Behavioral Drivers of Agricultural FinTech Adoption in India for Sustainable Digital and Financial Inclusion Using an Extended TAM Approach

Rathi R[1], Ashok Kumar Sahoo[2*]

[1] Research Scholar, Department of Commerce, Kalasalingam Academy of Research and Education, Krishnankoil, Tamil Nadu - 626126, India Email- shrishaa.net@gmail.com ORCID Id- https://orcid.org/0009-0008-1298-3418

[2*]Assistant Professor, Department of Commerce, Kalasalingam Academy of Research and Education, Krishnankoil, Tamilnadu -626126, India Email- rockashok555@gmail.com ORCID: https://orcid.org/0000-0001-9873-9599

Abstract

FinTech, or financial technology, has become a revolutionary force in advancing digital financial inclusion and sustainable agricultural growth, especially in emerging nations like India. This research examines the behavioral determinants affecting the acceptance of FinTech services within the Indian agriculture industry through an Extended Technology Acceptance Model (TAM).The suggested paradigm examines the impact of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TR), Government Support (GS), and Social Influence (SI) on Actual Adoption (AU), Behavioral Intention (BI), and Attitude Toward Using FinTech (ATU). A quantitative research methodology was employed using a structured questionnaire distributed among 400 farmers and agricultural stakeholders across different regions of India. Using SmartPLS software, structural equation modeling (SEM) was used to analyze the gathered data. The findings show that while perceived usefulness, trust, and government support have a favorable impact on farmers' views toward FinTech adoption, behavioral intention has a substantial impact on actual uptake of FinTech services. Although there is little correlation between Perceived Ease of Use and Attitude Toward Using FinTech, it has a positive impact on Behavioral Intention. Similarly, Social Influence shows no significant impact on farmers' attitudes toward adoption. The findings suggest that farmers prioritize the practical benefits, reliability, and institutional support associated with FinTech services over simplicity and peer influence. By expanding the TAM framework into the context of Indian agriculture, the study adds to the body of literature already in existence. It also has significant ramifications for financial institutions, policymakers, and FinTech companies looking to improve digital financial inclusion, rural economic development, and sustainable agricultural transformation in India.

Keywords: Financial Technology (FinTech); Technology Acceptance Model (TAM); Agricultural FinTech; Structural Equation Modeling (SEM); Behavioral Intention; Rural Digital Transformation; Smart Agriculture

1 Introduction

In the global financial ecosystem, financial technology (FinTech) has become one of the most revolutionary technologies. using digital technologies like blockchain systems, digital payments, and mobile banking to drastically transform traditional banking and financial services, artificial intelligence, cloud computing, and digital lending platforms [1, 2, 3]. The rapid advancement of Industry 4.0 technologies has accelerated the integration of FinTech into multiple economic sectors, creating new opportunities for improving operational ef- ficiency, financial accessibility, transparency, and customer engagement [6, 11]. In recent years, FinTech has attracted substantial attention from governments, policymakers, researchers, and financial institutions because of its important role in promoting digital transformation and financial inclusion, particularly in developing economies where large populations remain underserved by conventional financial systems [5, 10].

The creation of jobs, food security, rural livelihoods, and national economic development are all greatly aided by agriculture, which continues to be one of the most major economic sectors in India [34]. Despite its Kalasalingam Academy of Research and Education: Srivilliputhur, Tamil Nadu, IN, Full list of author information is available at the end of the article importance, Indian agriculture continues to face several structural, financial, and technological challenges that hinder sustainable agricultural growth and rural economic transformation [35, 36]. Farmers, particularly small and marginal landholders, often experience limited access to institutional credit, low financial literacy, dependency on informal money lenders, insufficient technological awareness, and inadequate digital infrastructure [37]. In addition, agricultural productivity is frequently affected by climate variability, unstable market conditions, fragmented landholdings, inefficient supply chain systems, and rising production costs, which significantly influence farmers' economic stability and sustainability [42].

The emergence of digital financial technologies provides significant opportunities to modernize agricultural systems and strengthen rural financial inclusion. Agricultural The term "fintech" describes how digital financial services and technologies are incorporated into agricultural operations. to facilitate financial transactions, improve access to credit, reduce transaction costs, strengthen risk management, and support smart agricultural practices [4, 24]. Farmers' access to financial resources and agricultural services is being increasingly transformed by technologies like digital wallets, digital lending platforms, online agricultural marketplaces, and mobile banking [27, 28]. Furthermore, digital financial systems can improve transparency, facilitate efficient subsidy distribution, enhance market participation, and strengthen farmers' economic resilience [39, 41].

In order to achieve sustainable agricultural development, digital agriculture and smart farming technologies have

grown in significance in recent years. Agricultural production and resource management are undergoing a revolution thanks to technologies like artificial intelligence, the Internet of Things (IoT), big data analytics, blockchain, satellite monitoring, and precision farming systems [29, 32]. These technologies can improve productivity, optimize resource utilization, reduce operational inefficiencies, and strengthen resilience against environmental and economic risks [21, 23]. Moreover, the integration of FinTech with smart agricultural technologies can significantly contribute to sustainable development, food security, rural economic growth, and financial inclusion [10, 33].

Although FinTech adoption has expanded rapidly in banking, e-commerce, and urban financial services, its adoption within the agricultural sector remains relatively limited, particularly among rural farmers in developing countries such as India [9]. The majority of the material currently available on FinTech adoption concentrates on urban consumers, banking clients, and organizational technology adoption [18, 19]. Comparatively fewer studies have examined farmers' behavioral intentions toward agricultural FinTech adoption in rural environments. Farmers often face additional barriers such as poor internet connectivity, low digital literacy, cybersecurity concerns, lack of technological awareness, trust-related issues, and limited institutional support [25, 38]. These barriers significantly influence farmers' willingness to adopt and continuously use FinTech services.

The Technology Acceptance Model (TAM), first put forth by Davis [14], has been widely used by researchers to comprehend users' technology adoption behavior.Perceived utility and perceived ease of use are the two main factors that TAM uses to explain technology acceptance. The model states that people are more likely to accept a technology if they think it enhances their performance and is simple to use [15]. TAM has been widely used in research on financial technology, e-commerce, digital banking, and mobile payments [17, 20]. However, agricultural Fin-Tech adoption in rural India involves additional behavioral and contextual factors that extend beyond the traditional TAM framework. Variables such as trust, government support, financial literacy, digital accessibility, and social influence may significantly influence farmers' attitudes and behavioral intentions toward adopting FinTech technologies [16, 18, 40]. The Indian government has implemented a number of programs and regulations to strengthen digital financial inclusion and smart agricultural transformation. Programs focusing on digital infrastructure, financial accessibility, and agricultural modernization aim to improve rural financial systems and encourage technology-driven agricultural development [34, 37]. However, farmers' behavioral adoption and ongoing use of digital financial tools are critical to the success of these projects. Due to worries about trust, complexity, pricing, security, and technical accessibility, many farmers are still reluctant to use FinTech services despite growing regulatory backing and technology breakthroughs [9, 31].

Thus, the current study uses an Extended Technology Acceptance Model (TAM) to examine the behavioral factors impacting agricultural FinTech uptake in India. Specifically, the study examines how Farmers' behavioral intentions to utilize FinTech services are influenced by perceived utility, perceived ease of use, trust, financial knowledge, government backing, and digital accessibility. The study also looks at how Fin-Tech adoption helps India's rural economic development, digital agricultural transformation, and sustainable financial inclusion.

This research specifically seeks to answer the following research questions:

- **RQ1:** What are the primary technological and behavioral elements affecting Indian farmers' use of FinTech services?
- **RQ2:** How do farmers' behavioral intentions toward the use of agricultural FinTech relate to perceived utility and perceived ease of use?
- **RQ3:** What roles do trust, financial literacy, and digital accessibility play in influencing FinTech adoption behavior among farmers?
- **RQ4:** How does government support contribute to sustainable financial inclusion and digital agricultural development through FinTech adoption?
- **RQ5:** How much does behavioral intention affect how FinTech services are actually used in India's agricultural sector?
- **RQ6:** How can FinTech adoption support sustainable agricultural transformation and rural economic development in India?

In order to contribute to sustainable agricultural development, financial inclusion, and rural economic growth, the current study intends to offer thorough insights into how FinTech can bridge the gap between traditional agricultural practices and contemporary digital technologies [10, 41]. It is anticipated that the results of this investigation will make significant theoretical advances to technology adoption literature and practical implications for policymakers, financial institutions, FinTech providers, and agricultural stakeholders seeking to strengthen sustainable digital agriculture and rural financial systems in India.

2 Review of the Literature

2.1 FinTech Overview

The term "financial technology" (FinTech) describes the incorporation of cutting-edge digital technologies into financial services to improve efficiency, accessibility, transparency, and customer experience within modern financial systems [1]. FinTech encompasses a range of digital financial services, including blockchain applications, digital wallets, online lending platforms, mobile banking, digital payment systems, and In-surTech solutions [3]. Artificial intelligence (AI), cloud computing, the Internet of Things (IoT), and big data analytics are examples of Industry 4.0 technologies that have advanced so quickly that they have expedited the growth and extension of FinTech throughout several sectors of the global economy [6].

The emergence of FinTech has transformed traditional banking and financial systems by introducing technology-driven platforms and digital service channels that facilitate faster transactions, lower operational costs, and improved financial accessibility [8]. By making financial services more accessible to underprivileged individuals, rural communities, and small enterprises that have limited access to traditional banking institutions, FinTech significantly contributes to financial inclusion in developing countries [5]. Moreover, FinTech contributes to sustainable economic development by reducing transaction barriers, improving financial transparency, and supporting digital economic transformation [10].

FinTech developments and digital financial services have been increasingly beneficial to the agricultural sector in recent years. The use of digital financial technology to enhance agricultural financing, digital payments, crop insurance, market accessibility, and smart farming operations is known as agricultural fintech [24]. Farmers may more effectively access financial resources, agricultural inputs, and market information thanks to technologies like blockchain-enabled supply chain systems, digital wallets, mobile banking apps, and online agricultural markets [27]. In addition, digital financial systems can strengthen agricultural productivity by improving access to institutional credit, reducing dependency on intermediaries, and facilitating transparent financial transactions [39].

Sustainable agricultural production and rural economic growth are further supported by the integration of FinTech with digital agriculture technologies including IoT, precision farming, artificial intelligence, and big data analytics [21]. These technologies enable farmers to improve resource management, monitor agricultural activities in real time, optimize production efficiency, and strengthen resilience against environmental and economic uncertainties [29]. Consequently, digital financial technologies are increasingly recognized as important tools for supporting sustainable agriculture, rural financial inclusion, and technology-driven agricultural transformation [33].

The adoption of digital financial services in rural and agricultural communities in India has accelerated due to government-led digital initiatives, smartphone penetration, internet accessibility, and the quick development of digital infrastructure [34]. Government programs focusing on digital inclusion and agricultural modernization have significantly improved financial accessibility and promoted cashless transaction systems among farmers and rural populations [37]. However, despite these advancements, obstacles such low digital literacy, insufficient technology understanding, poor internet access, trust issues, and cybersecurity threats continue to impede the adoption of FinTech services in agriculture [25]. Therefore, understanding the role of FinTech and the factors influencing its adoption is essential for promoting sustainable agricultural development, rural financial inclusion, and digital transformation in India [38].

2.2 The Indian Agricultural Sector's Challenges

Despite being one of the largest agricultural economies in the world, the Indian agricultural sector continues to face several structural, technological, financial, and environmental challenges that hinder sustainable agricultural development [35].The growing strain on agricultural resources brought on by fast population increase, dispersed landholdings, deteriorating soil fertility, and rising food consumption is one of the main issues. The long-term sustainability of farming systems is impacted by these problems, which place a heavy burden on land, water resources, and agricultural output [36].

Another major challenge is the low adoption of modern technologies and digital systems among farmers, particularly in rural and underdeveloped regions. Many farmers continue to rely on traditional farming methods due to limited technological awareness, inadequate digital literacy, and insufficient access to agricultural education and extension services [31]. In addition, weak digital infrastructure and poor internet connectivity in rural areas restrict farmers' ability to access modern agricultural technologies and digital financial services effectively [25]. The lack of technical training and awareness regarding smart farming technologies further limits the digital transformation of agriculture in India [29].

Financial exclusion also remains a serious issue affecting small and marginal farmers. A significant proportion of farmers have limited access to institutional credit, crop insurance, and formal banking systems because of collateral requirements, complex loan procedures, and perceived financial risks [37]. As a result, a lot of farmers still rely on unofficial lenders and non-institutional funding sources, which frequently lead to increased debt and financial instability [39]. Limited access to financial resources also reduces farmers' ability to invest in modern technologies, agricultural inputs, irrigation systems, and sustainable farming practices.

The agricultural sector in India is also highly vulnerable to climate change, environmental uncertainties, and external economic shocks. Irregular rainfall, floods, droughts, rising temperatures, and changing climatic conditions negatively affect crop productivity, food security, and farmers' income stability [42]. Additionally, vulnerabilities in agricultural supply chains, transportation networks, and market accessibility were revealed by interruptions brought on by incidents like the COVID-19 epidemic, especially for smallholder farmers [23]. These challenges significantly affected agricultural production, product distribution, and rural livelihoods.

The Indian government has launched a number of programs in recent years to improve financial inclusion, digital infrastructure, and agricultural modernization. The goal of initiatives supporting rural financial systems and digital agriculture is to increase farmers' access to technology and financial services [34]. However, despite these developments, the adoption of digital financial technologies and FinTech services among farmers remains relatively low due to trust issues, low digital skills, technological complexity, and lack of awareness regarding digital financial systems [38]. Therefore, addressing these challenges is essential for improving FinTech adoption and supporting sustainable agricultural transformation in India.

2.3 FinTech Adoption and Digital Transformation in Agriculture

FinTech advancements' incorporation into the agricultural industry has become increasingly important for promoting sustainable agricultural development, financial inclusion, and rural economic transformation [40]. The combination of digital financial technologies and smart agricultural systems has created new opportunities for improving agricultural productivity, market accessibility, financial management, and resource utilization. FinTech solutions enable farmers to access institutional credit, digital payment systems, crop insurance services, and agricultural marketplaces more efficiently, thereby reducing dependency on traditional financial systems and intermediaries [39].

Recent research has demonstrated the expanding significance of FinTech in promoting digital transformation and agricultural sustainability [24]. The adoption of digital financial technologies can significantly improve farmers' decision-making capabilities, increase access to financing, and strengthen agricultural supply chain systems [27]. Additionally, traditional agricultural practices are becoming more technologically advanced and efficient due to the integration of FinTech with digital agriculture technologies like blockchain, artificial intelligence (AI), IoT, big data analytics, and precision farming systems [21]. These technologies support real-time monitoring of agricultural activities, improve crop management, optimize resource utilization, and enhance productivity while reducing environmental risks [32].

Environmental preservation and sustainable agricultural methods are further benefits of digital agriculture technologies. Smart farming methods improve soil quality and agricultural efficiency while reducing overuse of pesticides, fertilizers, and water [29]. In addition, modern agricultural technologies create opportunities for improving transportation systems, agricultural logistics, market connectivity, and timely product delivery, thereby supporting responsible and sustainable agricultural production [33]. The use of technology-driven agricultural systems can therefore improve economic growth, reduce poverty, and strengthen rural livelihoods.

FinTech advancements also significantly contribute to farmers' increased financial accessibility. Farmers now have easier access to financial services and agricultural inputs thanks to mobile banking apps, digital wallets, online loan platforms, and digital payment systems [4]. Financial literacy initiatives and digital financial platforms further help farmers understand and utilize modern financial technologies effectively [9]. Moreover, digital financial systems reduce financing costs, improve transaction transparency, and expand financial service accessibility to remote and underserved rural areas [10].

The use of smart farming systems and precision agriculture technologies improves agricultural productivity and management even more. Farmers may monitor agricultural conditions, identify pests, control irrigation systems, and increase production efficiency with the use of technologies like drones, satellite monitoring, IoT sensors, and AI-based systems [25]. These technologies provide accurate and real-time agricultural information that supports better decision-making and efficient resource management [22]. As a result, digital financial technologies and smart agricultural innovations are increasingly recognized as essential drivers of sustainable agricultural transformation and rural economic development in India [23].

2.4 Extended TAM Framework for Agricultural FinTech One of the most popular theoretical models for understanding users'

acceptance and adoption of new technologies is the Technology Acceptance Model (TAM), which was first put forth by Davis [14]. TAM was created as an expansion of Ajzen [12]'s Theory of Reasoned Action (TRA), which explains how people's intentions, attitudes, and beliefs affect their actual action. According to TAM, perceived usefulness (PU) and perceived ease of use (PEOU) are the two fundamental factors that influence technology adoption behavior. Users' views on the adoption of technology are influenced by these elements, which in turn impact their behavioral intentions and actual usage behavior [15].

TAM offers a suitable theoretical framework for comprehending how farmers view and use digital financial technology in the context of agricultural FinTech adoption.Farmers' financial accessibility, operational efficiency, and decision-making skills can be enhanced by agricultural FinTech services such digital payments, online lending platforms, crop insurance applications, mobile banking, and digital agricultural marketplaces [24]. However, farmers' willingness to adopt these technologies largely depends on their perceptions regarding usefulness, simplicity, reliability, and trustworthiness. The degree to which farmers feel that utilizing Fin-Tech services might enhance farming efficiency, financial management, and agricultural productivity is known as perceived usefulness (PU) [14]. Farmers are more inclined to use digital financial technology if they believe that doing so will improve their access to finance, lower transaction costs, increase market involvement, and improve farming operations. Similarly, farmers' perception of how simple it is to understand and use FinTech services without a lot of technical complexity is known as Perceived Ease of Use (PEOU) [15]. Technologies that are user-friendly and require less technical expertise are expected to encourage higher adoption rates among farmers.

Trust is another important factor influencing agricultural FinTech adoption. Since digital financial systems involve online transactions and financial information sharing, farmers' confidence in the security, reliability, and credibility of FinTech platforms significantly affects their adoption behavior [17].Farmers are more inclined to accept FinTech services when they perceive that these technologies are secure and trustworthy. In contrast, worries over financial risks, cybersecurity dangers, and privacy issues may negatively influence their attitudes toward technology adoption [16].

FinTech uptake in agriculture is also greatly aided by government funding. Government initiatives related to digital infrastructure, financial inclusion, training programs, and agricultural modernization can improve farmers' awareness and accessibility to digital financial technologies [40]. In addition, social influence significantly affects farmers' adoption decisions, particularly in rural communities where technology-related decisions are often influenced by peer groups, local communities, extension workers, and social networks [19]. This study offers an expanded conceptual framework to investigate the elements impacting FinTech uptake in Indian agriculture, based

on the TAM framework and other research. Farmers' Attitude Toward Using FinTech (ATU) is influenced by a number of important factors, including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TR), Government Support (GS), and Social Influence (SI). Behavioral Intention (BI), which in turn drives the Actual Adoption of FinTech services in agriculture, is further influenced
by attitudes toward employing FinTech.
Based on the above discussion, the following hypotheses are proposed:
• **H1:** The Actual Adoption (AU) of FinTech in agriculture is positively impacted by Behavioral Intention (BI).
• **H2:** Attitude Toward Using FinTech (ATU) positively influences Behavioral Intention (BI).
• **H3:** Behavioral Intention (BI) is favorably influenced by Perceived Ease of Use (PEOU).

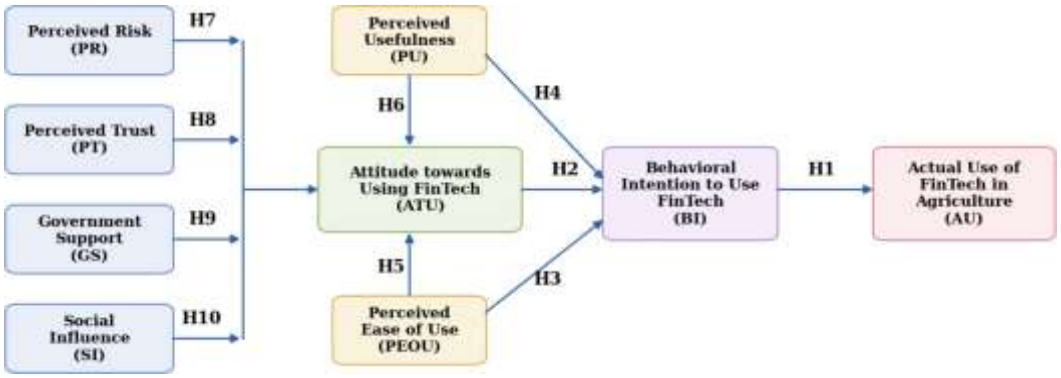

Figure 1 proposed conceptual framework for applying the Extended Technology Acceptance Model (TAM) to analyze FinTech adoption behavior in Indian agriculture.

• **H4:** Behavioral Intention (BI) is favorably influenced by Perceived Usefulness (PU).
• **H5:** Attitude Toward Using FinTech (ATU) is positively impacted by Perceived Ease of Use (PEOU).
• **H6:** Attitude Towards Using FinTech (ATU) is positively impacted by perceived usefulness (PU).
• **H7:** Trust (TR) positively influences Attitude Toward Using FinTech (ATU).
• **H8:** Government Support (GS) positively influences Attitude Toward Using FinTech (ATU).
• **H9:** Social Influence (SI) positively influences Attitude Toward Using FinTech (ATU).
According to the suggested paradigm, farmers' opinions about FinTech adoption are influenced by a variety of factors, including utility, ease of use, trust, government backing, and social impact. These attitudes subsequently influence behavioral intentions and actual adoption behavior. As a result, the framework offers a thorough grasp of the technological and behavioral aspects influencing FinTech adoption in Indian agriculture as well as its role in digital financial inclusion, sustainable agricultural development, and rural economic transformation.

3 Methodology

The factors impacting the adoption of Financial Technology (FinTech) in India's agriculture sector are examined in this study using a quantitative research design. The opinions, attitudes, and behavioral intentions of farmers about the employment of digital financial technologies in agricultural activities were investigated using a cross-sectional survey approach. The quantitative approach enables the study to analyze the relationships among multiple variables within the proposed Extended Technology Acceptance Model (TAM) framework and provides a comprehensive understanding of the determinants influencing agricultural Fin-Tech adoption.
Farmers, agribusiness participants, and rural agricultural stakeholders who are actively engaged in agricultural activities and have access to digital financial services comprise the study's target group. To produce a representative sample from various agricultural regions in India, a multi-stage sampling methodology combining purposive and random sampling methods was used. Initially, purposive sampling was used to identify major agricultural regions with significant farming activities and increasing digital financial participation. Subsequently, random sampling was applied to select individual respondents from these regions.
For the study, 400 respondents in total were chosen. According to Structural Equation Modeling (SEM) recommendations, which suggest optimal sample sizes for testing complicated theoretical models incorporating numerous components and hypotheses, the sample size is deemed appropriate [21]. In addition, previous studies related to TAM and FinTech adoption have commonly used sample sizes ranging between 200 and 500 respondents to ensure sufficient statistical power and reliability [9].
A systematic survey that was developed after a thorough analysis of prior research and verified measuring scales was used to collect data. The questionnaire was designed to capture demographic information and measure the constructs included in the proposed conceptual framework, specifically Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TR), Government Support (GS), Social Influence (SI), Attitude Toward FinTech Use (ATU), Behavioral Intention (BI), and Actual Adoption (AU). To guarantee content validity and reliability, the questionnaire items were modified from well-known TAM and FinTech adoption studies.
To improve clarity and understanding among respondents, the questionnaire was prepared in simple language and translated into regional languages where necessary. Data were collected through direct interaction with respondents,

including face-to-face surveys and assisted questionnaire administration in rural areas where digital literacy and educational levels may be limited. A pilot research with thirty respondents was carried out before the final survey to assess the reliability, relevance, and clarity of the questionnaire items. Feedback from the pilot testing phase was used to make the necessary adjustments.

A 7-point Likert scale, with 1 denoting "strongly dis-agree" and 7 denoting "strongly agree," was used to measure each component. Items modified from Davis's Technology Acceptance Model [14] were used to measure perceived usefulness and perceived ease of use. Scales modified from earlier research on technology adoption and digital banking systems were used to measure the constructs of trust, government support, and social influence [17, 19]. Behavioral Intention and Actual Adoption were measured using items reflecting respondents' willingness and actual usage behavior regarding FinTech services in agriculture.

Structural Equation Modeling (SEM) using Smart-PLS software and the Statistical Package for the Social Sciences (SPSS) were used to evaluate the gathered data. The demographic traits and overall response trends of the respondents were compiled using descriptive statistics. Cronbach's alpha and Composite Reliability (CR) were used for reliability analysis; values greater than 0.70 signify acceptable internal consistency. Average Variance Extracted (AVE) was used to measure convergent validity, while the Heterotrait–Monotrait Ratio (HTMT) was used to measure discriminant validity.

In order to investigate the direct connections between the constructs in the conceptual model, the suggested hypotheses were investigated using route analysis within the SEM framework. Path coefficients, T-statistics, and p-values were used to assess the importance of the proposed correlations. Statistical significance was defined as a p-value of less than 0.05. Furthermore, bootstrapping techniques were used to evaluate the robustness and stability of the calculated model parameters and hypothesis testing outcomes.

4 Analysis of Data and Findings

4.1 Features of Respondents

The demographic details of the study participants are shown in this section (see Table 1). The information was gathered in order to comprehend the technological profile and background of farmers and other agricultural stakeholders included in the study. Variables such as age, gender, education level, farming experience, income level, smartphone usage, internet accessibility, and experience with digital financial services were analyzed.

Among the 400 respondents, 71.00% were male (284 respondents), whereas 29.00% were female (116 respondents), indicating that male participants constituted the majority of respondents in the agricultural sector. The age distribution shows that the largest group of respondents, representing 34.00%, belonged to the 36–45 years category (136 respondents), followed by 29.50% in the 25–35 years category (118 respondents). Respondents below 25 years accounted for 10.50% (42 respondents), while those above 55 years
represented 7.50% (30 respondents). This indicates that most respondents belonged to the economically active and experienced farming population, which may influence their perception and adoption of FinTech services.

The respondents also exhibited diverse educational backgrounds. A total of 24.00% (96 respondents) had primary education or below, while 32.00% (128 respondents) completed secondary education. Furthermore, 26.00% (104 respondents) possessed undergraduate qualifications, and 18.00% (72 respondents) had postgraduate degrees. The educational profile suggests that a considerable proportion of respondents possessed moderate educational qualifications, which may significantly influence their awareness, understanding, and acceptance of digital financial technologies and FinTech services in agriculture.

The respondents' demographics offer valuable insights into the technological and socioeconomic elements driving FinTech adoption in India's agricultural industry. These characteristics may affect farmers' attitudes, intentions for behavior, and actual usage of digital financial technologies for agricultural activities.

Table 1 Respondents' Demographic Profile

Variables	Categories	Frequency	Percentage
Gender of respondent	Male	284	71.00
	Female	116	29.00
Respondent's age	Less than 25 years old	42	10.50
	25–35 years old	118	29.50
	36–45 years old	136	34.00
	46–55 years old	74	18.50
	Above 55 years old	30	7.50
Level of education	Primary or Below	96	24.00
	Secondary Education	128	32.00
	Undergraduate	104	26.00
	Postgraduate	72	18.00
Monthly income	Less than 10,000	88	22.00
	10,000–20,000	112	28.00
	20,001–30,000	84	21.00
	30,001–40,000	69	17.25
	Above 40,000	47	11.75
Region of operation	Tamil Nadu	74	18.50
	Karnataka	62	15.50
	Andhra Pradesh	58	14.50
	Telangana	49	12.25
	Kerala	41	10.25
	Maharashtra	67	16.75
	Punjab	27	6.75
	Uttar Pradesh	22	5.50
Years engaged in agriculture	Less than 5 years	68	17.00
	5–10 years	116	29.00
	11–20 years	138	34.50
	More than 20 years	78	19.50

4.2 Preliminary Statistical Analysis

The preliminary statistical analysis of the research variables, including multicollinearity evaluation and descriptive

statistics, is shown in Table 2. All con-structs' Variance Inflation Factor (VIF) values fell within the allowed range, suggesting that there are no appreciable multicollinearity problems between the independent variables. The constructs' acceptability for additional statistical analysis was confirmed by the fact that all VIF values stayed below the suggested limit of 5 [21].

The descriptive statistics indicate moderate standard deviation values, suggesting reasonable variability in respondents' perceptions regarding FinTech adoption in the agricultural sector. The factors' mean scores show that opinions about the application of digital financial technologies in agriculture are usually favourable.

Additionally, the distribution patterns of the variables did not exhibit any significant departures from normalcy, and the skewness and kurtosis values indicated that the data meet the normality requirements needed for structural equation modelling (SEM). There were no significant departures from normalcy in the variable distribution patterns. Overall, the statistical results confirm that the collected data are reliable and appropriate for further empirical analysis and hypothesis testing within the proposed research framework.

Table 2 Preliminary Statistical Analysis

Variables	VIF	Std. Deviation	Skewness	Kurtosis
TR	1.284	1.56342	−1.186	0.742
GS	1.331	1.48725	−1.274	0.915
SI	1.194	1.42163	−1.337	1.106
PU	1.102	1.53874	−0.954	0.284
PEOU	1.218	1.47218	−1.041	0.518
ATU	1.156	1.50632	−1.097	0.673
BI	1.000	1.54791	−0.986	0.321
AU	–	1.43267	−1.118	0.884

The profiles of the respondents offer valuable insights into the factors driving FinTech (financial technology) adoption in India's agriculture industry. Understanding these demographic and technological factors helps explain farmers' attitudes, behavioral intentions, and actual usage of FinTech services in agricultural activities.

4.3 Model Fit Assessment

The model fit evaluation results for the suggested study framework using various goodness-of-fit indices are shown in Table 3. Both the saturated and estimated models' Standardised Root Mean Square Residual (SRMR) values were below the suggested cutoff of 0.08, suggesting a satisfactory model fit and high prediction accuracy of the suggested framework [21].

The discrepancy measures, including d_{ULS} and d_G, also showed acceptable values for both models, suggesting that the differences between the observed and estimated covariance matrices were within an acceptable range. In addition, the chi-square values of the estimated model remained within tolerable limits, confirming the adequacy of the structural model.

Additionally, both the saturated and estimated models showed appropriate levels of model fitness according to the Normed Fit Index (NFI) values. The suggested Extended Technology Acceptance Model (TAM) framework is statistically sound and appropriate for investigating the elements impacting FinTech uptake in the Indian agriculture industry, as shown by the overall goodness-of-fit statistics. As a result, the model is suitable for additional structural analysis and hypothesis testing.

Table 3 Model Fit Assessment

Fit Measures	Baseline Model	Structural Model
SRMR	0.071	0.074
d_{ULS}	2.364	3.982
d_G	0.914	1.062
Chi-square	2486.317	2698.451
NFI	0.892	0.903

4.4 Reliability and Validity Analysis

The measurement model's validity and reliability evaluation for the suggested study framework is shown in Table 4. Strong item reliability and sufficient construct representation were indicated by the factor loadings of all measuring items exceeding the suggested criterion of 0.70 [21].

All constructs' Cronbach's alpha (CA) and Composite Reliability (CR) values were higher than the acceptable cutoff of 0.70, indicating that the measuring scales' internal consistency and reliability were satisfactory. Furthermore, all constructs' Average Variance Extracted (AVE) values were higher than the suggested value of 0.50, indicating sufficient convergent validity amongst the measuring items.

The measurement model has strong psychometric qualities, and the constructs utilised in the suggested Extended Technology Acceptance Model (TAM) framework are dependable and appropriate for additional structural model analysis and hypothesis testing, according to the reliability and validity results.

4.5 Discriminant Validity Assessment

The Heterotrait–Monotrait Ratio (HTMT) matrix used to evaluate the discriminant validity of the components

included in the suggested study framework is shown in Table 5. All constructs' HTMT values were below the suggested cutoff of 0.90, demonstrating adequate discriminant validity and verifying that the constructs differ statistically from one another [21].

The results demonstrate that the correlations among the constructs remain within acceptable limits, sug-gesting that each construct measures a unique concept within the proposed Extended Technology Acceptance Model (TAM) framework. Moderate relationships were observed between Behavioral Intention (BI) and Actual Adoption (AU), as well as between Attitude Toward Using FinTech (ATU) and Behavioral Intention (BI), indicating meaningful associations while maintaining construct distinctiveness.

Further supporting the measuring model's discriminant validity were comparatively lower HTMT values between Perceived Ease of Use (PEOU), Social Influence (SI), and other dimensions. All things considered, the HTMT analysis confirms that the suggested constructs are empirically unique and appropriate for additional structural model assessment and hypothesis testing..

Table 5 HTMT Discriminant Validity Matrix

Constructs	ATU	AU	BI	PEOU	GS	SI	TR	PU
ATU	—							
AU	0.582	—						
BI	0.614	0.792	—					
PEOU	0.168	0.184	0.247	—				
GS	0.438	0.571	0.486	0.214	—			
SI	0.082	0.116	0.094	0.137	0.341	—		
TR	0.351	0.602	0.471	0.301	0.654	0.274	—	
PU	0.428	0.446	0.553	0.162	0.287	0.074	0.158	—

ATU	0.831						
AU	0.514	0.810					
BI	0.536	0.701	0.807				
PEOU	−0.094	−0.126	−0.188	0.911			
GS	0.382	0.472	0.398	−0.147	0.788		
SI	0.071	0.063	0.041	0.118	0.264	0.842	
TR	0.281	0.426	0.351	−0.214	0.468	0.223	0.811
PU	0.391	0.402	0.481	−0.083	0.246	0.037	0.126 0.849

Fornell–Larcker Discriminant Validity Analysis

The results of the Fornell–Larcker criterion used to assess the discriminant validity of the constructs contained in the suggested study framework are shown in Table 6. The square roots of the Average Variance Extracted (AVE) for each construct are represented by the diagonal values in the matrix. The Fornell–Larcker criterion states that each construct's square root of the AVE must be higher than its correlations with other constructs in the model [21]. The findings show that for every construct, the square root values of the AVEs were consistently greater than the corresponding inter-construct correlation values. For instance, compared to its associations with Behavioural Intention (BI), Actual Adoption (AU), and other constructs, the square root of the AVE for Attitude Towards Using FinTech (ATU) was higher. Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TR), Government Support (GS), and Social Influence (SI) all showed similar trends.

These results verify that every construct in the suggested Extended Technology Acceptance Model (TAM) framework measures a distinct notion and is empirically distinct, with little to no overlap with other constructs. As a result, the Fornell–Larcker criterion supports the measurement model's eligibility for additional structural model analysis and hypothesis testing by confirming its satisfactory discriminant validity.

Table 6 Analysis of Fornell-Larcker Discriminant Validity

Constructs	ATU	AU	BI	PEOU	GS	SI	TR	PU
ATU	0.831							
AU	0.514	0.810						
BI	0.536	0.701	0.807					
PEOU	−0.094	−0.126	−0.188	0.911				
GS	0.382	0.472	0.398	−0.147	0.788			
SI	0.071	0.063	0.041	0.118	0.264	0.842		
TR	0.281	0.426	0.351	−0.214	0.468	0.223	0.811	
PU	0.391	0.402	0.481	−0.083	0.246	0.037	0.126	0.849

4.6 Assessment of Endogenous Constructs

The coefficient of determination (R^2) and adjusted R^2 values for the endogenous constructs included in the suggested study framework are shown in Table 7. These numbers show how well the model predicts changes

in the major constructs related to FinTech adoption in the agriculture industry.
The R^2 value for Attitude Toward Using FinTech (ATU) indicates that a substantial proportion of the variation in farmers' attitudes is explained by the independent variables included in the model. Similarly, the R^2 value for Behavioral Intention (BI) demonstrates that the proposed framework effectively explains farm-ers' intentions to adopt FinTech services in agricultural activities. In addition, the R^2 value for Actual Adoption (AU) confirms that the model adequately explains the actual usage behavior of FinTech services among farmers.

Table 4 Analysis of Validity and Reliability

Construct	Item Code	Factor Loading	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
	TR1	0.842	0.821	0.884	0.657
Trust (TR)	TR2	0.801			
	TR3	0.786			
	GS1	0.824	0.798	0.867	0.621
Government Support (GS)	GS2	0.817			
	GS3	0.742			
	SI1	0.873	0.861	0.907	0.709
Social Influence (SI)	SI2	0.851			
	SI3	0.798			
	PU1	0.846	0.872	0.912	0.722
Perceived Usefulness (PU)	PU2 PU3	0.891 0.834			
	PU4	0.816			
	PEOU1	0.918	0.903	0.936	0.831
Perceived Ease of Use (PEOU)	PEOU2	0.904			
	PEOU3	0.887			
	ATU1	0.861	0.889	0.918	0.691
	ATU2	0.782			
Attitude Toward Using FinTech (ATU)	ATU3	0.847			
	ATU4	0.876			
	ATU5	0.801			
	BI1	0.852	0.816	0.881	0.651
Behavioral Intention (BI)	BI2 BI3	0.791 0.824			
	BI4	0.756			
	AU1	0.844	0.742	0.851	0.656
Actual Adoption (AU)	AU2	0.793			
	AU3	0.781			

The adjusted R^2 values are also closely aligned with the corresponding R^2 values, indicating the stability and reliability of the proposed model after adjusting for the number of predictor variables. Overall, the results demonstrate that the proposed Extended Technology Acceptance Model (TAM) framework possesses strong explanatory power and effectively predicts Fin-Tech adoption behavior in the Indian agricultural sector.

Table 7 Assessment of Endogenous Constructs

Endogenous Constructs	R-square (R^2)	Adjusted R-square
ATU	0.861	0.847
AU	0.672	0.664
BI	0.701	0.693

4.7 Hypothesis Testing Results

The Extended Technology Acceptance Model (TAM) framework's hypothesis testing results are shown in Table 8. To ascertain the importance of the correlations between the constructs, the hypotheses were assessed using path coefficients (beta values), standard deviation (STDEV), T-statistics, and p-values.
The findings show strong correlations between the factors impacting FinTech adoption in the agricultural industry and show that the majority of the assumptions put forth were statistically supported. The results demonstrate that Actual Adoption (AU) of Fin-Tech services is strongly positively influenced by Behavioural Intention (BI), suggesting that farmers with stronger intentions are more likely to use digital financial technologies in their farming operations. Similar positive impacts on Behavioural Intention (BI) were demonstrated by Attitude Towards Using FinTech (ATU), Perceived Ease of Use (PEOU), and Perceived utility (PU), underscoring the significance of usability and utility in influencing farmers' adoption intentions. The results also reveal that Perceived Usefulness (PU), Trust (TR), and Government Support (GS) significantly influence

farmers' attitudes toward using FinTech services.
However, some relationships showed weaker or statistically insignificant effects, suggesting that not all external variables equally influence farmers' attitudes and aspirations to adopt FinTech through behaviour. Overall, the hypothesis testing results support the proposed conceptual framework and confirm the significant role of technological, behavioral, and institutional factors in encouraging the use of FinTech in India's agriculture industry.
Perceived Ease of Use (PEOU) does not significantly affect farmers' Attitude Towards Using Fin-Tech (ATU), according to H_5 (PEOU → ATU), which showed a statistically insignificant relationship with a low beta coefficient of 0.084, a T-statistic of 1.914, and a p-value greater than 0.05. This finding suggests that ease of use alone may not be sufficient to shape positive attitudes toward FinTech adoption in the agricultural sector.
In contrast, H_6 (PU → ATU), H_7 (TR → ATU), and H_8 (GS → ATU) were statistically supported, indicating that Perceived Usefulness (PU), Trust (TR), and Government Support (GS) significantly influence farmers' attitudes toward FinTech adoption. Among

Table 8 Path coefficients for hypothesis testing

Hypotheses	Paths	Beta	STDEV	T statistics	P values	Results
H_1	BI → AU	0.701	0.031	22.184	0.000	Recommended
H_2	ATU → BI	0.418	0.049	8.532	0.000	Recommended
H_3	PEOU → BI	0.163	0.041	3.972	0.000	Recommended
H_4	PU → BI	0.312	0.056	5.571	0.000	Recommended
H_5	PEOU → ATU	0.084	0.044	1.914	0.056	Not Recommended
H_6	PU → ATU	0.281	0.059	4.763	0.000	Recommended
H_7	TR → ATU	0.214	0.052	4.118	0.000	Recommended
H_8	GS → ATU	0.228	0.057	3.998	0.000	Recommended
H_9	SI → ATU	0.041	0.047	0.874	0.382	Not Recommended

these relationships, Attitude Towards Using FinTech was significantly positively impacted by perceived use-fulness,highlighting the importance of practical benefits and performance improvement in encouraging adoption behavior.
On the other hand, H_9 (SI → ATU) was not supported, as Social Influence (SI) showed an insignificant relationship with Attitude Toward Using Fin-Tech. This finding suggests that farmers' attitudes towards the use of FinTech services in agriculture may not be significantly influenced by peer pressure or societal pressure. Overall, the results indicate that when it comes to influencing FinTech adoption behaviour among Indian farmers, usefulness, trust, and institutional support are more significant than social influence and usability.
The estimated Structural Equation Model (SEM) showing the links between the constructs impacting FinTech adoption in the Indian agricultural industry is shown in Figure 2. Based on the suggested Extended Technology Acceptance Model (TAM), the findings demonstrate that Actual Adoption (AU) of FinTech services is strongly positively impacted by Behavioural Intention (BI). This suggests that farmers who have stronger behavioural intentions are more likely to use digital financial technologies in their agricultural operations.
The model further demonstrates that Attitude Toward Using FinTech (ATU) significantly influences Behavioral Intention (BI), suggesting that positive attitudes toward FinTech increase farmers' willingness to adopt such technologies. Perceived Usefulness (PU) emerged as one of the strongest determinants affecting both Attitude Toward Using FinTech (ATU) and Behavioural Intention (BI), which shows that when farmers believe FinTech will increase agricultural productivity, financial accessibility, and operational efficiency, they are more likely to adopt technology.
Although its effect on Attitude Towards Using Fin-Tech (ATU) was comparatively weaker and statistically insignificant, Perceived Ease of Use (PEOU) also demonstrated a positive influence on Behavioural Intention (BI). This finding suggests that ease of use alone may not be sufficient to shape favourable attitudes among farmers unless the technology also offers clear practical benefits. This conclusion implies that unless the technology also offers obvious practical advantages, ease of use might not be enough to influence positive sentiments among farmers.
In addition, Trust (TR) and Government Support (GS) demonstrated significant positive effects on farm-ers' attitudes toward FinTech adoption, highlighting the importance of institutional support, security, and confidence in digital financial systems. Conversely, Social Influence (SI) exhibited a weaker and statistically insignificant relationship with Attitude Toward Using FinTech, indicating that social pressure and peer influence may not substantially affect farmers' FinTech adoption decisions in this context.
Because the observed variables had acceptable psychometric qualities and appropriate standardised factor loadings, the measurement model also showed strong validity and reliability. Overall, the structural model demonstrates that the adoption of FinTech in the Indian agricultural industry is mostly driven by Perceived Usefulness, Behavioural Intention, Trust, and Government Support, promoting both digital financial inclusion and sustainable agricultural development.

5 Discussion

By using the Extended Technology Acceptance Model (TAM), the results of this study offer significant insights into the variables impacting FinTech uptake in the Indian agricultural sector. The results confirm that Behavioral Intention (BI) and Perceived Usefulness (PU) are among the most significant determinants of FinTech adoption

among farmers. These findings are consistent with the core assumptions of TAM, which suggest that individuals are more likely to use technology if they believe it will help them perform better and

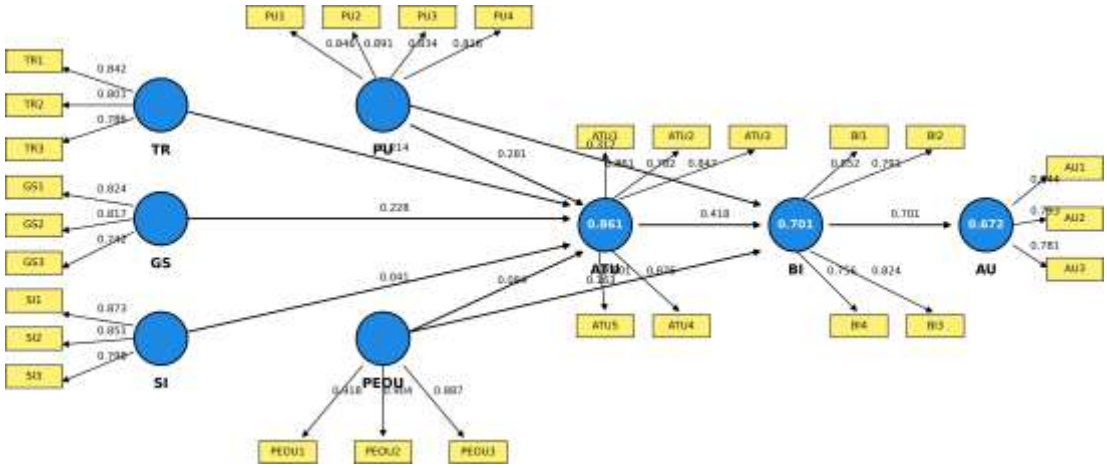

Figure 2 Structural Equation Model (SEM) illustrating the relationships among the constructs influencing FinTech adoption behavior in the Indian agricultural sector based on the proposed Extended Technology Acceptance Model (TAM).

be more productive [15].FinTech services that enhance access to digital payments, agricultural loans, crop insurance, and financial management solutions seem to be valued by farmers.

The study also demonstrates that Attitude Toward Using FinTech (ATU) significantly influences Behavioral Intention (BI), which subsequently affects Actual Adoption (AU) of FinTech services. This finding indicates that positive attitudes toward digital financial technologies play a major role in encouraging farmers to adopt such technologies in agricultural activities. The robust correlation between BI and AU provides more evidence that farmers' actual technology usage behaviour is still directly predicted by their behavioural intention.

Another important finding is the significant impact of Trust (TR) and Government Support (GS) on farm-ers' attitudes toward FinTech adoption. Farmers are more likely to have favourable opinions on digital financial systems. when they trust the security, reliability, and effectiveness of FinTech platforms. Similarly, supportive government initiatives, digital infrastructure development, training programs, and financial inclusion policies contribute positively toward enhancing technology adoption in rural agricultural communities. These results emphasise how crucial trust-building strategies and institutional assistance are to speeding the digital revolution of agriculture. It's interesting to note that there was no statistically significant correlation between Attitude Towards Using FinTech (ATU) and Perceived Ease of Use (PEOU). This suggests that farmers may prioritize the practical usefulness and economic benefits of FinTech services over the simplicity or ease of operating the technology. Farmers appear willing to adopt digital financial technologies if the technologies effectively address challenges related to financing, market access, and agricultural productivity, even when some learning effort is required.

Similarly, Social Influence (SI) showed an insignificant impact on Attitude Toward Using FinTech. This finding indicates that peer influence and social pressure may not strongly affect farmers' decisions regarding FinTech adoption in the Indian agricultural sector. Instead, farmers may rely more on their personal experiences, perceived benefits, and institutional support when making decisions about adopting digital financial technologies.

This study's focus on FinTech adoption in India's agriculture sector, which is still largely unexplored in the literature, is one of its significant contributions. By extending the TAM framework with additional constructs such as Trust, Government Support, and Social Influence, the study provides a broader understanding of the behavioral, technological, and institutional factors influencing FinTech adoption among farmers.

Overall, the results indicate that advancing digital financial inclusion and sustainable agricultural development in India requires boosting government support systems, bolstering digital trust, and raising the perceived value of FinTech services. Policymakers, financial institutions, and FinTech companies looking to increase rural farming communities' use of digital financial technologies can also benefit from the study's practical implications.

6 Conclusion

Using the Extended Technology Acceptance Model (TAM), this study examined the factors influencing FinTech adoption in the Indian agricultural sector. The results show that farmers' adoption of FinTech services is significantly influenced by Behavioural Intention (BI), Perceived Usefulness (PU), Trust (TR), and Government Support (GS). The study also confirms that Behavioural Intention is the strongest predictor of Actual Adoption (AU), meaning that farmers who have stronger intentions towards digital financial technologies

are more likely to use them in agricultural activities. The results show that farmers' adoption of FinTech services is strongly influenced by Behavioural Intention (BI), Perceived Usefulness (PU), Trust (TR), and Government Support (GS). The study also shows that the best predictor of Actual Adoption (AU) is Behavioural Intention, meaning that farmers who have more positive intents regarding digital financial technology are more likely to use them in their farming operations.

The findings also demonstrate that Behavioural Intention (BI) is positively impacted by Attitude Towards Using FinTech (ATU), highlighting the significance of favourable user experiences and perceptions in promoting FinTech adoption. One of the most significant factors influencing attitude and behavioural intention was found to be Perceived Usefulness (PU). This suggests that farmers are more inclined to adopt FinTech solutions when they perceive clear practical benefits like enhanced financial access, secure transactions, digital payments, agricultural loans, and improved farm management support.

Perceived Ease of Use (PEOU) has a positive impact on Behavioural Intention (BI), but it has no statistically significant effect on Attitude Towards Using FinTech (ATU). This research suggests that FinTech services' efficacy and utility are more important to Indian farmers than the technology's ease of use. If digital finance systems successfully solve their financial and agricultural problems, farmers are eager to embrace them.

Farmers are more likely to adopt FinTech services when they have faith in the dependability and security of digital platforms and when there are sufficient government initiatives, digital infrastructure, training programmes, and policy support available. In contrast, Social Influence (SI) was found to have an insignificant effect on farmers' attitudes, indicating that personal experience and perceived benefits are more significant than peer influence in determining FinTech adoption behaviour. When there are sufficient government efforts, digital infrastructure, training programmes, and policy support available, as well as when farmers have faith in the dependability and security of digital platforms, they are more inclined to use FinTech services. Conversely, farmers' views were found to be insignif-icantly impacted by Social Influence (SI), indicating that social pressure is less significant in influencing FinTech adoption behaviour than personal experience and perceived benefits.

By expanding the TAM framework in the context of Indian agriculture and incorporating other constructs like Trust, Government Support, and Social Influence, this study adds to the body of literature. The results have important ramifications for financial institutions, FinTech companies, and policymakers who want to enhance digital financial inclusion and sustainable agricultural development in India. For legislators, financial organisations, and FinTech companies looking to enhance digital financial inclusion and sustainable agricultural growth in India, the findings have important ramifications.

Overall, the report indicates that key tactics for boosting FinTech acceptance among farmers include increasing the practical utility of FinTech services, bolstering digital confidence, upgrading rural digital infrastructure, and offering efficient government support. The impact of digital literacy, cultural variables, technological awareness, and regional variations on Fin-Tech adoption behaviour in rural agricultural areas may be further investigated in future studies.

6.1 Implications for Policy

The study's conclusions have significant policy ramifications for boosting FinTech adoption in India's agriculture industry. First, increasing farmers' adoption of digital financial technologies requires raising their level of digital financial literacy. Policymakers should implement focused awareness and training programmes that highlight the useful advantages of FinTech services in agricultural financing, digital payments, crop insurance, and farm management since Behavioural Intention (BI) and Perceived Usefulness (PU) have a substantial impact on FinTech adoption. These programmes can aid farmers in comprehending and making efficient use of digital financial platforms.

Second, strengthening digital infrastructure in rural areas is crucial for promoting inclusive FinTech adop- tion. Limited internet connectivity, inadequate digital facilities, and technological barriers continue to restrict the effective use of FinTech services among farmers. Therefore, government agencies should prioritize investments in rural broadband connectivity, mobile network expansion, and digital service accessibility to support the digital transformation of agriculture.

Third, the significant influence of Trust (TR) on farmers' attitudes toward FinTech highlights the need for secure and reliable digital financial systems. Financial institutions and FinTech providers should enhance cybersecurity measures, ensure transaction transparency, and implement strong data privacy protections to increase users' confidence in digital platforms. Improving long-term adoption and usage of Fin-Tech services requires fostering trust among farmers.

Additionally, positive attitudes regarding the adoption of FinTech are shaped in large part by Government Support (GS). Policy-makers should therefore encourage collaboration between government agencies, agricultural institutions, financial service providers, and FinTech companies to develop farmer-friendly digital financial solutions. Providing subsidies, low-interest agricultural digital loans, digital training schemes, and financial incentives can further motivate farmers to adopt FinTech services.

In addition, integrating advanced technologies such as artificial intelligence, IoT-based monitoring systems, digital marketplaces, and mobile-based agricultural advisory services into FinTech platforms can improve agricultural productivity and sustainability. Fin-Tech platforms that offer weather forecasting, crop monitoring, market price information, and financial planning tools may significantly increase the perceived usefulness of digital technologies among farmers.

Overall, these policy measures can strengthen financial inclusion, accelerate digital transformation in agriculture, improve farmers' access to financial services, and encourage India's agricultural development to be sustainable.

6.2 Limitations and Future Research Directions

Several limitations should be noted, despite the fact that this study offers insightful information about the factors impacting FinTech adoption in the Indian agriculture industry. First, the study's primary focus was on respondents from particular Indian agricultural regions, which may limit the findings' applicability to all rural and agricultural groups. In order to assess Fin-Tech adoption behaviour under various socioeconomic and cultural contexts, future research may expand to other areas and developing nations.

Second, the study's cross-sectional research design makes it more difficult to track shifts in farmers' at- titudes and adoption patterns over time. Longitudinal studies could be used in future research to investigate how FinTech adoption changes in response to policy changes, technological advancements, and farmers' growing digital awareness.

Third, the Extended Technology Acceptance Model (TAM) framework's behavioural and technological components were the primary focus of this study. Not much research was done on external factors including internet accessibility, digital infrastructure, financial limitations, and regional technological inequalities. These factors could be included in future research to give a more thorough picture of the obstacles preventing rural agricultural communities from adopting FinTech.

Additionally, farmers' adoption behaviour may be greatly influenced by socioeconomic factors like age, education level, farming experience, income level, and digital literacy. Future studies could look into how these socioeconomic and demographic factors affect the adoption of FinTech in agriculture.

Future studies may also focus on particular Fin-Tech technologies including blockchain-based agricultural supply chains, digital lending, mobile banking, and crop insurance platforms,AI-enabled agricultural financial services to examine their individual impacts on agricultural productivity and financial inclusion.

To provide more comprehensive theoretical perspectives on technology adoption in agriculture, future research may incorporate alternative theoretical models like the Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovation (DOI), or Theory of Planned Behaviour (TPB), even though this study used the Extended Technology Acceptance Model (TAM).

Overall, resolving these issues can help design more effective digital financial solutions, policies, and strategies for sustainable agricultural growth and rural financial inclusion in India. It can also offer deeper insights into the adoption of FinTech in agriculture.

Author Contributions

Rathi R and Ashok Kumar Sahoo conceptualized the study, developed the research framework, conducted the formal analysis, and wrote the main manuscript text, including tables and figures. Both authors reviewed, edited, and approved the final version of the manuscript.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declarations

Ethics Approval and Consent to Participate

This study was conducted in accordance with standard academic research guidelines. The research did not involve any clinical experiments on humans or animals and therefore did not require formal ethical approval. Informed consent was obtained from all respondents before data collection.

Participation in the survey was voluntary, and respondents were assured that their responses would remain anonymous and confidential.

Consent for Publication

The authors consent to the publication of this manuscript. All participants were informed that the collected data would be used strictly for academic and research purposes. Consent for the publication of anonymized data was obtained from all participants involved in the study.

Competing Interests

The authors declare that they have no competing interests.

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