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Green Fields, Smart Tech: The Digital Transformation of Rural Farming

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ABSTRACT: This study examines how e-governance enhances agricultural practices and improves rural livelihoods in India, particularly addressing the digital divide. Using a mixed-method approach, it combines quantitative survey data from 757 rural farmers in Kerala with qualitative insights from interviews and case studies. Grounded in the Technology Acceptance Model (TAM), it incorporates Diffusion of Innovations Theory to explain adoption patterns and Innovation Resistance Theory to identify barriers. Partial least squares structural equation modeling validates adoption factors like awareness, attitudes, perceived ease of use, perceived usefulness, and actual system usage, with socio-demographic factors such as age, education, income, and digital literacy playing crucial roles. The qualitative analysis highlights infrastructural limitations, trust deficits, and inadequate training as major obstacles. By integrating statistical findings with farmer experiences, the study presents a refined conceptual model for effective e-governance implementation. Practical recommendations include targeted digital training, infrastructure development, and policy reforms to create accessible, farmer-centric solutions. These insights support policymakers, technology developers, and agricultural stakeholders in fostering sustainable agricultural development and maximizing farmer participation.

Keywords: e-governance, digital agriculture, technology acceptance model (TAM), rural farmers, digital divide.

I. INTRODUCTION

The concept of Electronic Governance has arisen as a transformative tool in public administration, intended to ensure transparency, efficiency, and corruption-free governance [54]. In India, with considerable efforts to implement e-governance, digital divide remains a significant barrier, predominantly in the agricultural sector, where the majority of the population resides in rural areas [18]. The initial principles of good governance, as articulated by researchers like [12], highlight the need for policies and procedures that are simple, moral, accountable, responsive, and transparent [37]. All these principles are summarized in the concept of SMART governance [42].

E-governance enhances service delivery, enables democratic participation, and improves operational efficiency, its effectiveness is often influenced by stakeholder perceptions [89, 66, 81]. When it comes to the agriculture context, e-governance can play an important role in endorsing sustainable practices, ensuring food security, and improving the livelihoods of farmers [51]. But still the agricultural sector faces multiple challenges, including the effect of climate change, natural disasters, and infrastructural deficiencies [84, 21, 22].

Beyond climate and infrastructure challenges, rural farmers also struggle with market access, financial inclusion, and bureaucratic hurdles that limit their ability to leverage government services effectively. Many farmers lack reliable internet connectivity, digital literacy, and trust in digital platforms, further hindering e-governance adoption. Complicated usage processes for subsidies, insurance, and financial aid discourage participation, leaving many farmers without the support they need. Addressing these systemic challenges requires a comprehensive digital transformation strategy, integrating user-friendly platforms, localized training programs, and policy reforms to bridge the gap between rural communities and digital governance initiatives.

The existing literature points out the growing importance of e-governance in the agricultural sector. [8] deliberate the complexities related to digitalizing agriculture and the progressive digitization efforts through the National E-governance Plan for Agriculture (NeGP-A). The India Digital Ecosystem of Agriculture (IDEA) framework, which includes Digital Agri Stack, is an important step towards integrating digital technologies and databases focusing on farmers and the agricultural industry [11].

While Kerala has made significant strides in digital governance through initiatives like the India Digital Ecosystem of Agriculture (IDEA) and the National E-Governance Plan for Agriculture (NeGP-A), similar efforts have been implemented in other regions. For instance, Maharashtra's Agri Stack initiative leverages big data and AI for precision farming, while Andhra Pradesh's Rythu Bharosa Kendras provide integrated digital services for farmers. Globally, China's Smart Agriculture Demonstration Zones and the EU's Farm to Fork Strategy emphasize digital innovation to enhance food security and sustainability. A comparative analysis of these models could provide deeper insights into regional best practices and challenges in e-governance adoption.

Study [27] investigate the use of artificial intelligence (AI) in e-governance for agriculture, underlining its potential to leverage big data and enhance public services. Climate change is considered a serious issue in the agriculture sector. Topical natural disasters, including consecutive floods and cyclones, have had overwhelming impacts, destroying around 40,960 hectares of agricultural land between 2019 and 2022 [56]. These events highlight the urgent need for sustainable and strong agricultural practices to safeguard the livelihoods of farmers and ensure long-term food security. Notwithstanding the governmental efforts, there are considerable gaps in the implementation of relief measures and support systems [77]. So many delays in processing claims and spending funds joined with technical challenges in accessing e-governance services, have worsened the distress faced by farmers [73].

The research focusing the effectiveness of e-governance services in the agricultural sector by assessing user awareness, attitudes, perceived ease of use, perceived usefulness, intention to use and actual system usage. Applying the Technology Acceptance Model (TAM), this research seeks to develop a new model that enhances the adoption and impact of e-governance projects among rural communities. By explaining these factors, the study contributes to the broader understanding of how digital tools can be effectively integrated into the agricultural sector, promoting sustainable development and improving the livelihoods of rural farmers in Kerala. TAM has been widely used to study technology adoption, but Diffusion of Innovations Theory (DOI) helps explain how innovations spread across farming communities, emphasizing the role of social influence, infrastructure, and communication channels. Then the Innovation Resistance Theory (IRT) highlights factors that contribute to farmers' reluctance, such as perceived risk, habit, and skepticism towards digital platforms.

The study also explores the socio-demographic factors influencing the acceptance of e-governance. Rural areas have diverse socio-economic profiles [74] and understanding these differences is vital for couture e-governance initiatives to meet the specific needs of various communities. Through examining variables like age, education level, and income the study will provide insights into the barriers and facilitators of e-governance adoption. Notwithstanding growing research on e-governance in agriculture, existing studies often focus on policy frameworks and technological advancements without adequately addressing user adoption challenges in rural contexts. Limited research explores how socio-demographic factors, digital literacy, and infrastructure gaps influence e-governance adoption among farmers. While studies discuss the potential of AI, big data, and blockchain in agriculture, there is insufficient empirical evidence on their real-world implementation and acceptance by rural communities. This research fills these gaps by providing a data- driven analysis of user adoption barriers and developing a conceptual design tailored to rural farmers.

The results improve digital customer service, encourage a healthy agricultural future, and enhance the overall prosperity of farming communities in rural areas by highlighting important adoption barriers and guides. This study is crucial since low levels of digital literacy, inadequate amenities, and economic disparity among rural farmers continue to impede the effective implementation of electronic governance in farming. Building targeted efforts requires a grasp of the elements that affect adoption, such as knowledge, beliefs, and believed perks.

1. KEY CONTRIBUTIONS

The key contributions of this study are:

- This research adopts a mixed methods approach, combining quantitative analysis using PLS-SEM with qualitative insights from interviews and case studies, providing a holistic understanding of e governance adoption in agriculture.

- A refined conceptual model is developed, integrating technology acceptance model with qualitative findings to raise e governance adoption strategies for rural farmers.
- By integrating the diffusion of innovations theory and innovation resistance theory with the technology acceptance model, this research provides a comprehensive framework explaining both adoption facilitators and resistance factors.
- The study extends TAM by incorporating DOI's perspective on adoption trends and IRT's focus on barriers, creating a more adaptable model for rural settings.
- The study provides data-driven insights into how age, education, income, and digital literacy impact farmers' willingness to adopt e-governance tools, highlighting key barriers and enablers.
- Through thematic analysis of qualitative data, the study uncovers infrastructural constraints, trust issues, and training gaps that hinder e-governance adoption, offering contextualized recommendations.
- The study proposes targeted digital literacy programs, improved infrastructure, and farmer-centric interventions, ensuring that e-governance initiatives are accessible, sustainable, and effective in improving agricultural productivity and rural livelihoods.

II.RELATED WORK

1. AWARENESS OF E-GOVERNANCE PROJECTS IN KERALA'S AGRICULTURE SECTOR

The awareness of e-governance projects is indispensable for their effective implementation and utilization. In the domain of e-governance, awareness refers to the extent to which farmers comprehend and acknowledge the available digital services and platforms designed to aid agricultural practices [63, 64]. Effective communication strategies and outreach programs are vital for boosting awareness and directly impact participation and usage rates [29].

The concept National e-Governance Plan (NeGP-A)'introduced in 2011, the NeGP-A aimed to provide complete information to farmers through various channels, such as websites and mobile applications [20]. Kerala, being one of the pilot states, has significantly benefited from this initiative, which has greatly increased awareness about available agricultural services. The project successfully registered nearly 20 lakh farmers, creating a robust database that facilitates targeted outreach and communication [39]. The AIMS has arisen as a transformative platform for distributing information and services to farmers. The SMART module within AIMS delivers real-time data on agricultural parameters, enhancing decision-making capabilities. Recent studies show that sensitive awareness of AIMS has led to improved service delivery, with farmers using the platform for subsidy applications, training registrations, and accessing advisory services [24].

There are various training programs have been organized to explain farmers with e-governance initiatives. Positive advancements and challenges persist regarding the overall awareness of e-governance projects. Factors like limited technological literacy, inadequate infrastructure in local areas, and insufficient outreach efforts can hamper awareness levels among certain farmer demographics [9]. Recent researches emphasize the requirement for targeted communication strategies to overcome these barriers and raise total engagement [62].

2. PERCEIVED EASE OF USE IN KERALA'S AGRICULTURE SECTOR

The variable perceived ease of use has an important part in the adoption of e-governance initiatives within the agricultural sector [58]. This review explains the influence of perceived ease of use on raising service delivery and decision-making processes for farmers in Kerala, focusing on the agriculture information management system and other digital platforms [78]. Perceived ease of use is explained as the degree to which an individual believes that utilizing a particular system will be effortless. This concept is central to the technology acceptance model, which suggests that perceived ease of use and perceived usefulness jointly influence users intentions to adopt new technologies [78]. In e-governance, perceived ease of use is a significant factor in farmers' willingness to engage with digital platforms designed to streamline agricultural services [79]. The agriculture information management system project, particularly its SMART module, has contributed to modernizing agriculture in Kerala. It consolidates various agricultural services onto a single platform, facilitating easier access to information on government schemes, subsidies, and market prices current research shows that this efficient access significantly enhances perceived ease of use for farmers, leading to higher engagement with the platform [79].

Executing online services via an agriculture information management system website has decreased bureaucratic problems for farmers. The aptitude to apply online for subsidies and training programs reduces paperwork and simplifies processes, positively affecting farmers' perceptions of ease of use [60]. This popularization encourages greater utilization of available resources by farmers. The introduction of virtual classrooms and video conferencing amenities has broadened training access and participation among farmers [83]. All these initiatives are perceived as user-friendly and easily accessible, enabling farmers to improve their skills without extensive travel. The ease of accessing training resources has raised knowledge distribution and the adoption of best practices in agriculture [14].

The progress, challenges persevere regarding farmers' technological literacy. The recent research indicates that while many farmers acknowledge the benefits of e governance initiatives, those with limited digital skills may struggle to navigate digital platforms effectively [76]. This digital gap can delay overall adoption rates, suggesting that improving digital literacy is critical for maximizing the benefits of e-governance. The success of e-governance initiatives also depends on adequate infrastructure. In rural areas the internet connectivity is inconsistent, perceived ease of use can be unfavorably affected. Ensuring reliable access to technology is essential for enhancing user experiences and promoting broader participation among farmers [69].

3. PERCEIVED USEFULNESS OF AGRICULTURAL PRACTICES

The variable perceived usefulness is an important factor in the adoption of technology in agriculture, influencing farmers decisions to integrate new practices and technologies into their operations [15]. This review creates recent literature on perceived usefulness within the agricultural context, emphasizing its implications for farmers. The concept perceived usefulness refers to the extent to which an individual believes that using a specific system or technology will enhance their job performance. This concept is central to the technology acceptance model, which suggests that' perceived usefulness, along with' perceived ease of use, significantly influences users' intentions to adopt new technologies [4].

Recent research specifies that technologies like drones and precision agriculture tools are perceived as helpful by farmers due to their ability to enhance productivity and efficiency [13]. Current studies shows that farmers who identify the benefits of drone technology for monitoring crop health are more likely to adopt it, leading to improved yields and resource management. The concept perceived usefulness of e-governance spreads to market access. AIMS facilitates direct connections between farmers and buyers, allowing for better price understanding for their produce. Farmers who find these market linkages beneficial are more inclined to engage with the platform, underlining the role of PU in economic outcomes [28]. The familiar benefits of various technologies, barriers such as high initial costs and lack of technological literacy can delay adoption. Recent studies shows that the farmers acknowledge the advantages of modern agricultural technologies, these barriers can affect their willingness to implement them [27]. The recent literatures highlight the important role of perceived usefulness in shaping technology adoption within the agricultural sector. In Kerala, initiatives like AIMS illustrate how enhancing PU can lead to improved agricultural practices and economic outcomes for farmers.

4. FARMERS' ATTITUDE TOWARDS E-GOVERNANCE PROJECTS IN KERALA'S AGRICULTURE SECTOR

Technology Acceptance Model (TAM), attitude mentions to an individual's general evaluation of using a specific technology. It includes the positive or negative feelings a user has about adopting the technology, based on their insights of its usefulness and ease of use. According to [21], attitude is shaped by two main factors: perceived usefulness (PU) and perceived ease of use (PEU)'. 'A positive attitude towards technology typically leads to a greater intention to use it, which influences actual usage behavior [54].

The recent research shows that awareness of e governance initiatives, like the agriculture information management system, greatly affects farmers attitudes [80]. Farmers who are knowledgeable about the benefits and functionalities of these systems tend to have a more positive attitude towards their adoption. Increased awareness is linked with higher perceived usefulness, fostering favorable attitudes towards using digital platforms for agricultural services [70].

Various training programs meant at raising digital literacy have been found to positively influence farmers attitudes. Research proposes that when farmers are trained on how to use electronic government tools, their confidence grows, leading to a more favorable attitude towards technology adoption [45]. This brings into line with technology acceptance models evidence that perceived ease of use can raise total attitude. Farmers attitudes towards electronic government projects are shaped by various socio-demographic factors like age, education level, and income [1]. Studies disclose that younger and more educated farmers usually have more positive attitudes towards accepting new technologies compared to older generations. This demographic variation underlines the need for targeted interventions that consider these socio-economic variables [50]. (Social validation through community engagement can raise total acceptance and encourage hesitant farmers to adopt similar practices.

The possible benefits of e governance initiatives, several barriers can negatively affect farmers attitudes. Concerns about past negative experiences with technology can lead to skepticism among farmers [46]. Projecting these concerns through transparent communication and robust support systems is crucial for fostering a positive attitude towards technology adoption [7].

5. FARMER'S 'INTENTION TO USE THE E-GOVERNANCE

The major intention is influenced by the users 'attitude towards the technology which is formed by their perceptions of it is perceived usefulness and perceived ease of use. A positive intention naturally results in actual usage behavior, making it a vital variable in understanding technology adoption [87]. The recent research reliably demonstrates that perceived usefulness significantly effects farmers intentions to use e governance initiatives like the agriculture information management system [26]. When farmers believe these platforms will raise their productivity and efficiency, their intention to adopt them increases. Recent studies indicate that farmers who see agriculture information management system as beneficial for accessing timely information are more likely to express a strong intention to use it [48].

The variable perceived ease of use is also an important factor in shaping farmers' intentions. Farmers are more motivated to adopt e-governance tools if they find them user-friendly and easy to navigate [1]. Research proposes that shortening the user interface and providing clear instructions can raise farmers' intentions to engage with digital platforms. The farmers' intentions to use e-governance projects within the agricultural sector are significantly influenced by perceived usefulness and perceived ease of use, as framed by the technology acceptance model [18]. Various training programs, socio-demographic factors, community influence, and addressing barriers also play critical parts in shaping these intentions. Considering these dynamics is essential for developing strategies aimed at enhancing technology adoption among farmers in Kerala [72].

Recent studies emphasize the integration of blockchain, artificial intelligence-driven predictive analytics, and Internet of things asked monitoring systems in digital farming. Works [35, 86, 88] highlights the role of blockchain in ensuring transparency and secure transactions in agricultural supply chains, falling dependency on intermediaries and also [3] explore how artificial intelligence powered crop monitoring and early disease detection raise productivity and sustainability, demonstrating the potential of machine learning models in immediate agricultural decision making.

The progressions in M-governance or the mobile-based e-governance platforms are reshaping farmer-government interactions. Works [82, 48] discuss how smartphone applications integrating government schemes, weather forecasts, and market trends improve access to vital information, especially in remote areas. This research underlines the growing need for user-friendly, localized digital platforms that cater to the specific requirements of small and marginal farmers, further reinforcing the importance of this research.

Current progress and development in artificial intelligence-driven decision support systems, internet of things- based smart agriculture, and blockchain for supply chain transparency are reshaping the agricultural landscape. Artificial intelligence-powered analytics help farmers optimize crop planning and disease detection, while Internet of Things sensors enable immediate monitoring of soil health and irrigation needs. The blockchain ensures transparency and security in agricultural transactions, preventing fraud and raising trust in electronic government platforms [71, 76]. Integrating these technologies into e-governance initiatives could significantly raise their effectiveness and adoption.

6. ACTUAL SYSTEM USAGE

Actual system usage in the technology acceptance model refers to the extent to which users engage with a technology post adoption. It serves as an important outcome that indicates how regularly and effectively a technology is utilized in practice [67, 75]. Actual usage is influenced by behavioral intentions and shaped by user's attitudes, perceived usefulness, and perceived ease of use [25, 23]. In the current viewpoint, perceived usefulness and perceived ease of use directly influence intention, and attitude functions as a vigorous intermediary that can either intensify or diminish these perceptions' effects on actual usage. The influence of contextual factors on actual system usage [40, 47]. These factors include local agricultural practices, community norms, and socio-economic conditions. Farmers in communities with strong social links might rely more on peer recommendations than their attitudes towards technology. In this situation, community influence can supersede individual attitudes, resulting in higher or lower actual usage based on collective mawkishness rather than personal beliefs.

But some researchers claim that an important gap can exist between behavioral intentions and actual system usage. This perspective underlines that even if farmers express a strong intention to use e-governance tools, various situational barriers such as time constraints during top agricultural seasons or unexpected technical difficulties can prevent them on their intentions [38, 19].

7. AWARENESS IN THE CONTEXT OF THE 'TECHNOLOGY ACCEPTANCE MODEL (TAM)

In this Technology Acceptance Model (TAM), awareness refers to the extent to which potential users are knowledgeable about a technology, including its functionalities, benefits, and effective usage [21, 85]. Awareness plays an important role in influencing both perceived usefulness (PU) and perceived ease of use (PEU), which are essential factors of users attitudes and intentions towards adopting a technology [68, 53].

The variable awareness directly affects farmers perceptions of the usefulness and ease of use of e-governance tools [61, 69]. When farmers comprehend how these technologies can enhance their productivity and rationalize processes, they are more likely to develop positive attitudes towards using them. This correlation underlines the importance of effective communication strategies that point to the practical benefits of e-governance initiatives [52, 16].

The Information and Communication Technology (ICT) has been instrumental in raising awareness among farmers. Mobile applications provide timely information directly to farmers' devices, increasing their awareness about market prices and agricultural practices [16, 43]. This straight access helps bridge information gaps that may exist due to geographical or infrastructural challenges. ICT tools ensure that farmers in remote areas also benefit from the latest information and resources [44, 11].

8. RESEARCH OBJECTIVES

The novel objectives of this study are:

- To analyze the impact of socio-demographic factors on the adoption of e-governance technologies in agriculture.
- To develop and validate a conceptual model that enhances the long-term sustainability of digital agriculture initiatives.
- To assess the role of awareness, perceived usefulness, and ease of use in influencing farmers' adoption and continued engagement with e-governance tools.
- To evaluate how digital agriculture and e-governance contribute to food security and improved agricultural productivity.
- To provide policy recommendations for enhancing digital literacy, bridging infrastructure gaps, and ensuring the long-term viability of e-governance in agriculture.

9. CONCEPTUAL FRAMEWORK FOR THE RESEARCH

To develop and validate a conceptual framework for this study, a wide review of theoretical contexts and empirical studies about awareness in the Technology Acceptance Model (TAM) was conducted. This research paper integrates technology acceptance model with diffusion of innovations theory, which emphasizes how farmers adoption of electronic government follows five stages: knowledge, persuasion, decision, implementation, and confirmation and also innovation resistance theory is incorporated to identify the reasons behind farmer's resistance, including perceived risk, trust issues, and complexity of digital platforms.

10. THE TECHNOLOGY ACCEPTANCE MODEL (TAM)

The technology acceptance model (TAM), developed by Fred Davis (1989) [22], describes how individuals adopt new technologies based on perceived usefulness and perceived ease of use. If a technology is seen as beneficial and easy to use, users are more likely to adopt it. In the context of electronic government in agriculture, the technology acceptance model helps assess farmers' willingness to use digital platforms. However, it does not fully capture social influences, infrastructure barriers, or resistance factors, which this study addresses by integrating diffusion of innovations theory and innovation resistance theory.

11. DIFFUSION OF INNOVATIONS THEORY (DOI)

Developed by Everett Rogers (1962), the developed by Everett Rogers explains how new ideas, technologies, and behaviors spread within a social system over time [65]. According to developed by Everett Rogers, individuals adopt innovations through five stages: knowledge, persuasion, decision, implementation, and confirmation. The adoption process depends on factors like relative advantage, compatibility, complexity, trialability, and observability. In the context of e-governance in agriculture, early adopters and opinion leaders play a crucial role in influencing others to adopt digital platforms [14, 33, 32].

12. INNOVATION RESISTANCE THEORY (IRT)

Developed by Ram & Sheth (1989) [57], the IRT explains why individuals resist adopting new technologies despite potential benefits. Resistance arises due to functional barriers (complexity, security concerns, and lack of compatibility) and psychological barriers (habitual behavior, skepticism, and perceived risks). In the case of e-governance in agriculture, many farmers resist digital platforms due to technological complexity, security concerns, and lack of digital literacy. Addressing these barriers through targeted awareness campaigns and training programs can accelerate adoption.

- This review mainly focused on how awareness impacts perceived usefulness (PU), perceived ease of use (PEU), attitudes, intentions, and actual system usage among farmers in the agricultural sector. The proposed model aims to explore how awareness affects these variables and ultimately influences the 'adoption of e-governance technologies in agriculture.
- Awareness (AW): This main variable covers farmers knowledge of e-governance initiatives, their functionalities, benefits, and effective usage. Increased awareness is expected to enhance both perceived usefulness and perceived ease of use [49, 8, 9].
- Perceived Usefulness (PU): This variable reproduces farmers' beliefs that using e-governance tools will enhance their agricultural productivity, performance, and quality of life, and provide cost-effective services. It is imagined that higher awareness levels will positively influence PU [31, 51].
- Perceived Ease of Use (PEU): This main variable specifies how easy farmers perceive the use of e-governance technologies. Awareness is predicted to improve PEU by providing information about user-friendly features and available support [30, 5, 6].
- Attitude towards Technology (ATT): This variable signifies farmers' overall evaluation of using e-governance tools, based on their perceptions of PU and PEU. Positive attitudes are expected from advanced PU and PEU levels [41, 57].
- Intention to Use (IU): Highlighting farmers' willingness to engage with e-governance technologies, this variable is assumed to be influenced by positive attitudes, leading to a stronger intention to use these tools [17, 67].
- Actual System Usage (ASU): The last variable measures the extent to which farmers actively use e-governance platforms after adoption. A strong intention to use is expected to positively impact actual usage [85, 55].

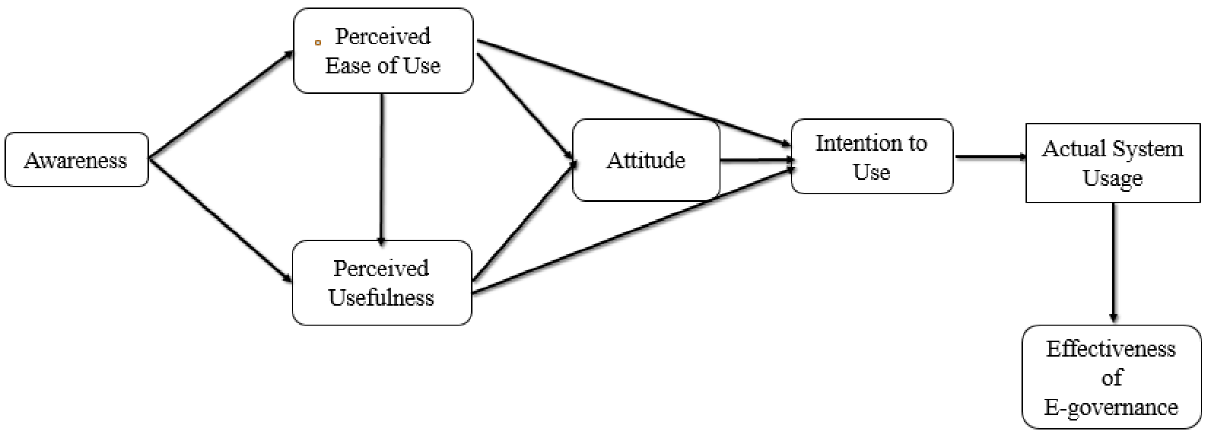

FIGURE 1: Research model.

13. HYPOTHESES

- H1: Awareness has a positive effect on Perceived Ease of Use.
- H2: Awareness has a positive effect on Perceived Usefulness.
- H3: Perceived Ease of Use has a positive effect on Perceived Usefulness.
- H4: Perceived Ease of Use has a positive effect on Attitude.
- H5: Perceived Usefulness has a positive effect on Attitude.
- H6: Perceived Ease of Use has a positive effect on Intention to Use.
- H7: Perceived Usefulness has a positive effect on Intention to Use.

- H8: Attitude has a positive effect on Intention to Use.
- H9: Intention to Use has a positive effect on Actual System Usage.
- H10: Actual System Usage has a positive effect on Effectiveness of e-Governance.

Table 1. Constructs and items taken for the study.

Latent variables	Items	Item Description
Awareness	AW1	I am familiar with the e-Governance websites of the Agriculture Sector.
	AW2	I understand the benefits of using these e-Governance websites.
	AW3	I have gone through schemes, fund allocation, and programs detailing the features of these e-Governance websites.
	AW4	I have cross-varified information through government officials, newspapers, advertisements, YouTube, and the AIMS handbook regarding these e-Governance platforms.
Perceived Ease of Use	PEU1	It is easy for me to learn how to use the AIMS website.
	PEU2	I find it easy to remember the process of using the AIMS website.
	PEU3	The AIMS website makes understanding new schemes.
	PEU4	I find it easy to identify the information needed for online applications and schemes on the AIMS website.
	PEU5	I find the AIMS website more user-friendly than traditional methods
Perceived Usefulness	PU1	The AIMS website enhances my performance.
	PU2	The AIMS website boosts my productivity.
	PU3	The AIMS website increases the likelihood of early fund allocations.
	PU4	I believe authorities will respond to my needs through the AIMS website.
	PU5	I feel using e-governance platforms will improve my quality of life.
	PU6	I believe that e-governance in the agriculture sector enhances service delivery.
	PU7	I feel that e-governance in the agriculture sector helps provide cost-effective services.
Attitude	ATT1	I believe that the e-Governance platform in the agriculture sector is beneficial to me.
	ATT2	I think using the AIMS website is a smart choice.
	ATT3	I support the implementation of e-Governance in the agriculture sector.
	ATT4	The AIMS website adds value to my farming process.
	ATT5	I have a positive attitude towards using e-Governance in the agriculture sector.
Intention to Use	IU1	I plan to keep obtaining necessary documents from e-governance services in the future.
	IU2	I will highly recommend e-governance services to others.
	IU3	I believe that using e-governance in the agriculture sector encourages ongoing usage.
	IU4	I find using this system interesting because it is easily adaptable.
Actual System Usage	ASU1	I appreciate the consistency in using AIMS.
	ASU2	I recognize the transparency in using AIMS.
	ASU3	I am satisfied with using AIMS.
	ASU4	I find the procedure of using AIMS suitable
Effectiveness	E1	I believe that e-governance reduces red tape.
	E2	I believe that e-governance has brought transparency in fund allocation, subsidies, aids, and grants.
	E3	I feel that e-governance in the agriculture sector reduces paperwork.
	E4	I believe that e-governance helps service providers improve the quality of services through feedback
	E5	I feel that e-governance assists in selecting the right beneficiaries.
	E6	I believe that e-governance services have enhanced the confidentiality of personal data.
	E7	I believe that e-governance improves trust between service providers and users.
	E8	I believe that e-governance services eliminate middleman interference
	E9	I believe that e-governance promotes initiatives towards e-literacy.

III.MATERIAL AND METHOD

1. DATA COLLECTION

Quantitative Data: A structured survey questionnaire with 44 items was distributed to 757 farmers across Kerala. The questionnaire included variables like Awareness, Perceived Ease of Use, Perceived Usefulness, Attitude, Intention to Use, Actual System Usage, and Effectiveness, measured using a five-point Likert scale. The survey instrument was validated using previous research recommendations and refined through a pilot study with 75 farmers.

Qualitative Data: Semi-structured interviews were conducted with key stakeholders, including farmers, agricultural officers, policymakers, and digital service providers, to gain deeper insights into e-governance adoption barriers, trust issues, and policy gaps.

2. RESEARCH DESIGN

This study employs a mixed-methods research design, integrating quantitative and qualitative approaches to comprehensively examine e-governance adoption among farmers in Kerala. Grounded in the Technology Acceptance Model (TAM), the research incorporates Diffusion of Innovations Theory to explain adoption trends and Innovation Resistance Theory to identify barriers hindering digital integration. To ensure methodological rigor, stratified random sampling was utilized, dividing Kerala's rural regions into three strata North, Central, and South—with one district randomly selected from each. Within each selected district, farmers were chosen based on key socio-demographic factors such as age, education, farm size, and income, ensuring diverse perspectives on e-governance adoption. The study followed the "10 times rule" introduced by [10, 2] and further validated by [80] to determine an appropriate minimum sample size for Partial Least Squares Structural Equation Modeling (PLS-SEM). Based on this criterion, the minimum sample size was calculated at 340 respondents; however, a more rigorous approach led to a final sample of 757 farmers. The questionnaire, adapted from previous studies by researchers including [59, 71, 65, 90, 48, 34], comprised 44 items categorized into Awareness, Perceived Ease of Use, Perceived Usefulness, Attitude, Intention to Use, Actual System Usage, and Effectiveness. A five-point Likert scale was used to ensure consistency and reliability, further validated through a pilot test conducted with 75 farmers.

Semi-structured interviews were conducted with key stakeholders, such as farmers, agricultural officers, policymakers, and digital service providers, to gain deeper qualitative insights into adoption barriers, trust issues, and policy gaps. Quantitative data was analyzed using PLS-SEM to validate relationships among adoption factors, while qualitative data underwent thematic analysis to identify contextual challenges affecting digital adoption. By integrating statistical modeling with farmers' lived experiences, the study develops a refined conceptual model that enhances the effectiveness of e-governance initiatives in agriculture [68]. The findings contribute to targeted digital training programs, improved infrastructure, and policy reforms, ensuring localized, accessible, and farmer-centric digital governance solutions for sustainable agricultural development. The comprehensive methodological framework strengthens the study's academic contribution, offering policymakers, technology developers, and agricultural stakeholder's actionable insights to bridge the digital divide and promote widespread farmer participation in e-governance initiatives.

1.1 Quantitative Research Design

This study employs a quantitative research design to systematically analyze numerical data, identify patterns, and validate relationships between key variables affecting e-governance adoption among farmers in Kerala. Grounded in the Technology Acceptance Model (TAM), the study incorporates Diffusion of Innovations Theory and Innovation Resistance Theory to enhance explanatory power. The structured survey questionnaire, comprising 44 items, was distributed to 757 farmers across Kerala, measuring key adoption factors such as Awareness, Perceived Ease of Use, Perceived Usefulness, Attitude toward Technology, Intention to Use, Actual System Usage, and Effectiveness using a five-point Likert scale for consistency. The sample size was determined using the 10 times rule [10] and validated through [88] stricter criteria, ensuring statistical robustness. Quantitative data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to validate relationships among variables, facilitating a data-driven understanding of e-governance adoption determinants.

1.2 Qualitative Research Design

To complement the quantitative analysis, the qualitative research design explores farmers experiences, perceptions, and challenges in adopting e-governance services. Semi-structured interviews were conducted with key stakeholders, including farmers, agricultural officers, policymakers, and digital service providers, to gain deeper insights into adoption barriers, trust concerns, and policy gaps. Thematic analysis was employed to analyze interview responses, identifying contextual barriers such as infrastructural limitations, trust deficits, and training gaps. By integrating narrative insights with statistical findings, the qualitative component enriches the study's conceptual framework, ensuring a holistic understanding of e-governance effectiveness in agriculture. The combination of quantitative modeling and qualitative exploration ensures methodological rigor, enabling the study to propose targeted digital training programs, infrastructure development, and policy reforms for localized, farmer-centric e-governance solutions.

IV.DATA ANALYSIS

1. QUANTITATIVE DATA ANALYSIS

1.1 Frequency Table

Table 2. Demographic analysis.

Attributes	Subgroups	Frequency	Percentage
Gender	Male	303	40%
	Female	454	60%
Age	18-24	35	4.6%
	25-34	97	12.8%
	35-44	189	25%
	45-54	216	28.5%
	55-64	159	21%
	65 & above	61	8.1%
Education	No Formal Education	37	4.9%
	Primary education (up to Grade 5)	62	8.2%
	Secondary education (up to Grade 10)	176	23.2%
	Higher secondary education (up to Grade 12)	267	35.3%
	Bachelor's degree or equivalent	200	26.4%
	Master's Degree	15	2%
Annual Income	Less than ₹50,000	22	2.9%
	₹50,000 - ₹100,000	124	16.4%
	₹100,001 – ₹200,000	142	18.8%
	₹200,001 - ₹300,000	172	22.7%
	₹300,001 - ₹500,000	230	30.4%
	More than ₹500,000	67	8.9%
Social Class	Lower class	205	27.1%
	Middle class	494	65.3%
	Upper class	58	7.7%
Region	Northern Kerala	251	33.3%
	Central Kerala	256	33.8%

Southern Kerala	250	33%

The demographic data showcases a diverse group of respondents, with a higher percentage of females (60%) compared to males (40%). In terms of age, the largest group is aged 45-54 years (28.5%), followed by those aged 35-44 years (25%) and 55-64 years (21%). Educationally, most participants have either higher secondary education (35.3%) or a bachelor's degree (26.4%). Regarding annual income, the largest segment earns between ₹300,001 and ₹500,000 (30.4%). Socially, a majority identifies as middle class (65.3%), with lower and upper classes making up 27.1% and 7.7%, respectively. The regional distribution is quite stable, with respondents from Northern Kerala (33.3%), Central Kerala (33.8%), and Southern Kerala (33%). This diverse demographic representation provides a broad perspective on the factors influencing e-governance adoption among farmers in Kerala. Figure 2 shows the demographic distribution of farmers.

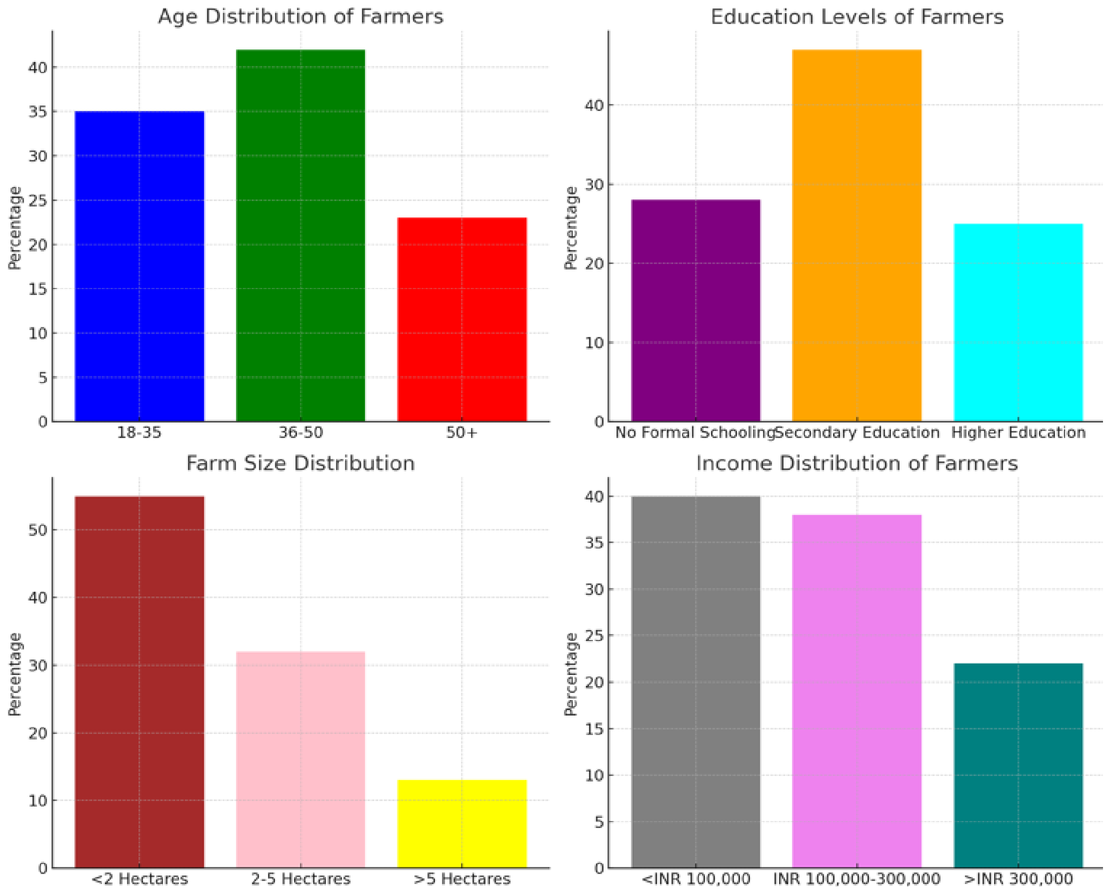

FIGURE 2. Demographic distribution of farmers.

1.2 Factor Analysis

Table 3. KMO and bartlett's test.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.992
Bartlett's Test of Sphericity	Approx. Chi-Square	40374.647
	df	703
	Sig	.000

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is remarkably high at 0.992, indicating that the sample is suitable for factor analysis. Additionally, Bartlett's Test of Sphericity shows a highly significant result with an approximate Chi-Square value of 40,374.647 and a significance level of 0.000, suggesting that there are correlations in the data set that are appropriate for structure detection.'

Table 4. Rotated component matrix.

	Component Matrix
	Component
	1
AW1	. 907
AW2	. 890
AW3	.890
AW4	903
PEU1	.846
PEU2	.870
PEU3	.891
PEU4	.883
PEU5	.890
PU1	.876
PU2	.874
PU3	.892
PU4	.882
PU5	.888
PU6	.891
PU7	897
ATT1	881
ATT2	.874
ATT3	.884
ATT4	885
ATT5	.888
IU1	.875
IU2	.867
IU3	.880
IU4	.872
ASU1	.852
ASU2	.856
ASU3	891
ASU4	.874
E1	.863
E2	.871
E3	.867
E4	.874
E5	.875
E6	.878
E7	.882
E8	.872
E9	.867

Extraction Method: Principal Component Analysis .
a. 1 components extracted

The Component Matrix from Principal Component analysis discloses high loading values for all variables on a single extracted component. Each item within the variables Awareness (AW), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude (ATT), Intention to Use (IU), Actual System Usage (ASU), and Effectiveness (E)' shows 'strong correlations, with loadings' generally 'above 0.85. This' indicates 'that these items are highly consistent in measuring their respective constructs and' significantly 'contribute to the overall model. The high loadings verify that the items effectively represent their underlying variables, demonstrating that the constructs in this study are well-defined and robust. The extraction of a single component underlines the internal consistency and reliability of the measurement model.

1.3 ANOVA

Table 5. Results provided using ANOVA.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	778.519	1	778.519	4035.641	.000[b]
	Residual	145.648	755	.193		
	Total	924.167	756			
a. Dependent Variable: Effectiveness						
b. Predictors: (Constant), Awareness						

The ANOVA table shows a statistically significant relationship between awareness and the effectiveness of e-governance projects. The regression sum of squares is 778.519 with 1 degree of freedom, resulting in a mean square of 778.519. The residual sum of squares is 145.648, with 755 degrees of freedom, giving a mean square of 0.193. The F-value is extremely high at 4035.641, and the significance level (Sig.) is .000, indicating that the model is highly significant. This' demonstrates 'that awareness is a strong predictor of the effectiveness of e-governance projects among farmers in Kerala.

Table 6. Coefficient table

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.802	.049		16.499	.000
	Awareness	.775	.012	.918	63.527	.000
a. Dependent Variable: Effectiveness						

The coefficients table shows that awareness significantly predicts the effectiveness of e-governance projects. The constant (intercept) value is 0.802 with a standard error of 0.049, indicating the baseline level of effectiveness when awareness is zero. Awareness has an unstandardized coefficient (B) of 0.775, meaning that for every one-unit increase in awareness, the effectiveness of e-governance projects increases by 0.775 units. The standardized coefficient (Beta) is 0.918, showing a strong positive relationship between awareness and effectiveness. The t-value of 63.527 and the significance level (Sig.) of 0.000 confirm that this relationship is statistically significant. This implies that improving awareness among farmers is crucial for enhancing the effectiveness of e-governance projects in Kerala.

$$y = a + bx + e \tag{1}$$

Where $y = DV$, e is the error. Errors can be reduced through the SEM Model, a indicated as constant value/intercept, b represents slope

$$\text{Effectiveness} = 0.802 + 0.775 \times \text{Awareness} \tag{2}$$

1.4 Discriminant Analysis

Discriminant analysis is active to identify the variables that differentiate between two or more naturally occurring groups. The analysis evaluates attitudes toward e-Governance projects within the agriculture sector among rural populations in Kerala, focusing on the Test Results, Eigenvalues, Wilks' Lambda and Standardized Canonical Discriminant Function Coefficients tables.

Table 7. Eigenvalues.

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	7.463[a]	99.6	99.6	939
2	.024[a]	.3	99.9	.153
3	.009[a]	.1	100.0	.096
4	.000[a]	.0	100.0	.003
a. First 4 canonical discriminant functions were used in the analysis				

The first discriminant function, with a high eigenvalue of 7.463, accounts for 99.6% of the variance, making it highly effective in distinguishing between groups, while the second function explains only 0.3% of the variance, contributing minimally to group separation. The first function has a strong canonical correlation of 0.939, indicating a robust relationship with group membership.

Table 8. Wilks lambda.

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 4	.114	1628.659	20	.000
2 through 4	.968	24.710	12	.016
3 through 4	.991	6.926	6	.328
4	1.000	.009	2	.996

Wilks Lambda is used to measure how effectively each function separates groups; lower values indicate better discrimination. The first test (1 through 4) has a significant Wilks' Lambda of 0.114 and a p-value of 0.000, meaning the model significantly differentiates between groups across all four functions. The second test (2 through 4) is also significant (p = .016), but subsequent tests show non-significant results, indicating diminishing discriminative power with additional functions.

Table 9. Standardized canonical discriminant function coefficients.

Standardized Canonical Discriminant Function Coefficients				
	Function			
	1	2	3	4
ATT1	.342	.464	.614	.332
ATT2	.389	.039	.641	.423
ATT3	.277	.680	.350	.098
ATT4	.349	.518	.116	.822
ATT5	.334	.633	.471	.623

These coefficients show how much each variable contributes to each discriminant function. Higher absolute values indicate a stronger influence on group separation. For instance, ATT2, with the highest coefficient (.389), significantly contributes to distinguishing between groups.

The discriminant analysis results reveal that awareness variables significantly influence attitudes towards e-Governance projects in agriculture among rural populations in Kerala. The high eigenvalue and canonical correlation for the first function suggest it effectively separates groups based on attitudes. Wilks' Lambda results confirm these relationships are statistically significant, with specific awareness variables having varying levels of influence on group differentiation.

Z= 0.342 f1 (e-Governance platform in the agriculture sector is beneficial to me.) + 0.389 f2 (Using the AIMS website is a smart choice.) + 0.277 f3 (the implementation of e-Governance in the agriculture sector.) + 0.349 f4 (The AIMS website adds value to my farming process.) + 0.334 f5 (Positive attitude towards using e-Governance in the agriculture sector.)

1.5 *Data Screening and Pre-analysis*

The data processing plan, a comprehensive review was conducted to check for outliers, missing values, demographic characteristics, and statistical errors related to normality. Given the minimal number of missing values, the widely recommended mean replacement method was employed to handle them. SmartPLS offers this feature, which replaces missing data points with the average of all data points for the same predictor. The main advantage of the mean replacement method is that, different list-wise and pair-wise deletion, it maintains the sample size while conserving the mean values of all variables [36].

1.6 *Analysis of the Measurement Model*

The computational model in this study uses reflective measurement models. The statistical criteria for reflective measurement models differ from those for formative measurement models. Internal consistency is not applicable for formative measurement models because the scale items in these models typically represent a single source and are not necessarily highly correlated with each other. Reflective measurement model items must be correlated and demonstrate significant outer loading values [36].

1.7 *Analysis of Reflective Measurement Model*

Table 10. Construct reliability and validity.

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE**
ASU	0.937	0.938	0.937	0.788
ATT	0.951	0.951	0.951	0.795
AW	0.952	0.952	0.952	0.833
E	0.973	0.974	0.973	0.803
IU	0.937	0.937	0.937	0.789
PEU	0.951	0.951	0.951	0.794
PU	0.966	0.966	0.966	0.804

The measures of construct reliability and validity indicate excellent internal consistency and validity for all variables used in the study. Cronbach's alpha values for all constructs are above 0.937', demonstrating 'high internal consistency. Composite reliability measures (rho_a and rho_c) exceed '0.937, confirming the reliable measurement of the constructs. The average variance extracted (AVE) values, ranging from 0.788 to 0.833, show good convergent validity by capturing a significant portion of variance for each construct. These results confirm 'that the constructs of Actual System Usage (ASU), Attitude (ATT), Awareness (AW), Effectiveness (E), Intention to Use (IU), Perceived Ease of Use (PEU), and Perceived Usefulness (PU) are both reliable and valid, supporting the robustness and credibility of the study's measurement model.

1.8 *Discriminant Validity*

Table 11. Discriminant validity.

	ASU	ATT	AW	E	IU	PEU	PU
ASU	0.888						
ATT	0.852	0.892					
AW	0.834	0.841	0.913				
E	0.837	0.841	0.841	0.896			
IU	0.854	0.854	0.825	0.850	0.888		
PEU	0.838	0.833	0.828	0.827	0.852	0.891	

PU	0.834	0.843	0.831	0.829	0.840	0.840	0.897

The Fornell-Larcker criterion analysis confirms the discriminant validity of the constructs in the study. Each construct's diagonal value (indicating its internal consistency) is higher than its correlation with any other construct, showing that each construct is distinct and measures a specific aspect of the model. This ensures that the variables Awareness (AW), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude (ATT), and Intention to Use (IU), Actual System Usage (ASU), and Effectiveness (E) are accurately represented and contribute meaningfully to the model. These' findings 'validate the structure and reliability of the measurement model used in the study.

1.9 Analysis of Structural Model

Table 12. Hypothesis testing.

Hypothesis	Original sample (O)	Sample mean (M)	'Standard deviation (STDEV)	T-statistics (|O/STDEV|)	P values	Decisions
AW -> PEU (H1)	0.912	0.912	0.016	57.072	0.000	Accepted
AW -> PU (H2)	0.463	0.467	0.051	9.119	0.000	Accepted
PEU -> PU (H3)	0.514	0.510	0.053	9.732	0.000	Accepted
PEU -> ATT (H4)	0.316	0.322	0.070	4.502	0.000	Accepted
PU -> ATT (H5)	0.654	0.647	0.069	9.492	0.000	Accepted
PEU -> IU (H6)	0.237	0.238	0.068	3.488	0.000	Accepted
PU -> IU (H7)	0.246	0.243	0.078	3.169	0.002	Accepted
ATT -> IU (H8)	0.486	0.488	0.071	6.862	0.000	Accepted
IU -> ASU (H9)	0.930	0.931	0.007	127.819	0.000	Accepted
ASU -> E (H10)	0.938	0.938	0.010	91.051	0.000	Accepted

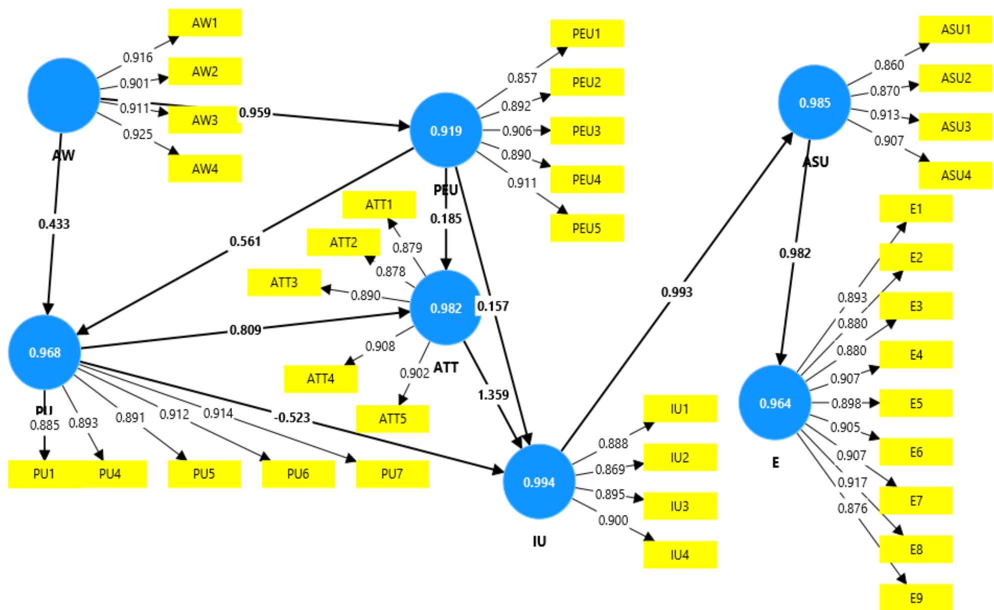

FIGURE 3. Standardized result of SEM.

The analysis indicates that awareness, perceived ease of use (PEU), and perceived usefulness (PU) all play significant roles in determining the effectiveness of e-governance projects among Kerala's farmers. Awareness greatly boosts both PEU (O = 0.912, T = 57.072) and PU (O = 0.463, T = 9.119). PEU significantly influences PU (O = 0.514, T = 9.732) and shapes attitudes towards these technologies (O = 0.316, T = 4.502). Positive attitudes towards the tools enhance the ‘intention to use them (O = 0.486, T = 6.862), leading to actual system usage (O = 0.930, T = 127.819). All relationships in the model are statistically significant, highlighting that increasing awareness and improving the PEU and PU of these tools are essential for their successful adoption and effective use in the agricultural sector.

1.10 Model fit Summary

Table 13. Model fit summary.

Model Fit summary		
	Saturated model	Estimated model
SRMR	0.020	0.021
d_ULS	0.282	0.341
d_G	0.810	0.845
Chi-square	1725.263	1785.392
NFI	0.926	0.924

The model fit summary indicates that the estimated model is closely allied with the saturated model. The Standardized Root Mean Square Residual (SRMR) values are very low (0.020 for the saturated model and 0.021 for the estimated model), indicating a good fit. The d_ULS and d_G values are relatively similar ‘between the models, showing stability. The Chi-square values (1725.263 for the saturated model and 1785.392 for the estimated model) are also close, suggesting a consistent model structure. The Normed Fit Index (NFI) is high for both models (0.926 and 0.924), reflecting an excellent fit. These results indicate ‘that the model is well-fitting and robust.

Table 14. R-square and R-square adjusted.

Overview		
	R-square	R-square adjusted
ASU	0.985	0.980
ATT	0.982	0.978
E	0.964	0.960
IU	0.994	0.992
PEU	0.919	0.915
PU	0.968	0.964

The R-square values disclose the proportion of variance in the dependent variables that the independent variables can explain. Actual System Usage (ASU) has an R-square value of 0.985, indicating that ‘98.5% of its variance is explained by the model, showcasing very strong predictive power. Attitude (ATT) has an R-square of 0.982, Intention to Use (IU) has an R-square of 0.994, and Perceived Usefulness (PU) has an R-square of 0.968, all demonstrating high explanatory power. Effectiveness (E) and Perceived Ease of Use (PEU) also show strong explanatory power with R-square values of 0.964 and 0.919, respectively. The adjusted R-square values, which consider the number of predictors in the model, are slightly lower but still indicate an excellent model fit and predictive strength, highlighting the model's robustness in explaining the variance across all constructs.

1.11 Mediating effect

Table 15. Indirect and total effect.

Relationship	ASU	ATT	AW	E	IU	PEU	PU
Total Indirect Effects							
ASU	-	-	-	-	-	-	-
ATT	1.349	-	-	1.324	-	-	-
AW	0.945	0.963	-	0.927	0.952	-	0.538
E	-	-	-	-	-	-	-
IU	-	-	-	0.974	-	-	-
PEU	0.727	0.454	-	0.714	0.576	-	-
PU	0.572	-	-	0.562	1.099	-	-
Total Effects							
ASU	-	-	-	0.982	-	-	-
ATT	1.349	-	-	1.324	1.359	-	-
AW	0.945	0.963		0.927	0.952	0.959	0.971
E	-	-	-	-	-	-	-
IU	0.993	-	-	0.974	-	-	-
PEU	0.727	0.640	-	0.714	0.733	-	0.561
PU	0.572	0.809	-	0.562	0.577	-	-

The table provides an overview of the total indirect and total effects among various constructs in the model. In terms of total indirect effects, Actual System Usage (ASU) has significant indirect influences on Attitude (ATT) (1.349) and Intention to Use (IU) (1.324). Awareness (AW) shows indirect effects on several constructs, including ASU (0.945), ATT (0.963), Effectiveness (E) (0.952), IU (0.927), Perceived Ease of Use (PEU) (0.538), and Perceived Usefulness (PU) (0.714). This indicates that awareness plays a considerable mediating role. Perceived Ease of Use (PEU) also has important indirect effects on ATT (0.454), IU (0.576), and PU (1.099), highlighting its significance as a mediator. Perceived Usefulness (PU) has substantial indirect effects on IU (1.099).

In total effects, ASU strongly impacts Effectiveness (0.982), and ATT directly influences IU (1.349) and E (1.359). Awareness (AW) has strong total effects on multiple constructs, including ASU (0.945), ATT (0.963), E (0.952), IU (0.959), PEU (0.971), and PU (0.927). PEU significantly influences ASU (0.727), ATT (0.640), E (0.733), IU (0.561), and PU (0.714). These findings underscore the critical roles of Awareness (AW) and Perceived Ease of Use (PEU) in the adoption ‘and effectiveness of e-governance projects in Kerala's agricultural sector.

The analysis of mediating effects within the model underlines the crucial roles of Awareness (AW) and Perceived Ease of Use (PEU) in the adoption and effectiveness of e-governance projects in Kerala's agricultural sector. Awareness meaningfully impacts multiple constructs, including Perceived Ease of Use, Intention to Use (IU), and Attitude (ATT), indicating that increasing awareness can lead to better overall acceptance and utilization of digital tools. Similarly, perceived ease of use serves as a vital mediator, influencing attitude, intention to use, and perceived usefulness, which highlights the importance of designing user-friendly e-governance platforms.

Perceived usefulness also arises as a significant mediator, mainly in its effect on intention to use and attitude, reinforcing the need to communicate the practical benefits of e-governance tools to farmers. These findings suggest that raising awareness and ease of use, together with demonstrating the usefulness of e-governance tools, can drive higher adoption rates and more effective use among farmers.

The analysis reveals notable variations in e-governance adoption across demographic groups, with younger farmers, those with higher education levels, and those with greater digital exposure demonstrating significantly higher adoption rates. In contrast, older farmers and those with lower literacy levels showed more reluctance, citing technological barriers and lack of awareness as key challenges.

The study highlights that these mediating factors can help for better interventions to enhance technology acceptance and the overall success of e-governance initiatives. By concentrating on these key elements, e-governance projects can significantly contribute to sustainable agricultural development and improved livelihoods for rural farmers in Kerala.

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1.12 Importance Performance Mapping (IPMA)

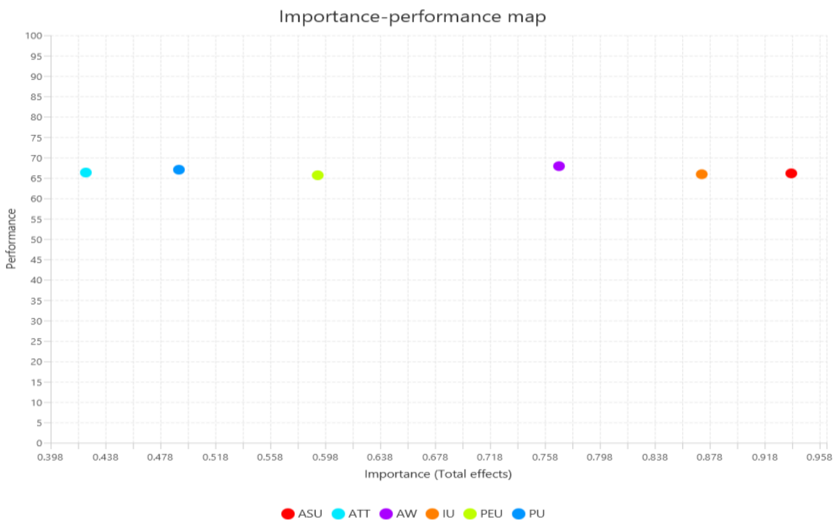

FIGURE 4. Importance-performance map analysis.

Table 16. Importance and performance of constructs.

Construct	Importance	Performance
ASU	0.938	66.122
ATT	0.424	66.321
AW	0.769	67.893
IU	0.873	65.907
PEU	0.593	65.658
PU	0.492	67.020

The importance-performance map for Effectiveness (E) combines the total effects of various constructs on Effectiveness with their performance scores. Actual System Usage (ASU) has the highest total effect (0.938) on Effectiveness and a performance score of 66.122, indicating its crucial role and strong performance. Intention to Use (IU) also has a distinguished total effect (0.873) and a performance score of 65.907, emphasizing its importance. Awareness (AW) has a significant total effect (0.769) and the highest performance score (67.893), showing its strong influence on effectiveness. Perceived Ease of Use (PEU) and Perceived Usefulness (PU) have moderate total effects (0.593 and 0.492, respectively) with performance scores of 65.658 and 67.020, respectively. Although Attitude (ATT) has a lower total effect (0.424), it still maintains a good performance score (66.321). Awareness (AW) has the most significant mediating effect by balancing high total effect and performance, highlighting its crucial role in enhancing the effectiveness of e-governance projects in Kerala's agricultural sector.

2. QUALITATIVE DATA ANALYSIS

To gain deeper insights into the factors influencing e-governance adoption in agriculture, semi-structured interviews were conducted with key stakeholders, including farmers, agricultural officers, policymakers, and digital service providers. These interviews aimed to explore their perspectives on digital adoption, challenges, and policy implications. Responses were analyzed using a thematic coding approach, and the most frequently discussed terms were visually represented in Figure 6, which highlights key themes such as digital literacy, technology adoption, e-governance, subsidies, agriculture, and accessibility.

The prominence of terms such as awareness and training suggest that many farmers still require targeted interventions to improve digital literacy and platform usability. Additionally, words like policy, government support, and market access indicate concerns regarding regulatory frameworks, incentives, and infrastructure limitations in rural areas. By analyzing these recurring themes, policymakers can refine e-governance strategies to better address the needs of rural farmers, ensuring greater adoption and long-term sustainability of digital agricultural practices.

Figure 6 shows a word cloud of key themes in the research paper. The word cloud in Figure 7 is based on the frequency of key responses obtained during interviews, visually representing the most emphasized challenges and opportunities in digital agriculture. The qualitative data was preprocessed by categorizing responses, deleting redundant phrases, and normalizing key terms for consistency. A thematic frequency analysis was performed, where more frequently mentioned issues appear larger in the word cloud, highlighting key discussion points across stakeholder groups.

While primarily exploratory, the qualitative responses were further analyzed using sentiment analysis, categorizing discussions into positive, negative, and neutral perspectives. For example, accessibility, awareness, and government support were frequently associated with positive feedback, reflecting areas of successful intervention and progress. Meanwhile, words like digital illiteracy, infrastructure, and barriers were more common in responses expressing concerns and challenges that need further policy attention.

This interview-driven approach provides a qualitative lens into stakeholder perspectives, enabling policymakers, researchers, and industry leaders to identify areas requiring immediate policy action to enhance digital adoption in agriculture. By incorporating firsthand insights from key stakeholders, this research reinforces the need for sustainable digital transformation strategies tailored to the realities of rural agricultural communities.

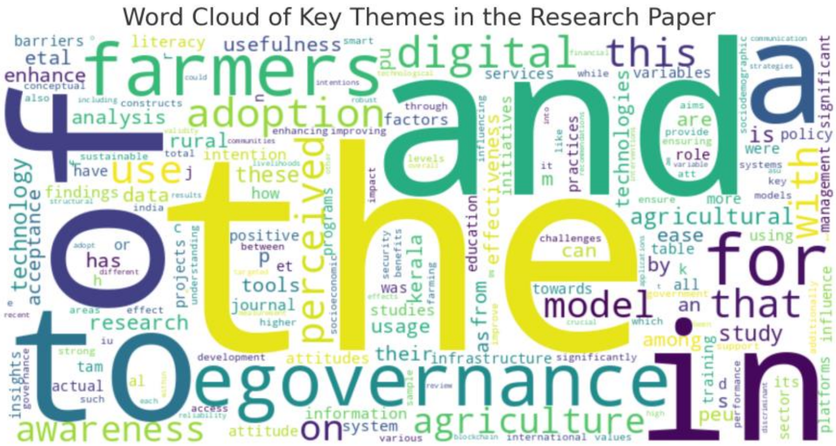

FIGURE 5. Word cloud of key themes in the research paper.

FIGURE 6. Interview-based word cloud representation of key themes in e-governance adoption.

1.1. Case Studies

1.1.1. Comparative Case Studies: Global and Regional E-Governance Initiatives in Agriculture

To better understand the role of e-governance in agriculture, this research compares case studies from various regions, highlighting how various initiatives have raised digital adoption among farmers. In India, the Telangana Rythu Bandhu scheme provides direct income support to farmers through a digital framework, eliminating bureaucratic delays and increasing financial inclusion. Similarly, Andhra Pradesh Rythu Bharosa Kendras serve as digital one-stop centers for farmers, offering advisory services, input supplies, and immediate market intelligence, significantly raising farmers' access to e-governance services. The Karnataka Bhoomi project, which digitized land records, has streamlined property transactions and subsidy uses, ensuring transparency and reducing corruption in agricultural governance.

Globally, China's smart agriculture demonstration zones leverage big data, artificial intelligence, and internet of things technologies to raise precision farming, raising efficiency and sustainability. The European Union's fork strategy integrates e-governance into agricultural policies to create transparent, sustainable, and fair food systems. These global models emphasize the importance of digital literacy programs, financial incentives, and infrastructure investment in driving e-governance adoption. Comparing these initiatives with the current indian scenario reveals that while India has made progress, issues like digital illiteracy, lack of trust in digital platforms, and inconsistent internet access remain significant barriers. By adopting best practices from these case studies, policymakers can design targeted interventions to strengthen e-governance adoption, raise farmer engagement, and ensure the continuous sustainability of digital agricultural policies.

1.1.2. Case Study: Digital agriculture in Kerala Smart Farming Initiative

A case study of the Kerala Smart Farming Initiative demonstrates the potential of e-governance in agriculture. The program integrates digital platforms with immediate data analytics to support farmers in decision-making. The adoption of the agriculture information management system has significantly improved farmers access to government schemes, training programs, and market prices, leading to increased participation and engagement. This initiative has addressed key challenges such as limited awareness, infrastructure constraints, and inefficient subsidy distribution, making it a model for other states to replicate. By utilizing mobile-based advisories, artificial intelligence-driven crop recommendations, and blockchain-backed financial transactions, the smart farming initiative has helped bridge the digital divide in agriculture. This case study highlights the role of structured digital platforms in overcoming adoption barriers and ensuring the effective use of e-governance tools, aligning with the research findings on awareness and accessibility as critical enablers of digital adoption.

1.1.3. Discussion and Implications for Managerial Action

The findings directly address the research objectives by demonstrating how socio-demographic factors influence e-governance adoption, confirming that awareness, perceived ease of use, and perceived usefulness significantly impact farmers' attitudes and intentions to adopt digital tools. The validation of the conceptual model highlights key adoption barriers and facilitators, providing insights for enhancing e-governance effectiveness. Also, the study's results align with existing literature while extending knowledge on technology acceptance in rural agriculture, offering actionable recommendations for improving policy frameworks, digital infrastructure, and farmer outreach programs.

The study's findings suggest that while e-governance adoption remains low due to digital literacy and infrastructure gaps, emerging technologies like AI, IoT, and blockchain offer potential solutions. Artificial intelligence (AI) -driven decision-making could provide personalized recommendations to farmers, the internet of things could raise immediate data access, and blockchain could secure financial transactions and supply chains. Future research has explored how these technologies can be seamlessly integrated into existing electronic government frameworks to drive adoption and maximize benefits.

The results demonstrate statistically significant connections among key variables, with all hypotheses supported at a p-value < 0.05, confirming the robustness of the findings. The research highlights that awareness is a primary driver of electronic government adoption, as farmers with greater exposure to digital literacy programs and government initiatives were more inclined to use these technologies. Perceived ease of use emerged as a critical factor, with farmers showing a preference for simple, mobile-friendly platforms that require minimal technical expertise. Also, perceived usefulness directly influenced sustained engagement, as farmers who experienced tangible benefits like raised market access, immediate weather updates, and streamlined subsidy uses were more likely to continue using e-governance tools. Socioeconomic factors like income and landholding size also played a part, as larger-scale farmers had greater incentives and financial resources to integrate digital solutions into their agricultural practices. The strong influence of awareness, perceived ease of use, and perceived usefulness on farmers' intention to adopt e-governance aligns with existing research on technology acceptance in agriculture. These findings reinforce the applicability of the technology acceptance model in rural settings while highlighting the need for raised digital literacy and infrastructure to raise adoption.

Findings indicate that the adoption of electronic government tools aligns with diffusion of innovations theory, as early adopters tend to influence others in their community. Innovation resistance theory helps explain reluctance among older farmers and those with limited digital literacy, reinforcing the need for tailored interventions to overcome adoption barriers. These challenges align with patterns observed in other developing economies, such as Kenya and Brazil, where limited internet infrastructure and lack of trust in digital systems hinder technology uptake. In contrast, countries like Estonia and the Netherlands have successfully integrated e-governance in agriculture through high digital penetration, simplified farmer interfaces, and robust data security policies. By drawing comparisons with these global experiences, policymakers can adopt successful strategies and overcome key adoption barriers to improve digital transformation in agriculture.

This research paper assesses the influence of e-governance in the agricultural sector, focusing on the challenges and opportunities faced by rural farmers in Kerala. It points to several 'areas for managerial intervention, starting with the importance of awareness. The study discloses that a lack of knowledge about digital tools among many farmers delays their participation. It recommends that the government 'develop targeted communication strategies and complete training programs to boost awareness. The study also underlines the significance of perceived ease of use, suggesting the need for user-friendly borders and ongoing technical support. To enhance perceived usefulness, the government could highlight success stories and ensure real-time data access. Socio-demographic factors like age and education level are crucial in technology adoption, so modified interventions and community engagement are advised. Overcoming barriers such as data privacy concerns and inadequate infrastructure is vital, with transparent communication and infrastructure development being key strategies. To implement e-governance initiatives effectively, the government should focus on strategic partnerships, continuous feedback mechanisms, and resource allocation towards improving technological infrastructure. Pointing these areas will enhance the effectiveness of e-governance projects, leading to improved agricultural productivity and better livelihoods for rural farmers in Kerala.

To raise the effectiveness of e-governance adoption in agriculture, policymakers should implement targeted initiatives, including: (1) Expanding digital literacy programs through farmer training centers, mobile-based tutorials, and interactive workshops tailored to different literacy levels. (2) Developing user-friendly platforms with multilingual support and simplified interfaces to raise accessibility. (3) Investing in rural digital infrastructure, like expanding broadband access, setting up digital service kiosks, and providing subsidies for smartphone purchases among small and marginal farmers. (4) Rising data security measures to build trust in e-governance systems, ensuring privacy and protection against cyber threats. (5) Strengthening public-private partnerships to promote the integration of emerging technologies like artificial intelligence and blockchain in agricultural governance. These actions will not only bridge the digital divide but also foster the continuous adoption of digital solutions, ultimately improving productivity and rural livelihoods.

The findings directly address the original research questions by identifying key factors influencing e-governance adoption among rural farmers. The research confirms that awareness, perceived ease of use, and perceived usefulness are significant predictors of adoption, aligning with the first research question on identifying the primary drivers of e-governance usage. The impact of socio-demographic variables, such as age, education, and income, provides insight into the second research question, which explores how different farmer groups engage with digital tools. The study's validation of a conceptual model tailored for rural communities addresses the third research question regarding the development of strategies to improve adoption rates. By linking these findings to the research objectives, this study provides actionable insights for policymakers and digital service providers to enhance e-governance initiatives in the agricultural sector.

Beyond practical implications, this study contributes to the theoretical understanding of digital transformation in agriculture by expanding the application of the Technology Acceptance Model (TAM) and integrating insights from Diffusion of Innovations Theory (DOI) and Innovation Resistance Theory (IRT). Unlike traditional TAM applications, which focus on general technology adoption, this research highlights socio-demographic and infrastructural constraints unique to rural agricultural settings, filling a critical gap in the literature. The study advances existing theories by incorporating the role of policy interventions, localized digital training, and infrastructure accessibility as key mediators influencing e-governance adoption. By aligning these findings with prior research, this study refines the conceptualization of digital governance in resource-limited environments and offers a more context-specific theoretical framework for future studies.

1.2. Limitation of the Study

This research paper delivers valuable visions but also presents several limitations. The select focus on Kerala restricts the applicability of the findings to other regions in India or different agricultural contexts, considering the socio-economic, technological, and cultural differences across states. The sample size and variety may not fully represent the broader farmer population, possibly skewing the results and affecting the reliability of conclusions about e-governance awareness and attitudes. The study acknowledges variations in technological literacy among farmers, it may not fully address how these differences impact the adoption of e-governance tools, leading to hypothetically inadequate recommendations for targeted interventions. The external factors like economic conditions, political influences, and environmental challenges, all these are important in shaping farmers' attitudes and behaviors, may not be comprehensively explored, affecting the overall effectiveness of e-governance initiatives. The study suggests a snapshot of current attitudes rather than a longitudinal analysis, which would provide a more detailed understanding of how perceptions change over time with evolving technology and policies.

It is challenging to ascertain whether the issues found are specific to Kerala or a result of a larger trend in agricultural electronic government due to the lack of contrast with comparable studies from other areas or sectors. Future studies ought to tackle these constraints in order to enhance comprehension of e-governance popularity in farming along with successfully supporting the development of policies and implementation plans. Notwithstanding these drawbacks, the study offers insightful information about how electronic governance tools are being adopted in the agricultural sector. The empirical stances to creativity battle theory and diffusion of concepts, which provide an organized framework for comprehending adoption trends and resistance variables among farmers, are helpful in further elucidating the difficulties in integrating technology and resistance.

Overcoming the introduction disparity: Perspectives from against innovation concepts and circulation of advances. The diffusion of inventions theory emphasizes the critical role that pioneers and opinion leaders play to impact the agricultural embrace of electronic government services in light of these outcomes. Within rural areas, their adoption and promotion can hasten the digitization process. However, as stated in the resisting innovation theory, addressing important barriers is crucial for broad adoption. Farmer intention to switch to digital places is hampered by issues like complex technology, security worries, and a deep-rooted dependence on conventional methods.

To overcome these barriers, farmer-centric digital literacy programs, targeted awareness campaigns, and trust-building initiatives should be implemented. These strategies will raise technological confidence, reduce perceived risks, and ensure a smoother transition to electronic government places, ultimately driving sustainable adoption.

1.3. Recommendations

- To develop a targeted training program to improve technological literacy among farmers, mainly those from marginalized backgrounds. These programs should highlight practical, hands-on training to ensure effective use of e-governance tools.
- To create a speech-based interface for accessing the Agriculture Information Management System (AIMS) website in local languages. This will contribute to farmers who may have difficulty with literacy or navigating text-based systems, making it easier for them to obtain vital information and services.
- Discover the addition of advanced technologies like artificial intelligence (AI) and big data analytics within e-governance frameworks. These technologies can enhance service delivery, optimize resource management, and improve decision-making processes for farmers.
- Supporter for the creation of supportive policies that foster the adoption of e-governance in agriculture. These policies should point to identified barriers and create a favorable environment for implementing and scaling digital initiatives.
- Improve rural internet connectivity and technological infrastructure to ensure that farmers have reliable access to e-governance tools. This will help bridge the digital divide and facilitate the broader adoption of digital services.
- Address anxieties related to data privacy by applying robust security measures. Communicate these measures to farmers to build trust and encourage the adoption of e-governance tools.
- Familiarize financial incentives or subsidies for farmers who adopt e-governance tools. This can motivate farmers to engage with digital platforms and offset the initial costs associated with the technology.
- Start continuous feedback mechanisms to fold input from farmers on the usability and effectiveness of e-governance tools. Use this feedback to make improvements and ensure that the tools meet farmers' needs.

1.4. Future Scope of the Research

This research on e-governance awareness and adoption among local farmers highlights several areas for future research and practical uses.

- Expanding geographic scope: Future studies should extend beyond Kerala to other Indian states and international contexts to assess regional variations in digital adoption, helping policymakers design localized strategies for raising e-governance in agriculture.
- Longitudinal studies: Examining how awareness, attitudes, and usage of e-governance tools evolve will provide deeper insights into the sustained effect of digital interventions and inform better continuous policy decisions. Follow-up surveys at regular intervals could help assess how technology adoption evolves, identifying trends

in continued usage, emerging challenges, and the effectiveness of digital interventions over time. This approach would provide policymakers with immediate data to refine e-governance strategies and enhance continuous sustainability.

- Integrating Advanced Technologies: Research should explore how AI, machine learning, and big data analytics can enhance e-governance frameworks, particularly in areas such as precision farming, automated advisory systems, and predictive analytics for crop and market trends.
- Impact of Digital Literacy Programs: Future studies should assess the effectiveness of targeted digital training programs for farmers, especially those in marginalized and digitally excluded communities, to determine the best approaches for increasing technology adoption.
- Climate Resilience and Disaster Management: Investigating how e-governance tools can support climate adaptation strategies such as early warning systems, crop risk assessment, and disaster relief coordination—would contribute to more resilient agricultural practices.
- Community-Based Adoption Models: Future research could analyze the role of farmer cooperatives, local networks, and peer-driven training programs in improving the acceptance and sustained use of e-governance platforms.
- Comparative Sectoral Analysis: Conducting comparative studies between agriculture and other industries (such as health and education) where e-governance has been successfully implemented could provide best practices for scaling digital services in farming communities.

By exploring these areas, future research can provide stronger empirical evidence to refine policy frameworks, enhance technological interventions, and foster greater digital inclusion in rural agriculture, ultimately improving livelihoods and food security.

V. CONCLUSION

This paper systematically examines how e-governance can enhance agricultural practices and improve the livelihoods of farmers in Kerala. By applying the Technology Acceptance Model (TAM), the study explores how awareness, attitudes, perceived ease of use (PEU), and perceived usefulness (PU) influence the adoption of digital tools among rural farmers. The findings confirm that higher awareness levels lead to positive attitudes and a greater intention to use e-governance technologies, addressing the first objective of analyzing socio-demographic factors influencing adoption. A key contribution of this research is the development and validation of a new conceptual model, which enhances understanding of the barriers and facilitators of e-governance adoption, fulfilling the second research objective. The study also demonstrates that the readiness of farmers to use technology is significantly influenced by perceived utility and usability, which is consistent with the third goal of assessing such variables in adoption. Furthermore, the present investigation offers practical policy suggestions regarding the fourth goal of closing a digital gap, such as expanding digital literacy initiatives, improving connectivity in rural areas, and tailoring outreach tactics. Beyond Kerala, its conclusions have wider ramifications, providing guidance for international farmers in areas dealing with comparable economic hurdles to technology. Many developing countries with large local populations experience digital infrastructure gaps, low digital literacy, and limited e-governance adoption in agriculture. The research emphasizes that awareness programs, localized training, and simplified digital platforms can inform policies in countries across South Asia, Africa, and Latin America, where farmers encounter comparable adoption barriers. Furthermore, the incorporation of innovative products like the technology into electronic government systems may serve as a template for the global expansion of digital farming services. These revelations support organic farming, food availability, and fiscal stability in local communities by advancing a more globally relevant policy for digitization in agriculture. It provides important insights for officials, agricultural clients, and technologists in order to increase the adoption of electronic government initiatives, guaranteeing environmental sustainability and online access in the local agriculture sector by directly connecting findings to the goals of the study.

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Author Contributions

Author 1: Conducted all the research, performed the analysis, and wrote the paper. Their extensive work and dedication have been the backbone of this research. Author 2: Took charge of proofreading the manuscript, ensuring the quality and coherence of the final document. Their attention to detail was essential for presenting the research in the best possible light. Author 3: Assisted in the analysis part, providing valuable insights and contributing to the interpretation of the data. Their support has been instrumental in refining the research findings.

Conflicts of Interest

The data supporting the findings of this research are available within the article and its supplementary materials. Any additional data required to replicate the research findings or for further analysis can be obtained from the corresponding author upon reasonable request. The authors are committed to transparency and openness in their research and are willing to share raw data, detailed methodologies, and any other necessary information to facilitate scientific integrity and reproducibility.

Data Availability Statement

The data supporting the findings of this research are available within the article and its supplementary materials. Any additional data required to replicate the research findings or for further analysis can be obtained from the corresponding author upon reasonable request. The authors are committed to transparency and openness in their research and are willing to share raw data, detailed methodologies, and any other necessary information to facilitate scientific integrity and reproducibility.

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