turn to social media platforms for agricultural information primarily when they perceive tangible benefits from doing so and when the enabling infrastructure (network access, device availability, digital literacy support) is in place, rather than as a function of general perception or performance-related beliefs alone.

The model predicting Intention to Use ($R = .913$, $R^2 = .833$) showed that Effort Expectancy ($\beta = .252$, $p = .014$) and prior Technology Adoption ($\beta = .234$, $p = .008$) were significant predictors, with Perceived Usefulness approaching significance ($\beta = .144$, $p = .060$). Social Media itself was not a significant independent predictor of Intention to Use once these variables were included ($\beta = .111$, $p = .241$). Read together with the two preceding models, this pattern indicates that social media's relationship with adoption operates indirectly: it is strongly and positively correlated with adoption at the bivariate level ($r = .723$), and it is itself shaped by perceived benefit and facilitating conditions, but it does not retain independent explanatory power once those enabling conditions are entered into the regression alongside it. In other words, the data are more consistent with social media and technology adoption being jointly driven by shared facilitating conditions and social influence than with social media acting as a standalone mediating mechanism in the strict Baron-and-Kenny sense. This nuances, rather than confirms, the third research objective, and is an important finding in its own right: it suggests that policy interventions aimed solely at increasing farmers' social media usage are unlikely to translate into higher technology adoption unless they are paired with investments in facilitating conditions and peer/community influence networks.

Overall, the results lend partial support to the study's objectives. Farmers' perception was not a significant direct predictor of adoption in the presence of the other UTAUT2 constructs (Objective 1 is only partially supported), while Facilitating Conditions and Social Influence consistently emerged as the dominant drivers across all three outcome variables. Social media's role, while empirically important as a correlate of adoption, is better characterised as operating through shared antecedents with adoption (Facilitating Conditions, Social Influence, Perceived Benefit) rather than as an independent mediating pathway (Objective 2 is partially supported). These findings are broadly consistent with prior UTAUT2-based studies in the literature review (e.g., Schukat & Heise, 2021; Mishra et al., 2024), which similarly identify facilitating conditions and social influence as dominant predictors of smart agricultural technology adoption.

IMPLICATIONS AND CONCLUSION

THEORETICAL IMPLICATIONS

This study extends the TAM/UTAUT2 literature on agricultural technology adoption by empirically testing social media engagement alongside the established constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions. The finding that facilitating conditions and social influence consistently dominate as predictors, while attitudinal constructs such as perceived usefulness and farmers' general perception carry comparatively little independent weight, supports a growing body of evidence (Schukat & Heise, 2021; Mishra et al., 2024; Li et al., 2023) that infrastructural and social enablement, rather than individual belief formation alone, is the binding constraint on technology adoption in agrarian, resource-constrained settings. The study also contributes methodologically by showing that social media, though strongly correlated with adoption, does not behave as a classical statistical mediator once shared antecedents are controlled for, a nuance that qualifies the growing assumption in the literature that social media is an independent lever for technology diffusion in agriculture.

PRACTICAL AND MANAGERIAL IMPLICATIONS

For policymakers and agricultural extension agencies, the results suggest that investment in facilitating conditions, such as reliable internet connectivity, affordable devices, accessible credit for technology purchase, and on-the-ground technical support, will yield greater returns on adoption than awareness campaigns focused purely on persuading farmers of a technology's usefulness. Because social influence is a strong predictor of adoption, extension programmes built

around peer demonstration, farmer-to-farmer champions, and community-based training are likely to be more effective than mass-media messaging alone. For agri-tech firms, the finding that perceived benefit and facilitating conditions jointly drive social media engagement implies that platform design should foreground concrete, farm-level benefits (cost savings, yield improvements) and should be paired with digital-literacy support rather than treated as a stand-alone marketing channel.

CONCLUSION

This study set out to examine the effect of farmers' perception on smart agricultural technology adoption and to assess the mediating role of social media in that relationship, using primary data from 102 farmers analysed through descriptive statistics, correlation, and multiple regression. The findings show that facilitating conditions and social influence are the most consistent and statistically significant drivers of both technology adoption and social media engagement, while farmers' general perception and perceived usefulness carry limited independent explanatory power once these enabling factors are accounted for. Social media engagement, while strongly correlated with adoption, is better understood as sharing common antecedents with adoption, principally facilitating conditions and perceived benefit, than as an independent causal mediator. These findings offer a more infrastructure- and community-centred picture of smart agricultural technology adoption than purely attitudinal models would suggest, and they carry direct implications for how policymakers, extension agencies, and agri-tech firms should sequence their interventions to accelerate the transition toward sustainable, technology-enabled farming.

FUTURE RESEARCH DIRECTIONS

Building on the findings and limitations of this study, several directions merit further investigation.

1. Longitudinal and panel-based designs that track farmers over multiple growing seasons would help establish the causal ordering between perception, social media engagement, and actual (rather than intended) adoption behaviour.
2. Future studies should test social media as a formal statistical mediator using bootstrapped indirect-effect procedures (e.g., Hayes' PROCESS macro) rather than sequential regression alone, to more precisely quantify any indirect effect net of shared antecedents.
3. Comparative studies across regions, crop types, and farm sizes would clarify whether the dominance of facilitating conditions and social influence observed here generalises beyond the present sample.
4. Given the high inter-correlation among UTAUT2 constructs observed in this study, future research could apply structural equation modelling (SEM) with formally specified latent constructs to better partition shared and unique variance.
5. Future work could disaggregate social media by platform type (e.g., WhatsApp farmer groups versus YouTube advisory content) since different platforms may play qualitatively different roles in the adoption process.
6. Qualitative or mixed-methods follow-up work would help explain why facilitating conditions and social influence dominate over attitudinal constructs, adding contextual depth to the quantitative findings reported here.

LIMITATIONS

7. The sample size ($N = 102$ for the regression analyses) is modest relative to the number of predictors, which limits statistical power for detecting smaller effects and constrains the generalisability of the findings.
8. The high correlations among the UTAUT2-based constructs, and the correspondingly elevated Variance Inflation Factors observed in the regression models, indicate a meaningful degree of multicollinearity; individual regression coefficients should therefore be interpreted with caution.
9. The cross-sectional design captures perceptions and intentions at a single point in time and cannot establish causal direction between the study's constructs.

10. Data were collected through self-reported Likert-scale responses, which are subject to common-method bias and social-desirability effects.
11. The sample was drawn via purposive sampling from farmers already exposed to smart agricultural technologies, which may overstate the role of facilitating conditions relative to a more representative sample that includes non-adopters with no prior exposure.
12. Social media was measured as engagement/frequency of use rather than tested as a formal statistical mediator with bootstrapped indirect effects, so the conclusion that it operates through shared antecedents rather than as an independent mediator should be treated as indicative rather than definitive.

REFERENCES

- Li, J., Liu, G., Chen, Y., & Li, R. (2023). Study on the influence mechanism of adoption of smart agriculture technology behavior. *Scientific Reports*, 13, Article 8571. <https://doi.org/10.1038/s41598-023-35091-x>
- Mishra, N., Bhandari, N., Maraseni, T., Devkota, N., Khanal, G., Bhusal, B., Basyal, D. K., Paudel, U. R., & Danuwar, R. K. (2024). Technology in farming: Unleashing farmers' behavioral intention for the adoption of agriculture 5.0. *PLOS ONE*, 19(8), Article e0308883. <https://doi.org/10.1371/journal.pone.0308883>
- Schukat, S., & Heise, H. (2021). Towards an understanding of the behavioral intentions and actual use of smart products among German farmers. *Sustainability*, 13(12), Article 6666. <https://doi.org/10.3390/su13126666>
- Yadav, J., Yadav, A., Misra, M., Rana, N. P., & Zhou, J. (2023). Role of social media in technology adoption for sustainable agriculture practices: Evidence from Twitter analytics. *Communications of the Association for Information Systems*, 52, 833–851. <https://doi.org/10.17705/1CAIS.05240>
- Xu, J., Cui, Z., Wang, T., Wang, J., Yu, Z., & Li, C. (2023). Influence of agricultural technology extension and social networks on Chinese farmers' adoption of conservation tillage technology. *Land*, 12(6), 1215.
- Yu, L., Shi, H., Wu, H., Hu, X., Ge, Y., Yu, L., & Cao, W. (2024). The role of climate change perceptions in sustainable agricultural development: evidence from conservation tillage technology adoption in Northern China. *Land*, 13(5), 705.
- Hu, H., Cao, A., Chen, S., & Li, H. (2022). Effects of risk perception of pests and diseases on tea famers' green control techniques adoption. *International journal of environmental research and public health*, 19(14), 8465.
- Chuang, J. H., Wang, J. H., & Liang, C. (2020). Implementation of Internet of Things depends on intention: Young farmers' willingness to accept innovative technology. *International Food and Agribusiness Management Review*, 23(2), 253-266.
- Onyari, C. (2021). Adoption determinants of adapted climate smart agriculture technologies among smallholder farmers in Machakos, Makueni, and Kitui Counties of Kenya. *The Journal of Agricultural Extension*.
- Gong, C., Liu, G., Wang, J., & Liu, X. (2025). Digital Technology Usage and Family Farms' Uptake of Green Production Technologies—Evidence from Citrus Family Farms in Jiangxi Province. *Sustainability*, 17(22), 10334.
- Haque, A., Islam, N., Samrat, N. H., Dey, S., & Ray, B. (2021). Smart farming through responsible leadership in Bangladesh: Possibilities, opportunities, and beyond. *Sustainability*, 13(8), 4511.
- Shi, Y., Siddik, A. B., Masukujjaman, M., Zheng, G., Hamayun, M., & Ibrahim, A. M. (2022). The antecedents of willingness to adopt and pay for the IoT in the agricultural industry: an application of the UTAUT 2 theory. *Sustainability*, 14(11), 6640.
- Chen, C., Peng, R., Ye, F., & Liao, W. (2025). The role of cooperative membership in promoting agricultural green production technologies among rice farmers in rural China. *Scientific Reports*, 15(1), 31044.
- Rosário, J., Madureira, L., Marques, C., & Silva, R. (2022). Understanding farmers' adoption of sustainable agriculture innovations: A systematic literature review. *Agronomy*, 12(11), 2879.

- Li, J., Liu, G., Chen, Y., & Li, R. (2023). Study on the influence mechanism of adoption of smart agriculture technology behavior. *Scientific reports*, 13(1), 8554.
- Molina-Maturano, J., Verhulst, N., Tur-Cardona, J., Güereña, D. T., Gardeazábal-Monsalve, A., Govaerts, B., & Speelman, S. (2021). Understanding smallholder farmers' intention to adopt agricultural apps: The role of mastery approach and innovation hubs in Mexico. *Agronomy*, 11(2), 194.
- Verhulst, N., Tur-Cardona, J., Güereña, D., Gardeazábal-Monsalve, A., Govaerts, B., & Speelman, S. (2020). Understanding Smallholder Farmers' Intention to Adopt Agricultural Apps: The Role of Mastery-Approach and Innovation Hubs.
- Mishra, N., Bhandari, N., Maraseni, T., Devkota, N., Khanal, G., Bhusal, B., ... & Danuwar, R. K. (2024). Technology in farming: Unleashing farmers' behavioral intention for the adoption of agriculture 5.0. *Plos one*, 19(8), e0308883.
- Schukat, S., & Heise, H. (2021). Towards an understanding of the behavioral intentions and actual use of smart products among German farmers. *Sustainability*, 13(12), 6666.
- Ma, Q., Zheng, S., & Deng, P. (2022). Impact of internet use on farmers' organic fertilizer application behavior under the climate change context: The role of social network. *Land*, 11(9), 1601.
- Ninsiima, R., Mshenga, P., & Okello, D. (2025). Influence of social norms on blockchain technology adoption: a structural equation modelling approach among smallholder barley farmers in Uganda. *Discover Agriculture*, 3(1), 89.
- Caffaro, F., & Cavallo, E. (2019). The effects of individual variables, farming system characteristics and perceived barriers on actual use of smart farming technologies: Evidence from the Piedmont region, northwestern Italy. *Agriculture*, 9(5), 111.
- Nayeem, T., Pawsey, N., Asmi, F., & Baumgartner, L. (2026). How Media Trust Mediates the Adoption of Fish Screens by Irrigators in Australia: The Intermediate Effect of Resource Efficacy. *Sustainability*, 18(3), 1297.
- Zhang, T., Lang, L., Zhao, N., Lu, Q., & Sun, B. (2024). Perceived organizational support, inter-temporal choice, and farmer conservation tillage adoption. *Agriculture*, 14(5), 667.