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# ADOPTION OF CLIMATE-SMART AGRICULTURE TECHNOLOGIES BY AGRIPRENEURS: AN INTEGRATED DOI AND TAM APPROACH

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Original Article

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## Abstract

This study investigates the key factors influencing Agripreneurs' adoption of Climate-Smart Agriculture (CSA) technologies in Karnataka, India, by integrating Diffusion of Innovation (DOI) theory and the Technology Acceptance Model (TAM). A quantitative cross-sectional survey was conducted with 306 agripreneurs across three agro-climatic regions: Bayaluseeme, Malenadu, and Karavali. Structural equation modelling using SmartPLS 4.0 was applied to assess the relationships between constructs, such as Relative Advantage (RA), Compatibility (COMP), Observability (OBS), Trialability (TR), Perceived Usefulness (PU), Perceived Ease of Use (PEOU) and Intention to adopt Climate-Smart Agriculture (CSA) technologies (IAT). PU emerged as the strongest predictor of adoption intention, followed by COMP and OBS. While PEOU significantly influenced PU, it showed a direct negative relationship with intention. Although TR was hypothesised to have a positive influence on adoption intention, the results showed no statistically significant effect. Predictive assessment using PLS-Predict confirmed the strong out-of-sample predictive performance of the model. The findings suggest that CSA technology adoption strategies should focus on showcasing visible success stories, ensuring the local COMP of technologies, and highlighting tangible benefits. Training and extension programs should prioritise usefulness over ease, ensuring region-specific and gender-inclusive delivery. This study contributes to the growing literature on sustainable agriculture by applying an integrated TAM–DOI framework in the context of Indian agripreneurs.

***Keywords: Agripreneurs; Climate-Smart Agriculture Technology; Diffusion of Innovation; SmartPLS; Technology Adoption; Technology Acceptance Model***

## Introduction

With digital and smart technologies, India's agriculture has grown significantly. Precision farming, AI, big data, IoT, and nanotechnology let farmers produce more with less. These technologies increase yield while protecting the environment and ensuring farming's future [1, 2]. Climate Smart Agriculture (CSA) is a major growth. CSA uses IoT, AI, big data, and nano sensors to combat the change of climate and save water and soil [3, 4]. CSA awareness is expanding in India, but many farmers and Agripreneurs, particularly in rural regions, are still not using it. This study focuses on Agripreneurs across Karnataka, covering three main regions – Bayaluseeme, Malenadu, and Karavali – where CSA is becoming important due to different local challenges. In Bayaluseeme, a dry region with limited rainfall and poor soil,



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Agripreneurs use new ideas to cope with climate problems. For example, in Bagalkot, farmers use drip irrigation and integrated farming systems with the help of NGOs. In Dharwad, inventors, such as Abdul Khadar Nadakattin, developed solar traps and low-cost machines to help farmers. In Chitradurga, young Agripreneurs are growing millets and using mobile advisory apps to manage dryland farming. In Vijayapura, Agripreneurs have adopted greenhouses and precision tools to save water and increase crop output. Entrepreneurs focus on organic and sustainable farming in the Malenadu region, which is hilly and receives more rainfall. In Sirsi (Uttara Kannada), farmers organically grow spices, save seeds, and sell value-added products. In Thirthahalli (Shivamogga), local farmers used vermicomposting, agroforestry, and water conservation methods. In Madikeri (Kodagu), entrepreneurs grow coffee and pepper using eco-friendly shade-based farming. In Siddapur, cooperative groups promote natural farming, which supports local biodiversity. In Karavali, the coastal region of Karnataka, entrepreneurs use technology and innovation to address coastal farming challenges. Mangalore (Dakshina Kannada) uses smart irrigation and composting with the support of agri-tech suppliers. In Udupi, AIC-Nitte helps young entrepreneurs develop CSA tools using the IoT and digital platforms. In Karwar (Uttara Kannada), the ICAR-CCARI trains people in organic farming, drone use, beekeeping, and crab culture. In Kundapura, many entrepreneurs follow poultry-based CSA models and backyard farming to improve their income and food security. Although CSA tools are available, not all entrepreneurs use them. Research shows that adoption depends not only on access to technology but also on Agripreneurs' behaviour, trust, background, and the support they receive from institutions and training programs [5, 6]. In Karnataka, successful entrepreneurs are often more confident, motivated, and innovative than others [7].

To better understand these factors, this study uses two important theories: "Diffusion of Innovation (DOI)" and the "TAM". DOI talks about how new technologies and ideas get around in society, while TAM focuses on how useful and easy a person feels a technology is. When combined, these models help explain why some entrepreneurs adopt smart technologies while others do not. Earlier studies used these models in areas such as smart farming and supply chains of halal meat [8, 9]. However, most past studies have focused on developed countries or have not clearly explained how these models work in Indian villages. In addition, there is very little data on how Agripreneurs behave after they begin using CSA tools. Present study tries to close this gap by integrating DOI and TAM models together using constructs, such as Relative Advantage (RA), Compatibility (COMP), Observability (OBS), Trialability (TR), Perceived Usefulness (PU), Perceived Ease of Use (PEOU) and Intention to adopt Climate-Smart Agriculture (CSA) technologies (IAT) and studying Agripreneurs across Karnataka. This will help policymakers, agriculture officers, and agri-tech developers understand what supports or stops the adoption of CSA. This can also be a model for other states in India and other developing countries where farmers face both climate and economic difficulties.

**Objectives of the Study**

[1] To examine the role of training, institutional support, and access to extension services in enhancing Agripreneurs' capacity to adopt CSA technologies.

[2] The existing literature analyzes how training, capacity-building, and gender-related factors shape Agripreneurs' readiness and involvement in agricultural innovation.

[3] Integrate insights from the TAM and DOI frameworks to develop a comprehensive understanding of the drivers influencing Agripreneurs' adoption of CSA technologies.

## Literature Review

### Role of Training, Institutional Support, and Extension Services

Training, extension services, and institutional support are widely recognised as essential enablers for Agripreneurs adopting Climate-Smart Agriculture (CSA). In India, Brahma and Tripathi [10] showed how ISAP trained over 2,400 Agripreneurs using a mix of integrated farming, mentoring, and ICT-based dissemination such as radio and mobile apps. Their efforts have contributed to both climate and income stability. In Odisha, Tanti et al. [11] found that adoption of CSA was significantly brought about by access to extension services, government subsidies, credit, and farmer field schools, all of which enabled bottom-up adaptation. Studies in other countries have also supported the value of institutional linkages. For instance, Okello et al. [12] highlighted that youth dairy entrepreneurs in Tanzania benefitted from ICT access, particularly when supported by electricity infrastructure and frequent extension contact. Kademani et al. [13] introduced the ISAD-S tool to assess support gaps. Their study found strong institutional support for product development and marketing but limited access to financial resources, such as credit and subsidies. These studies show that a strong support system combining training, extension, and institutional access plays a central role in promoting CSA technologies among entrepreneurs.

**Influence of Capacity-Building, Personal Traits, and Gender on Agripreneurial Readiness**

Capacity-building programs and individual characteristics such as motivation, self-confidence, and gender influence the readiness of Agripreneurs to adopt CSA. Adeyanju et al. [14] found that youth in Kenya, Nigeria, and Uganda who took part in the ENABLE-TAAT program showed a 20% improvement in skills. Participation was higher when the youth viewed training as useful. Thomas and Murali [15] developed and validated a competency measurement scale with eight entrepreneurial dimensions aligned with SDG 2, making it useful for identifying high-potential individuals.

Kaur and Kameswari [16] found that rural entrepreneurs in Uttarakhand lacked both technical and motivational readiness, indicating the need to address the psychological aspects of training. Likewise, Jayasudha and Shantha Sheela [17] found that in Tamil Nadu, Agripreneurs with self-confidence, innovativeness, family support, and access to finance performed better. In Western Greece, Pliakoura et al. [18] noted that internal funding, training, and personal traits influenced agripreneurs success, while education had a negative relationship, suggesting that hands-on skills may matter more than formal education.

Gender plays a crucial role in innovation readiness. Obossou et al. [19] showed that while men in Benin applied high CSA practices, women are likely to choose improved crop technologies and rely heavily on peer networks. Mahoukede et al. [20] found that women-to-women demonstrations helped increase female access to technologies. Similarly, Prakash et al. [21] noted that in Haryana and Bihar, involvement of women in decision-making improved CSA adoption, although social perceptions still favoured men as 'Kisans'. On the other hand, Tsige [22] found that in Ethiopia, CSA adoption did not significantly alter patriarchal norms, with women's roles still restricted by cultural expectations and limited access to resources.

**Economic and Environmental Impacts of CSA Adoption**

CSA practices have proven to be effective in improving yield, income, and resilience, especially in drought-prone regions. Khatri-Chhetri et al. [23] in Rajasthan, identified that farmers valued insurance of crop, rainwater harvesting, and agro-advisory services, although preferences differed by region. In Karnataka, Pal et al. [24] showed that using laser land levelling (LLL) increased paddy yield by 12% and income by 16%, offering a practical CSA solution for drought mitigation. Similar results have been reported in Africa and Asia. Lupogo and Mkuna [25] observed a 234% increase in cashew income through CSA adoption in Tanzania, with credit access and cooperative membership acting as key enablers. In Vietnam, Lam et al. [26] showed that gender, trust in extension workers, and previous climate shocks influenced the adoption of water-saving and stress-tolerant rice varieties. Mwongera et al. [27] developed the CSA-RA tool to prioritise locally relevant CSA interventions through participatory methods. In Kenya, Mumo et al. [28] discovered that risk-averse farmers were not really interested to adopt CSA, underlining the need for strategies that address behavioural barriers. Research from Ethiopia shows that CSA technologies reduce multidimensional poverty more effectively than income alone, particularly in the Amhara and Oromiya regions [29]. Andati et al. [30] added that entrepreneurial orientation—especially traits like innovativeness and risk-taking—was crucial in CSA technology adoption among Kenyan potato farmers.

**Behavioural Models and Technology Adoption: Integrating TAM and DOI**

To better understand Agripreneurs' adoption behaviour, several studies have applied the TAM and DOI theory. For instance, Agag and El-Masry [31] examined that COMP, PEOU, trust, and Perceived Usefulness (PU) influence consumer engagement in communities of online travel. This is relevant to CSA adoption, in which user trust and perceived utility also matter. Alhammadi et al. [32] studied smart learning in the UAE and found that technological readiness and attitude were key behavioural predictors. Similarly, Uyob et al. [33] showed that system cost and COMP in Malaysia influenced the PU of MBRS, affecting adoption rates. In Taiwan's green transportation study, Chen and Lu [34] examined that green usefulness and PEOU significantly affected user intentions. Zhou [35] showed that among Chinese journalists, voluntary adopters were more tech-positive and benefited from organisational support—similar to how Agripreneurs respond to supportive ecosystems. A review by Musa et al. [36] found that TAM-based research in marketing continues to expand, particularly in mobile and AI-related areas. Khan et al. [37] reported that social commerce adoption in Bangladesh is shaped by PU, PEOU, and trust. Mahmood et al. [38] developed the TRAM model by combining TAM and technology readiness and found that self-efficacy and subjective norms influenced adoption. Marasinghe et al. [39] found that among distance learners, PEOU had more influence than usefulness in using e-resources. In higher education, Miao and Ahmed [40] showed that autonomous motivation (from Self-Determination Theory) and PU are major drivers of micro-credential adoption. Jasimuddin [41] highlighted the trust's role and influence of social in digital service acceptance in the UAE. Finally, Hanna and Alyouzbaky [42] showed that COMP and trust are the strongest factors behind Bitcoin adoption in Iraq. These studies confirm the relevance of the TAM and DOI frameworks for analysing behavioural drivers in technology adoption, including CSA.

The reviewed literature was categorised into four thematic areas aligned with the objectives of the study (as displayed in Table 1).

***Table 1: Categorisation of Reviewed Literature***

| **Section Heading** | **Number of Studies** | **Studies Included** |
| --- | --- | --- |
| **Role of Training, Institutional Support, and Extension Services** | 5 studies | Brahma & Tripathi [10]; Tanti et al. [11]; Okello et al. [12]; Kademani et al. [13]; Khatri-Chhetri et al. [23] |
| **Influence of Capacity-Building, Personal Traits, and Gender** | 11 studies | Adeyanju et al. [14]; Thomas & Murali [15]; Kaur [16]; Jayasudha & Shantha Sheela; Pliakoura et al. [18]; Obossou et al. [19]; Mahoukede et al. [20]; Prakash et al. [21]; Tsige et al. [22]; Mwongera et al. [27]; Mulugeta et al. [29] |
| **Economic and Environmental Impacts of CSA Adoption** | 10 studies | Pal et al. [24]; Lupogo et al. [25]; Lam et al. [26]; Mumo et al. [28]; Andati et al. [30]; Long et al; Khatri-Chhetri et al.; Tanti et al. [11]; Mwongera et al. [27]; Mulugeta et al. [29] |
| **Behavioural Models and Technology Adoption: Integrating TAM and DOI** | 10 studies | Agag & El-Masry [31]; Alhammadi et al. [32]; Uyob et al. [33]; Chen & Lu [34]; Zhou [35]; Musa et al. [36]; Khan et al. [37]; Mahmood et al. [38]; Marasinghe et al. [39]; Miao et al. [40]; Jasimuddin [41]; Hanna & Alyouzbaky [42] |

*Source: Researcher's work*

### Hypotheses Development

#### RA and Intention to Adopt

When farmers feel that a new farming method or technology provides better results than what they are currently using, they are more likely to accept it. This is known as comparative benefit. Agag and El-Masry [31] showed that when users saw more benefits from using online travel communities, they were more willing to join. Similarly, Alhammadi et al. [32] proved that when learners find smart learning more useful than traditional methods, their interest increases. If farmers in drought-prone areas see CSA (Climate-Smart Agriculture) as more beneficial than regular methods, they will likely adopt it.

***H1**: The RA of CSA technology positively influences the IAT.*

#### OBS and Intention to Adopt

OBS refers to how clearly others see the results of a new method or tool. When farmers see visible success in nearby farms using CSA practices, they also become curious to try. Zhou [35] explained that when internet use became visible among journalists in China, it influenced others to follow. Similarly, Agag and El-Masry [31] found that when people saw benefits through online travel communities, they encouraged others to join them. Thus, when CSA benefits are visible in a community, adoption increases.

***H2**: The OBS of CSA technologies positively influence IAT.*

#### COMP and Adoption Intention

COMP refers to how well a new technology fits with the farmer's existing work, culture, or values. If CSA practices match traditional farming methods or tools already in use, farmers will easily adopt them. This was observed in Bitcoin adoption, where trust and COMP increased usage in Iraq [42]. Similarly, Agag and El-Masry [31] found that users were more active in travel communities when the platform suited their preferences. Uyob et al. [33] also observed that COMP influenced how accountants viewed the usefulness of new reporting systems.

***H3***: *COMP of CSA technologies with existing farming practices positively influences the IAT.*

**TR and Intention to Adopt**

TR involves giving farmers a chance to test CSA methods on a small scale before making full decisions. This builds confidence. Chen and Lu [34] showed how in green transport, people tried systems like YouBike before making it a regular part of life. In education and financial reporting, new systems are more acceptable when users can try them first [32, 33]. Therefore, farmers should be allowed to safely test CSA tools before full adoption.

***H4***: *The TR of CSA technologies positively influence IAT.*

**PEOU and PU**

People think technology is more useful when it is simple and easy to use. This is called PEOU, and it is utilised to make PU higher. A number of studies have backed up this result. Agag and El-Masry (2016) [31] showed that travel platforms are more useful when they are easier to use, for example. Uyob et al. [33] found that how easy it was to use had a big effect on how beneficial it was for business reporting. The same idea holds true for farming: farmers will think CSA tools are high beneficial if they are user-friendly.

***H5***: *PEOU positively influences the PU of CSA.*

**PU and Intention to Adopt**

*PU* means to how much the user feels that the technology improves their work or life. This factor strongly influences whether someone adopts technology. Miao et al. [40] showed that students found micro-credential programs useful and were more likely to use them. Marasinghe et al. [39] also noted that students who found digital resources useful wanted to continue using them. Similarly, in transportation and finance, usefulness increases technology usage. If CSA tools help improve crop output in agriculture, farmers will want to use them [34, 38].

***H6***: *PU positively influences the IAT.*

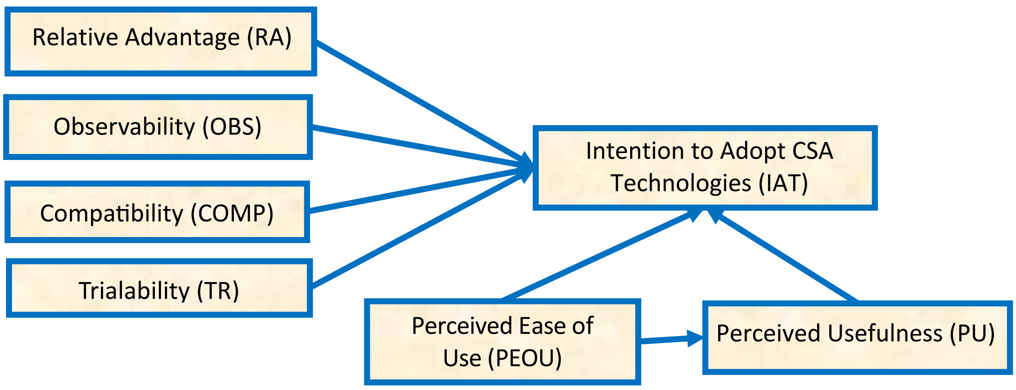
**PEOU and Intention to Adopt**

If a system is simple and user friendly, Individuals are more inclined to embrace it. This was demonstrated by Miao et al. [40] in education and Zhou [35] in the media. Uyob et al. [33] found that PEOU had a direct influence on the decision to use digital reporting systems. This means that CSA technologies should be made farmer-friendly to increase their adoption.

***H7***: *PEOU positively influences the IAT.*

The proposed conceptual framework showing the relationships among the key constructs is illustrated in Figure 1.

***Figure 1: Proposed Conceptual Framework Model***



## Methodology

This study employed a quantitative research technique to look at the factors that make businesses in Karnataka want to adopt Climate-Smart Agriculture (CSA) technology. This research looks at how personal attitudes, PU, and outside support affect the adoption of technology in agriculture using two well-known theories: DOI and TAM. This study looked at Agripreneurs in Karnataka, specifically in the Bayaluseeme, Malenadu, and Karavali districts, which are known for having different weather and farming methods. A purposive sample of 306 Agripreneurs was selected, making sure that only those who are actively involved in innovative or sustainable agriculture were included. The authors collected the data by utilising a standardised questionnaire that included items that had been tested in earlier studies on DOI and TAM. The questionnaire used a 5-point Likert scale. A small group tested the tool to make sure it was clear and useful before starting to collect data on a larger scale. They used both online and offline sources. Field trips, agricultural events, and training centres gave us data that wasn't online, while WhatsApp groups, farmer networks, and startup platforms shared forms that were available. Participants were informed of the research purpose, and participation was voluntary. Confidentiality and anonymity were ensured throughout the study. The research used partial least squares structural equation modelling (PLS-SEM). This technique works well for intricate models and the data doesn't have to be spread out evenly. There were two components to this study. They began by assessing the validity and reliability of the measurement model using HTMT ratio, Cronbach's alpha, Composite reliability, and Average Variance Extracted (AVE). Second, we used bootstrapping (5,000 samples) to evaluate the structural model and find out how strong and important the correlations between variables were. They also utilised $R^2$ values, effect size ($f^2$), and Importance-Performance Map Analysis (IPMA) to see how well the model explained the results and found the most important factors. They also utilised descriptive statistics like means and standard deviations to look at response patterns more closely. The skewness and kurtosis measurements were just used as references since PLS-SEM doesn't need the data to follow a normal distribution. Lastly, the inquiry met all moral requirements. People who agreed to take part in the research were told what it was about and only those who did were included. The collected information was used exclusively for academic purposes, and respondents' identities were kept confidential.

## Result

### Frequency Distribution

Table 2 presents the demographic distribution of respondents categorised by gender, age group, and place residence.

***Table 2: Frequency Distribution of Respondents***

| Category | Option | Frequency | Percent (%) |
|---|---|---|---|
| **Gender** | Male | 203 | 66.3 |
| | Female | 103 | 33.7 |
| | **Total** | **306** | **100.0** |
| **Age Group** | 18–28 years | 27 | 8.8 |
| | 28–38 years | 88 | 28.8 |
| | 38–48 years | 125 | 40.8 |
| | 48 years and above | 66 | 21.6 |
| | **Total** | **306** | **100.0** |
| **Place of Residence** | Karavali | 129 | 42.2 |
| | Malenadu | 104 | 34.0 |
| | Bayaluseeme | 73 | 23.9 |
| | **Total** | **306** | **100.0** |

*Source: Survey data*

The data show that most of the Agripreneurs in the study were male (66.3%), while 33.7% were female. This means that more men are involved in entrepreneurship in Dakshina Kannada compared to women. For age, the largest number of respondents are from the 38 to 48 years group (40.8%), followed by 28–38 years (28.8%), and 48 years and above (21.6%). Very few Agripreneurs were in the 18–28 years age group (8.8%), which shows that middle-aged people are more active in this field. The Karavali region had the highest number of entrepreneurs (42.2%), followed by Malenadu

(34%) and Bayaluseeme (23.9%). This means that Agripreneurship is more common in coastal and hilly areas, possibly because these places have better resources, support, and access to markets than dry regions.

**Constructs Descriptive Statistics**

This included mean and standard deviation, were calculated to understand the central tendency and variability of responses from the Agripreneurs. Although skewness and kurtosis values were also computed and suggested a fairly normal distribution, they were not critical for current study as it uses SmartPLS and which is non-parametric and does not assume data normality (see Table 3). Hence, these values are reported only for descriptive understanding and not for testing the assumptions.

***Table 3: Constructs Descriptive Statistics***

| Item Code | Mean | Std. Deviation | Skewness | Kurtosis |
|---|---|---|---|---|
| RA1 | 3.63 | 1.042 | -0.869 | 0.516 |
| RA2 | 3.62 | 0.965 | -0.733 | 0.648 |
| RA3 | 3.61 | 1.073 | -0.740 | 0.165 |
| IAT1 | 3.54 | 0.979 | -1.125 | 0.846 |
| IAT2 | 3.58 | 1.031 | -0.753 | 0.424 |
| IAT3 | 2.55 | 1.086 | -0.575 | -0.204 |
| TR1 | 2.56 | 0.971 | -0.569 | 0.412 |
| TR2 | 2.57 | 0.889 | -1.283 | 1.437 |
| TR3 | 3.47 | 1.028 | -0.358 | -0.309 |
| OBS1 | 3.50 | 0.999 | -0.666 | 0.226 |
| OBS2 | 3.60 | 0.957 | -0.664 | 0.655 |
| OBS3 | 3.67 | 1.004 | -0.864 | 0.605 |
| COMP1 | 3.57 | 0.993 | -0.756 | 0.403 |
| COMP2 | 3.49 | 1.031 | -0.542 | 0.177 |
| COMP3 | 3.66 | 1.022 | -0.838 | 0.354 |
| PEOU1 | 3.63 | 0.863 | -1.253 | 1.819 |
| PEOU2 | 3.71 | 0.894 | -0.719 | 0.781 |
| PEOU3 | 3.66 | 0.966 | -0.592 | 0.267 |
| PU1 | 3.47 | 0.989 | -1.066 | 0.593 |
| PU2 | 3.59 | 1.053 | -0.804 | 0.430 |
| PU3 | 3.53 | 1.084 | -0.589 | -0.174 |

*Source: Researcher's work*

Descriptive statistics show that most Agripreneurs gave positive responses, with mean scores above 3.5 and moderate variation in answers.

**Measurement Model Assessment**

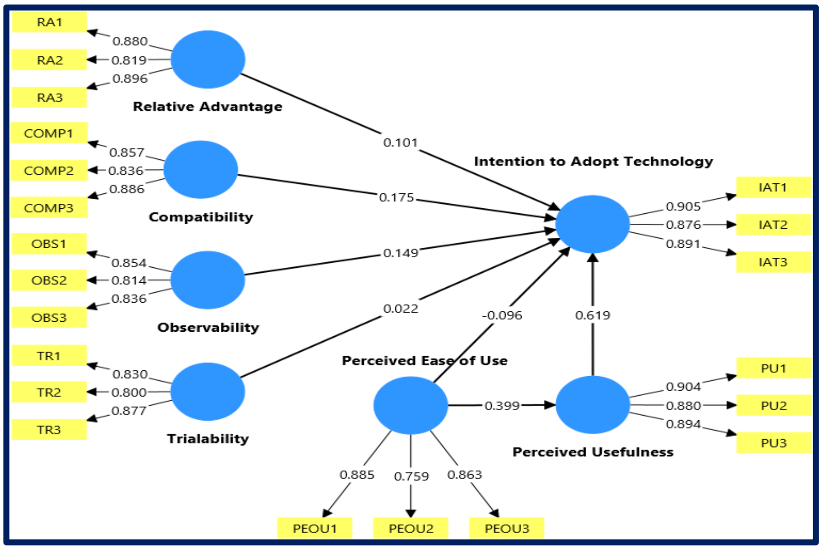
They used the PLS-SEM method to look at the measurement structure and see how well the components worked as psychometric tests, as Hair et al. [43] indicated. This test looks at outer loadings to check the indicators' reliability, Cronbach's alpha (CA) Composite reliability (CR) to check the internal consistency, and Average Variance Extracted (AVE) to check the convergent validity. They employed both the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) analysis to find out whether anything was discriminant valid. They also looked at the Variance Inflation Factor (VIF) data to see whether there was multicollinearity among the indicators. These tests are necessary to make sure that the constructs are unique, reliable, and valid, which is the first step in evaluating the structural model. Table 4 shows the specific limits and standards for each of this research. Figure 2 shows the PLS-SEM model, which includes both the measurement model (the links between latent components and indicators) and the structural model.

*Table 4: Measurement Model Evaluation Criteria in PLS-SEM*

| | Threshold / Guideline | Reference |
|---|---|---|
| **Indicator Reliability** | Outer loadings ≥ 0.708 | Hair et al. [43] Raghavendra et al. [44] |
| CA | ≥ 0.70 (≥ 0.60 for exploratory research), ≤ 0.95 | |
| CR | 0.70 to 0.90 ideal; < 0.60 (poor); > 0.95 (redundancy concern) | |
| **AVE** | AVE ≥ 0.50 | |
| **Discriminant Validity** – Fornell-Larcker Criterion | AVE square root > inter-construct correlations | |
| **Discriminant Validity** – HTMT Ratio | HTMT < 0.85 (distinct constructs), < 0.90 (similar constructs) | |
| **Collinearity - VIF** | VIF < 5 acceptable; VIF < 3 ideal | |

*Source: Researcher's work*

***Figure 2: PLS SEM Model***




*Source: Researcher's work*

**Outer loadings**

Outer loadings were checked to see how strongly each question was connected to the topic it was meant to measure. If a question matches its topic well, this proves that the question is useful and reliable. This test confirmed that the indicators properly represented the constructs being studied (*refer to Table 5: Outer Loadings*).

***Table 5: Outer Loadings***

| | COMP | IAT | OBS | PEOU | PU | RA | TR |
|---|---|---|---|---|---|---|---|
| **COMP1** | 0.857 | | | | | | |
| **COMP2** | 0.836 | | | | | | |
| **COMP3** | 0.886 | | | | | | |
| **IAT1** | | 0.905 | | | | | |
| **IAT2** | | 0.876 | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **IAT3** | | 0.891 | | | | | |
| **OBS1** | | | 0.854 | | | | |
| **OBS2** | | | 0.814 | | | | |
| **OBS3** | | | 0.836 | | | | |
| **PEOU1** | | | | 0.885 | | | |
| **PEOU2** | | | | 0.759 | | | |
| **PEOU3** | | | | 0.863 | | | |
| **PU1** | | | | | 0.904 | | |
| **PU2** | | | | | 0.880 | | |
| **PU3** | | | | | 0.894 | | |
| **RA1** | | | | | | 0.880 | |
| **RA2** | | | | | | 0.819 | |
| **RA3** | | | | | | 0.896 | |
| **TR1** | | | | | | | 0.830 |
| **TR2** | | | | | | | 0.800 |
| **TR3** | | | | | | | 0.877 |

*Source: Researcher's work*

All indicators showed satisfactory loadings, above the recommended threshold of 0.708. The COMP items ranged from 0.836 to 0.886, IAT from 0.876 to 0.905, and OBS from 0.814 to 0.854. PEOU indicators ranged from 0.759 to 0.885, PU from 0.880 to 0.904, RA from 0.819 to 0.896, and TR from 0.800 to 0.877. These values confirm adequate indicator reliability across all the constructs.

**Reliability and Validity of the Construct**

These tests check to see whether all questions about a topic provide responses that are consistent and useful. Reliability makes ensuring that the questions in each construct provide the same answers every time, and validity makes sure that the questions measure what they are meant to. Table 6: Construct Reliability and Validity says that CA was applied to check how consistent the items were with each other. This helps to see whether questions on the same topic have similar answers, which means they are working well together. The authors also used composite reliability to check the questions' consistency, although it gives stronger items a little more weight, which makes it a more accurate test than Cronbach's alpha. They also applied the AVE to find out how much meaningful information the set of questions gave us. A higher AVE means that the questions are more relevant to the topic and that the answers are not random. When done collectively, these tests make the measurements of each construct more reliable and valid.

***Table 6: Reliability and Validity of the Constructs***

| | **CA** | **CR** | **AVE** |
|---|---|---|---|
| **COMP** | 0.824 | 0.826 | 0.740 |
| **IAT** | 0.869 | 0.870 | 0.793 |
| **OBS** | 0.783 | 0.783 | 0.697 |

| | | | |
|---|---|---|---|
| **Perceived Ease of Use** | 0.786 | 0.802 | 0.701 |
| **Perceived Usefulness** | 0.873 | 0.873 | 0.797 |
| **RA** | 0.832 | 0.834 | 0.750 |
| **TR** | 0.784 | 0.784 | 0.699 |

*Source: Researcher's work*

CA numbers lie between 0.783 and 0.873, and CR numbers lie between 0.783 and 0.873, indicating consistent measurement. The AVE values exceed 0.50 for all constructs, ranging from 0.697 (OBS) to 0.797 (PU), confirming adequate convergent validity.

**Discriminant Validity Analysis**

This analysis aimed to ascertain whether the different subjects or constructions in the research were indeed distinct from one another. This guarantees that each construct exclusively measures its specific concept without any overlap with other constructs. The assessment was conducted using two tests: the HTMT and the Fornell-Larcker criteria. The HTMT assesses the degree of similarity between responses from two independent constructs and evaluates whether they are excessively correlated. A very high HTMT score may indicate insufficient diversity between the two subjects. Table 7 illustrates that most construct pairings in this study met the necessary threshold for the HTMT, indicating discriminant validity. However, a few values were slightly elevated and warrant cautious interpretation. The Fornell-Larcker criteria, presented in Table 8: Fornell-Larcker Criteria Analysis, assesses whether a construct exhibits a stronger association with its own indicators compared to those of other constructs. This was achieved by matching the AVE's square root with the construct's correlations. This investigation revealed that the diagonal values, representing the AVE's square roots crossed the corresponding correlations, thereby indicating distinctiveness among the constructs. Collectively, these two experiments offered significant evidence that supports the discriminant validity of the measurement model.

***Table 7: HTMT Analysis Results***

| | **COMP** | **IAT** | **OBS** | **PEOU** | **PU** | **RA** | **TR** |
|---|---|---|---|---|---|---|---|
| **COMP** | | | | | | | |
| **IAT** | 0.769 | | | | | | |
| **OBS** | 0.845 | 0.821 | | | | | |
| **PEOU** | 0.425 | 0.353 | 0.423 | | | | |
| **PU** | 0.592 | 0.824 | 0.661 | 0.481 | | | |
| **RA** | 0.872 | 0.731 | 0.830 | 0.364 | 0.572 | | |
| **TR** | 0.658 | 0.470 | 0.678 | 0.286 | 0.335 | 0.544 | |

*Source: Researcher's work*

The HTMT values range from 0.286 to 0.872. Most values were below the 0.85 threshold, indicating acceptable discriminant validity. Only one pair, COMP and RA (0.872), slightly exceeds 0.85, but remains below 0.90, suggesting no serious concerns.

***Table 8: Fornell Larker Criterion Analysis***

| | COMP | IAT | OBS | PEOU | PU | RA | TR |
|---|---|---|---|---|---|---|---|
| **COMP** | 0.860 | | | | | | |
| **IAT** | 0.652 | 0.890 | | | | | |
| **OBS** | 0.767 | 0.677 | 0.835 | | | | |
| **PEOU** | 0.346 | 0.296 | 0.330 | 0.837 | | | |
| **PU** | 0.502 | 0.805 | 0.546 | 0.399 | 0.893 | | |
| **RA** | 0.721 | 0.622 | 0.749 | 0.292 | 0.488 | 0.866 | |
| **TR** | 0.530 | 0.390 | 0.532 | 0.226 | 0.280 | 0.439 | 0.836 |

*Source: Researcher's work*

The diagonal values exceeded the corresponding off-diagonal inter-construct correlations for all constructs. For example, COMP's AVE square root is 0.860, which is higher than its correlation with OBS (0.767) and RA (0.721). This supports the discriminant validity across all constructs based on this criterion.

**VIF analysis to check multicollinearity**

To check whether there was no high overlap or redundancy among the indicators within each construct, multicollinearity was checked using the VIF. The VIF helps identify whether any item repeats the same information as another item in the model. High multicollinearity can affect the accuracy of the model's results; therefore, checking VIF values ensures that each indicator contributes uniquely. Table 9 presents the results of this analysis.

***Table 9: VIF Analysis***

| Items | VIF | Items | VIF |
|---|---|---|---|
| **COMP1** | 1.898 | **PU1** | 2.540 |
| **COMP2** | 1.710 | **PU2** | 2.124 |
| **COMP3** | 2.094 | **PU3** | 2.441 |
| **IAT1** | 2.504 | **RA1** | 2.176 |
| **IAT2** | 2.093 | **RA2** | 1.633 |
| **IAT3** | 2.368 | **RA3** | 2.399 |
| **OBS1** | 1.773 | **TR1** | 1.839 |
| **OBS2** | 1.520 | **TR2** | 1.425 |
| **OBS3** | 1.658 | **TR3** | 2.076 |
| **PEOU1** | 1.968 | | |
| **PEOU2** | 1.394 | | |
| **PEOU3** | 1.954 | | |

*Source: Researcher's work*

All VIF values are between 1.394 (PEOU2) to 2.540 (PU1), which were significantly below the critical threshold of 5. This indicates the no presence of problematic multicollinearity and confirms that the indicators uniquely contribute to their respective constructs.

**Structural Model Assessment**

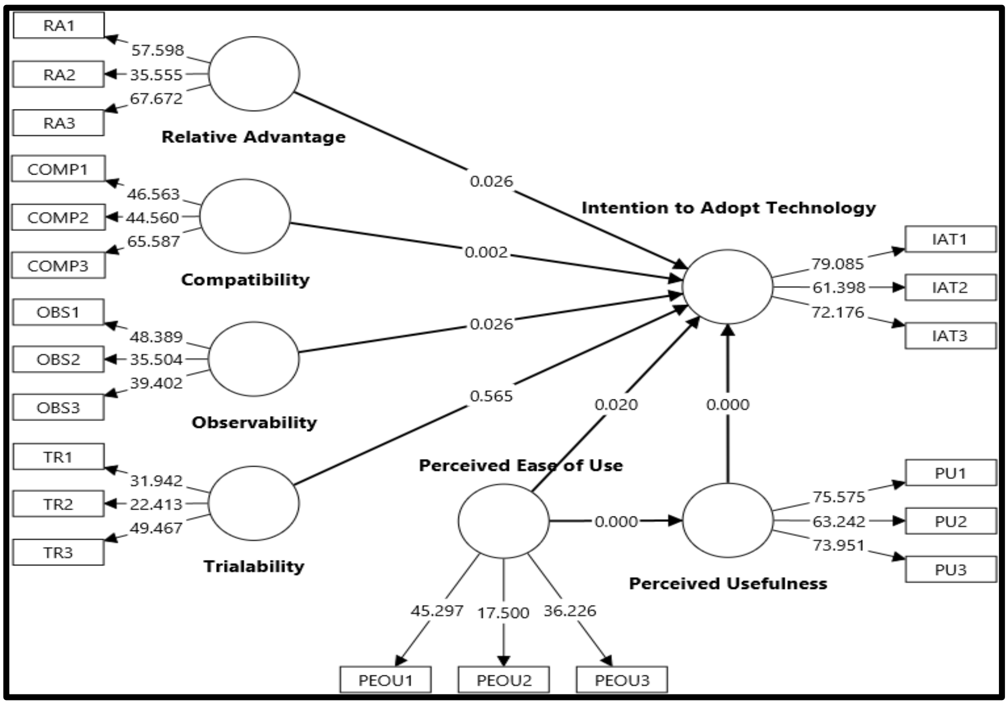
This was done to check the hypothesised relationships and the model's explanatory power. This phase in PLS-SEM entails evaluating the degree to which the independent (exogenous) constructs are responsible for the variation in the dependent (endogenous) constructs, along with evaluating the strength and importance of each path in the model. The assessment of the structural model commenced with hypothesis testing using a bootstrapping method involving 5,000 subsamples. This produced path coefficients, standard errors, *t*-values, and *p*-values for each proposed relationship between constructs. Table 11 provides a summary of the details related to hypothesis testing, encompassing statistical significance and the direction of effects. This initial assessment determines if theoretical connections are supported by empirical evidence. The model's explanatory capability was evaluated through the coefficient of determination ($R^2$) and adjusted $R^2$ values. The data demonstrate the extent of variance in the dependent constructs explained by their respective predictors. Table 12 displays the $R^2$ values for all endogenous variables. The effect size ($f^2$) was analysed in conjunction with $R^2$ to evaluate the individual influence of each exogenous variable on the $R^2$ of the corresponding endogenous variable. The effect size is used to analyse the relative impact of the constructs and determine the strength of each predictor's influence on outcomes. Table 13 presents the values. The impact of each independent construct on the dependent constructs was evaluated. This measurement encompasses both direct and indirect pathways, enabling a thorough comprehension of the overall influence of each construct on the model. Table 14 presents the overall effect values. The model was evaluated using an importance-performance map analysis (IPMA) to improve practical comprehension. This method links the relevance of each construct, defined as total impact, to its average performance score on a scale from 0 to 100. The IPMA identifies key areas for strategic development by emphasising constructions that are significant yet underperforming. Table 15 displays the results of the IPMA. The evaluation of the structural model conformed to the PLS-SEM criteria, demonstrating values for $R^2$, $f^2$, and IPMA, as shown in Table 10 [43]. This multi-step method offers a thorough understanding of the model's theoretical and practical implications, establishing a solid foundation for conclusions regarding agripreneurs' adoption of climate-smart agricultural technology. Figure 3 presents the bootstrapped model, detailing the significance levels and path coefficients derived from the PLS-SEM bootstrapping technique. Figure 4 presents the relevance-performance map, highlighting the relative importance and efficacy of constructs in affecting the target variable within the PLS-SEM framework.

***Table 10: Thresholds for Structural Model Assessment***

| Assessment Component | Threshold / Interpretation |
|---|---|
| **$R^2$ (Coefficient of Determination)** | $\geq 0.75$ = significant, $\geq 0.50$ = moderate, $\geq 0.25$ = weak |
| **Adjusted $R^2$** | No fixed threshold; used to account for model complexity |
| **$f^2$ (Effect Size)** | $\geq 0.35$ = large, $\geq 0.15$ = medium, $\geq 0.02$ = small, $< 0.02$ = negligible |
| **Total Effects** | No fixed cutoff; higher values indicate greater overall influence |
| **IPMA – Performance Score** | Ranges from 0 to 100; interpreted relative to total effect for prioritization |

*Source: Researcher's work [43]*

***Figure 3: Bootstrapped Model***




*Source: Researcher's work*

## Hypotheses Test Summary

***Table 11: Hypotheses Test Summary***

| Hypotheses Number | Hypothesised Relationships | Original sample (O) | Standard deviation (STDEV) | *T* statistics | *P* values | Decision on Hypotheses |
|---|---|---|---|---|---|---|
| **H1** | **RA -> IAT** | 0.101 | 0.045 | 2.226 | **0.026** | **Accept** |
| **H2** | **OBS -> IAT** | 0.149 | 0.067 | 2.228 | **0.026** | **Accept** |
| **H3** | **COMP -> IAT** | 0.175 | 0.056 | 3.133 | **0.002** | **Accept** |
| **H4** | **TR -> IAT** | 0.022 | 0.038 | 0.576 | **0.565** | **Reject** |
| **H5** | **PEOU -> PU** | 0.399 | 0.066 | 6.080 | **0.000** | **Accept** |
| **H6** | **PU -> IAT** | 0.619 | 0.076 | 8.158 | **0.000** | **Accept** |
| **H7** | **PEOU -> IAT** | -0.096 | 0.041 | 2.322 | **0.020** | **Accept** |

*Source: Researcher's work*

Out of the seven hypotheses, six received support while one did not. The study demonstrated that RA significantly influences the IAT ($\beta = 0.101$, $p = 0.026$). This indicates that agripreneurs are more inclined to adopt CSA when they perceive it as superior to traditional methods. OBS was significant ($\beta = 0.149$, $p = 0.026$), indicating that when entrepreneurs perceive visible benefits of CSA on other farms, it promotes the adoption of these technologies. The effect of COMP was notably significant ($\beta = 0.175$, $p = 0.002$), indicating that a strong alignment between CSA and established farming practices facilitates adoption. While H4 hypothesised a positive relationship between TR and IAT, the statistical test indicated non-significance, leading to rejection of the hypothesis ($\beta = 0.022$, $p = 0.565$). Regarding TAM constructs, PEOU significantly influenced PU ($\beta = 0.399$, $p = 0.000$), indicating that technologies that are user-friendly are perceived as more beneficial. PU exhibited the most significant direct impact on the intention to adopt ($\beta = 0.619$, $p = 0.000$), thereby affirming its status as the primary factor. PEOU exhibited a significant negative direct relationship with intention ($\beta = -0.096$, $p = 0.020$), indicating that PEOU alone may not enhance intention when entrepreneurs already perceive the technology as useful.

**$R^2$ and Adjusted $R^2$**

***Table 12: $R^2$ and Adjusted $R^2$ Values for Endogenous Constructs***

| | R-square | R-square adjusted |
|---|---|---|
| **IAT** | 0.756 | 0.751 |
| **PU** | 0.160 | 0.157 |

*Source: Researcher's work*

The $R^2$ value for IAT demonstrates a significant proportion of variance accounted for by the model, whereas the adjusted $R^2$ reflects a minimal adjustment for the number of predictors. Conversely, the values for PU suggest that a lesser portion of the variance in this construct is elucidated by its predictor.

**Effect Size ($f^2$)**

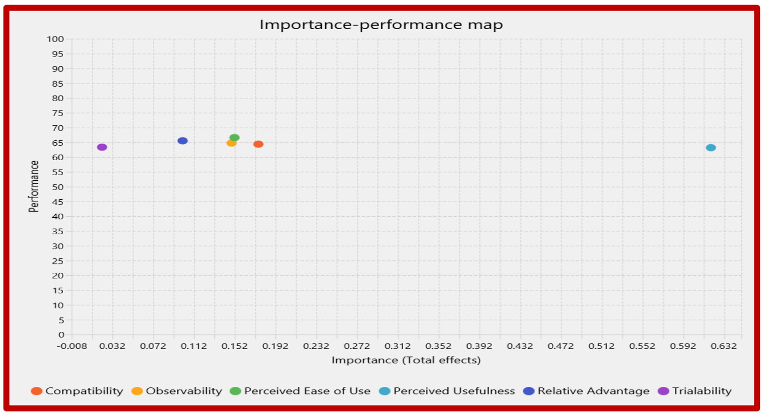
***Table 13: Effect Size ($f^2$) for Structural Model Relationships***

| | f-square |
|---|---|
| COMP -> IAT | 0.042 |
| OBS -> IAT | 0.027 |
| PEOU -> IAT | 0.030 |
| PEOU -> PU | 0.190 |
| PU -> IAT | 0.992 |
| RA -> IAT | 0.016 |
| TR -> IAT | 0.001 |

*Source: Researcher's work*

The effect size results indicate that PU exerts the most significant influence on the IAT, with PEOU having a moderate impact on PU. Other predictors, including COMP, OBS, and PEOU, exert comparatively minor effects on the IAT, whereas RA and TR demonstrate negligible contributions (see Figure 4 below).

***Figure 4: Important Performance Map***




*Source: Researcher's work*

***Table 14: Total Effects of Predictor Constructs on IAT***

| | **IAT** |
|---|---|
| **COMP** | 0.175 |
| **OBS** | 0.149 |
| **Perceived Ease of Use** | 0.152 |
| **Perceived Usefulness** | 0.619 |
| **RA** | 0.101 |
| **TR** | 0.022 |

*Source: Researcher's work*

PU was identified as the primary predictor of the IAT, accounting for both direct and indirect effects. COMP, PEOU, and OBS exert significant influences, while RA and TR have a comparatively minor impact on the intention construct (refer to Table 14).

***Table 15: Construct Performance Scores (Importance-Performance Map Analysis – IPMA)***

| | **Performance** |
|---|---|
| **Compatibility** | 64.380 |
| **Observability** | 64.735 |
| **Perceived Ease of Use** | 66.584 |
| **Perceived Usefulness** | 63.171 |
| **Relative Advantage** | 65.504 |
| **Trialability** | 63.348 |

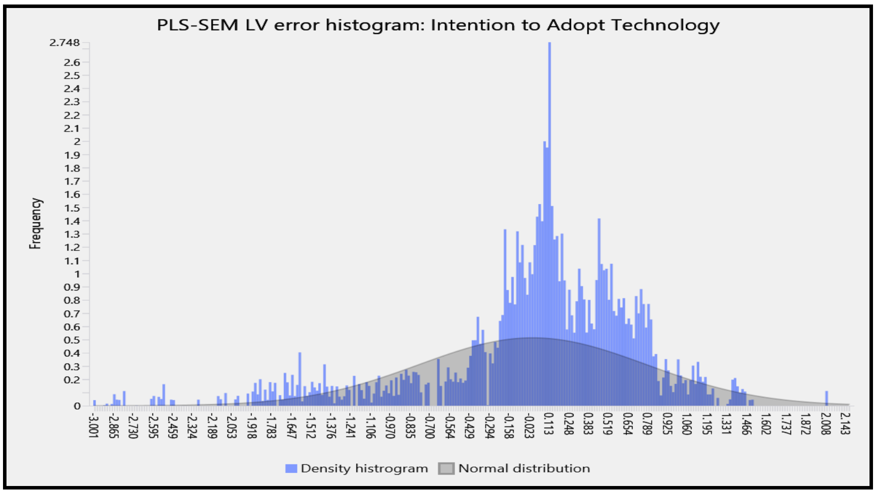
*Source: Researcher's work*

Among all predictor constructs, PU displayed the highest performance score, followed closely by *RA*, *OBS*, and *COMP*. *PU* and *TR,* and *PEOU* demonstrate slightly lower performance levels in comparison (refer to Table 15).

**Predictive Analysis**

This study also incorporated a predictive assessment utilising the PLS-Predict approach. Predictive assessment extends beyond elucidating relationships within the sample to evaluate the model's capacity to predict future data. This step enhances the model's practical applicability by assessing its utility in real-world contexts, including the prediction of agripreneurs' behaviour and the facilitation of agricultural policy decisions. The model's predictive relevance was evaluated through $Q^2$ prediction, RMSE, and MAE, offering insights into its forecasting capabilities beyond the sample data (see Table 16). The predictive performance was further assessed by comparing the PLS model with a linear benchmark model through average prediction loss and significance testing. The comparison validates the enhanced utility of the PLS model in out-of-sample prediction (refer to Table 17 and Figure 5) for the PLS SEM LV error histogram.

*Figure 5: PLS SEM LV error Histogram*




*Source: Researcher's work*

## PLS-Predict

*Table 16: PLS-Predict Results*

| Construct | Q²predict | RMSE | MAE | Predictive Relevance |
|---|---|---|---|---|
| IAT | 0.410 | 0.777 | 0.547 | Strong |
| PU | 0.148 | 0.931 | 0.661 | Moderate |

*Source: Researcher's work*

The Q² prediction value for 'IAT' was 0.410, which indicates strong predictive relevance. For PU', the Q² prediction was 0.148, suggesting a moderate predictive relevance. Lower values of RMSE (0.777) and MAE (0.547) for intention also indicated satisfactory prediction accuracy. This means that the model performs well in predicting how likely entrepreneurs are to adopt CSA technologies.

## Predictive Model Evaluation

*Table 17: PLS vs. Benchmark Model (PLS-Predict Output)*

| Construct | PLS Loss | IA Loss | Avg. Loss Difference | *t*-value | *p*-value |
|---|---|---|---|---|---|
| IAT | 0.726 | 1.071 | -0.345 | 5.644 | 0.000 |
| PU | 0.963 | 1.091 | -0.128 | 2.568 | 0.011 |
| **Overall** | 0.845 | 1.081 | -0.236 | 4.859 | 0.000 |

*Source: Researcher's work*

The PLS model shows lower prediction error (loss) for both IAT and PU. The average loss difference was negative, and the *p*-values were below 0.05, demonstrating that the disparity was statistically significant. This confirms that the PLS model is more accurate and reliable in predicting outcomes than the benchmark model.

# Discussion

### Influence of Institutional Support and Training

This study emphasises the significance of institutional factors, training, and extension services in influencing agripreneurs' adoption intention of Climate-Smart Agriculture (CSA). The effects of COMP and OBS indicate that agripreneurs have a greater propensity to embrace CSA technologies when these technologies align with their current farming systems and when they can observe successful implementations on other farms. These findings support earlier works, such as Zhou [35] and Agag and El-Masry [31], who emphasised that technologies that are visible and compatible with the adopters' context tend to diffuse more easily. The results suggest that state extension services and NGOs should prioritise hands-on training, field demonstrations, and peer-led exposure visits to increase CSA visibility and compatibility with local practices.

### Capacity Building and Innovation Readiness

The study indicated that, concerning capacity building and innovation readiness (Objective 2), PU emerged as the primary factor influencing the IAT, whereas TR exhibited no significant impact. This result contrasts with findings from prior studies, including Chen and Lu [34] and Alhammadi et al. [32], which indicated that TR positively influenced early technology adoption scenarios. The lack of significance of TR among Karnataka's agripreneurs suggests that restricted opportunities for experimentation or pilot use impede its impact on decision-making. The findings underscore the necessity for improved access to low-risk trial environments, such as community demonstration farms, especially in resource-limited districts. This gap underscores the necessity for inclusive training frameworks, particularly those that are gender-responsive and accessible to women entrepreneurs, as highlighted by Mahoukede et al. [20] and Obossou et al. [19].

### Integration of TAM and DOI: A Theoretical Perspective

The integration of the TAM and the DOI theory provide a thorough framework for elucidating the technology adoption decisions of agripreneurs. This study established that PEOU significantly affects PU, consistent with the traditional TAM framework suggested by Davis [45] and corroborated by Agag and El-Masry [31] and Uyob et al. [33]. The direct relationship between PEOU and IAT was significant yet negative, indicating a more complex interaction. This finding suggests that PEOU, by itself, is inadequate to promote adoption unless it also enhances perceived benefits. The findings align with the observations of Marasinghe et al. [39] and Miao et al. [40], indicating that PEOU must be coupled with demonstrable usefulness to effectively influence intention, especially in practical fields like education and agriculture.

### Agripreneurs as Utility-Driven Innovators

The dominant influence of PU in predicting adoption intention supports the idea that agripreneurs are utility-driven decision-makers. They are motivated by clear and measurable benefits such as higher yield, improved income, or better climate risk management. This is supported by the findings reported by Pal et al. [24], Mulugeta [29], and Lupogo et al. [25], who observed that CSA adoption in India, Ethiopia, and Tanzania was strongly driven by practical value and income gains. The results highlight that agripreneurs value CSA tools not for their novelty or TR but for their proven impact and alignment with economic goals. This finding has significant implications for communication strategies related to CSA, which must emphasise outcome-based messaging rather than generic awareness.

### Predictive Strength and Practical Relevance

The study also assessed the predictive performance using PLS-Predict. The model showed strong predictive power for intention to adopt and moderate predictive ability for PU. Moreover, it outperforms the linear regression benchmark model in both cases. This confirms that the model not only explains the variance in the sample but is also capable of forecasting future behaviour, which enhances its practical relevance. This is particularly useful for policy planners and agritech innovators seeking data-driven approaches to scale CSA adoption across diverse regions. As recommended by Shmueli et al. [46], such predictive validation makes the model more suitable for real-world applications and not just for theoretical testing.

### Summary of Theoretical and Practical Contributions

This study contributes to the theoretical literature by validating the combined use of TAM and DOI in a rural, agrarian setting, particularly among agripreneurs, rather than general farmers. It highlights the context-specific behaviour of constructs such as TR, which may not always play a significant role, and emphasises the consistent strength of PU, COMP, and OBS [47]. Practically, this study offers direction for designing CSA interventions through visibility, relevance to local practices, and strong communication of benefits. It supports earlier calls from Hanna and Alyouzbaky [42] for CSA strategies rooted in behavioural understanding, local knowledge, and targeted innovation support.

### Limitations And Future Research

This research presents multiple limitations. The study employed data collection at a single point in time, which may not accurately represent behavioural changes over time. Secondly, while the sample comprised agripreneurs from various regions of Karnataka, the findings may not be applicable to all Indian states. The study relied on self-reported perceptions, which may not consistently align with actual adoption behaviours. Additionally, the model does not include factors such as risk perception, cost, or infrastructure access, which could influence CSA adoption. Further research should consider longitudinal studies to track actual adoption over time and expand the sample across more regions for broader validation. Mixed-method approaches, including interviews and focus groups, can offer more profound insights, especially regarding why TR is not significant. Adding variables such as market access, digital literacy, and financial support can also enhance the model accuracy and relevance for policy and practice.

## Conclusion

The findings indicated that PU emerged as the primary predictor of adoption, succeeded by COMP, OBS, and RA. The model confirmed that PEOU affects PU but does not directly influence intention. Interestingly, TR was not found to be a significant factor, suggesting that simply offering the chance to test CSA technologies may not be sufficient without strong support systems and visible success cases. The study also demonstrated strong predictive power using PLS-Predict, confirming that the model can effectively forecast future behaviour. Theoretically, this study supports the integration of TAM and DOI as a useful approach to understanding CSA adoption in agrarian contexts. Practically, it offers suggestions for policymakers, extension agencies, and agritech developers to focus on visible benefits, local relevance, and training, underscoring its practical relevance. Overall, this research offers a timely contribution to supporting climate-resilient farming and innovation adoption in India's changing agricultural landscape.

### Conflict of Interest

The authors declare no conflict of interest associated with this study. The research was conducted independently by the authors without any financial, commercial, or personal relationships that could have influenced the results or interpretations. Data collection, analysis, and reporting were conducted ethically and solely for academic and research purposes.

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## References

1. Devarajan Y. Investigation of Emerging Technologies in Agriculture: An In-depth Look at Smart Farming, Nano-agriculture, AI, and Big Data. Journal of Biosystems Engineering. 2025 Apr 4:1-23. https://doi.org/10.1007/s42853-025-00258-z
2. Javaid M, Haleem A, Singh RP, Suman R. Enhancing smart farming through the applications of Agriculture 4.0 technologies. International Journal of Intelligent Networks. 2022 Jan 1;3:150-64. https://doi.org/10.1016/j.ijin.2022.09.004
3. Garg S, Rumjit NP, Roy S. Smart agriculture and nanotechnology: Technology, challenges, and new perspective. Advanced Agrochem. 2024 Jun 1;3(2):115-25. https://doi.org/10.1016/j.aac.2023.11.001
4. Pathmudi VR, Khatri N, Kumar S, Abdul-Qawy AS, Vyas AK. A systematic review of IoT technologies and their constituents for smart and sustainable agriculture applications. Scientific African. 2023 Mar 1;19:e01577. https://doi.org/10.1016/j.sciaf.2023.e01577
5. Bekee B, Segovia MS, Valdivia C. Adoption of smart farm networks: a translational process to inform digital agricultural technologies. Agriculture and Human Values. 2024 Dec;41(4):1573-90. https://doi.org/10.1007/s10460-024-10566-3
6. Thomas RJ, O'Hare G, Coyle D. Understanding technology acceptance in smart agriculture: A systematic review of empirical research in crop production. Technological Forecasting and Social Change. 2023 Apr 1;189:122374. https://doi.org/10.1016/j.techfore.2023.122374

7. Balaganoormth L. Socio Economic Profile of Agripreneurs and Their Clients: A Study of Karnataka State. Journal of Global Communication. 2017;10(1):54-7. https://doi.org/10.5958/0976-2442.2017.00009.X

8. Amin H. Zakat Wakalah system in Malaysia: an extension of innovation diffusion theory. The Bottom Line. 2024 Sep 30. https://doi.org/10.1108/BL-02-2024-0020

9. Qader G, Shahid ZA, Junaid M, Shaikh IM, Qureshi MA. The role of diffusion of innovation theory towards the adoption of halal meat supply chain. Journal of Islamic Marketing. 2023 Apr 4;14(5):1211-28. https://doi.org/10.1108/JIMA-01-2021-0032

10. Brahma M, S. Tripathi S. Indian society of agribusiness professionals: Helping Agripreneurs innovate. Emerging Economies Cases Journal. 2020 Jun;2(1):15-23. https://doi.org/10.1177/2516604220920752

11. Tanti PC, Jena PR, Aryal JP. Role of institutional factors in climate-smart technology adoption in agriculture: Evidence from an Eastern Indian state. Environmental Challenges. 2022 Apr 1;7:100498. https://doi.org/10.1016/j.envc.2022.100498

12. Okello DO, Feleke S, Gathungu E, Owuor G, Ayuya OI. Effect of ICT tools attributes in accessing technical, market and financial information among youth dairy agripreneurs in Tanzania. Cogent Food & Agriculture. 2020 Jan 1;6(1):1817287. https://doi.org/10.1080/23311932.2020.1817287

13. Kademani S, Nain MS, Singh R, Roy SK, Prabhakar I, Ranjan A, Karjigi KD, Patil M, Dash D, Quader SW. Quantifying support for agripreneurs: a multidimensional scale development and analysis of institutional mechanisms. Journal of Global Entrepreneurship Research. 2025 Dec;15(1):12. https://doi.org/10.1007/s40497-025-00429-4

14. Adeyanju D, Mburu J, Gituro W, Chumo C, Mignouna D, Mulinganya N, Ashagidigbi W. Can young agripreneurs improve their skills through agripreneurship empowerment programmes? Evidence from Africa. Heliyon. 2023 Jan 1;9(1). https://doi.org/10.1016/j.heliyon.2023.e12876

15. Thomas KV, Murali S. Validation and testing of a measurement model for the assessment of agripreneurial competencies. Journal of Agribusiness in Developing and Emerging Economies. 2025 Jan 30;15(2):351-67. https://doi.org/10.1108/JADEE-07-2022-0139

16. Kaur S, Kameswari VL. Training needs of rural agripreneurs of Uttarakhand. Journal of Krishi Vigyan. 2020;9(1):327-32. https://doi.org/10.5958/2349-4433.2020.00185.3

17. Jayasudha J, Shantha Sheela M. Factors influencing the success of agripreneurs in Tamil Nadu. Economic Affairs. 2022 Mar;67(2):31-35. https://doi.org/10.46852/0424-2513.2.2022.6

18. Pliakoura A, Beligiannis G, Mavrommati A, Kontogeorgos A. Exploring the determinants of young agripreneurs' success toward sustainable agriculture: a regression approach. Management & Sustainability: An Arab Review. 2024 Nov 8;3(4):462-83. https://doi.org/10.1108/MSAR-05-2023-0027

19. Obossou EA, Chah JM, Anugwa IQ, Reyes-Garcia V. Gender dimensions in the adoption of climate-smart agriculture technologies in response to climate change extremes in Benin. Regional Environmental Change. 2023 Sep;23(3):93. https://doi.org/10.1007/s10113-023-02085-4

20. Kinkingninhoun Medagbe FM, Floquet A, Mongbo RL, Aoudji KN, Mujawamariya G, Ahoyo Adjovi NR. Gender and access to complex and gender-biased agricultural technology information and knowledge: Evidence from smart-valleys in West Africa. Outlook on Agriculture. 2023 Mar;52(1):22-33. https://doi.org/10.1177/00307270221150659

21. Aryal JP, Farnworth CR, Khurana R, Ray S, Sapkota TB, Rahut DB. Does women's participation in agricultural technology adoption decisions affect the adoption of climate-smart agriculture? Insights from Indo-Gangetic Plains of India. Review of Development Economics. 2020 Aug;24(3):973-90. https://doi.org/10.1111/rode.12670

22. Tsige M. Who benefits from production outcomes? Gendered production relations among climate-smart agriculture technology users in rural Ethiopia. Rural Sociology. 2019 Dec;84(4):799-825. https://doi.org/10.1111/ruso.12263

23. Khatri-Chhetri A, Aggarwal PK, Joshi PK, Vyas S. Farmers' prioritization of climate-smart agriculture (CSA) technologies. Agricultural systems. 2017 Feb 1;151:184-91. https://doi.org/10.1016/j.agsy.2016.10.005

24. Pal BD, Kapoor S, Saroj S, Jat ML, Kumar Y, Anantha KH. Adoption of climate-smart agriculture technology in drought-prone area of India–implications on farmers' livelihoods. Journal of Agribusiness in Developing and Emerging Economies. 2022 Oct 4;12(5):824-48. https://doi.org/10.1108/jadee-01-2021-0033

25. Lupogo DD, Mkuna E. Climate-Smart Agriculture Technologies and Smallholder Farmers' Welfare: Evidence from Cashew Nuts (Anacardium occidentale) Farming System in Lindi, Tanzania. Global Social Welfare. 2023 Sep;10(3):207-23. https://doi.org/10.1007/s40609-023-00266-x

26. Tran NL, Rañola RF, Ole Sander B, Reiner W, Nguyen DT, Nong NK. Determinants of adoption of climate-smart agriculture technologies in rice production in Vietnam. International journal of climate change strategies and management. 2020 Mar 9;12(2):238-56. https://doi.org/10.1108/ijccsm-01-2019-0003

27. Mwongera C, Shikuku KM, Twyman J, Läderach P, Ampaire E, Van Asten P, Twomlow S, Winowiecki LA. Climate smart agriculture rapid appraisal (CSA-RA): A tool for prioritizing context-specific climate smart agriculture technologies. Agricultural systems. 2017 Feb 1;151:192-203. https://doi.org/10.1016/j.agsy.2016.05.009

28. Musyoki ME, Busienei JR, Gathiaka JK, Karuku GN. Linking farmers' risk attitudes, livelihood diversification and adoption of climate smart agriculture technologies in the Nyando basin, South-Western Kenya. Heliyon. 2022 Apr 1;8(4). https://doi.org/10.1016/j.heliyon.2022.e09305

29. Habtewold TM. Impact of climate-smart agricultural technology on multidimensional poverty in rural Ethiopia. Journal of Integrative Agriculture. 2021 Apr 1;20(4):1021-41. https://doi.org/10.1016/S2095-3119(21)63637-7

30. Andati P, Majiwa E, Ngigi M, Mbeche R, Ateka J. Determinants of adoption of climate smart agricultural technologies among potato farmers in Kenya: does entrepreneurial orientation play a role?. Sustainable Technology and Entrepreneurship. 2022 May 1;1(2):100017. https://doi.org/10.1016/j.stae.2022.100017

31. Agag G, El-Masry AA. Understanding consumer intention to participate in online travel community and effects on consumer intention to purchase travel online and WOM: An integration of innovation diffusion theory and TAM with trust. Computers in human behavior. 2016 Jul 1;60:97-111. https://doi.org/10.1016/j.chb.2016.02.038

32. Alhammadi K, Marashdeh H, Hussain M. Assessing the effect of innovation diffusion and technology readiness theories on attitude, behavioral intention and implementation of smart learning. Cross cultural & strategic management. 2023 Jul 24;30(4):657-75. https://doi.org/10.1108/ccsm-12-2022-0213

33. Uyob R, Ku Bahador KM, Saad RA. Integrating technology acceptance model with diffusion of innovation theory: an empirical investigation of the usage behaviour of XBRL-based Malaysia business reporting system. Accounting Research Journal. 2023 Oct 17;36(4/5):453-70. https://doi.org/10.1108/arj-02-2023-0063

34. Chen SY, Lu CC. Exploring the relationships of green perceived value, the diffusion of innovations, and the technology acceptance model of green transportation. Transportation Journal. 2016 Jan 1;55(1):51-77. https://doi.org/10.5325/transportationj.55.1.0051

35. Zhou Y. Voluntary adopters versus forced adopters: integrating the diffusion of innovation theory and the technology acceptance model to study intra-organizational adoption. New media & society. 2008 Jun;10(3):475-96. https://doi.org/10.1177/1461444807085382

36. Musa HG, Fatmawati I, Nuryakin N, Suyanto M. Marketing research trends using technology acceptance model (TAM): A comprehensive review of researches (2002–2022). Cogent business & management. 2024 Dec 31;11(1):2329375. https://doi.org/10.1080/23311975.2024.2329375
37. Khan AG, Hasan N, Ali MR. Unmasking the behavioural intention of social commerce in developing countries: Integrating technology acceptance model. Global Business Review. 2023:09721509231180701. https://doi.org/10.1177/09721509231180701
38. Mahmood A, Imran M, Adil K. Modeling individual beliefs to transfigure technology readiness into technology acceptance in financial institutions. Sage Open. 2023 Jan;13(1):21582440221149718. https://doi.org/10.1177/21582440221149718
39. Marasinghe IK, Weerasooriya WA, Rathnabahu N. Behavioral intention to use electronic resources by distance learners: An extension of the technology acceptance model. Journal of Librarianship and Information Science. 2024 Sep;56(3):594-606. https://doi.org/10.1177/09610006231154538
40. Miao M, Ahmed M, Ahsan N, Qamar B. Intention to use technology for micro-credential programs: evidence from technology acceptance and self-determination model. International Journal of Educational Management. 2024 Jun 25;38(4):948-77. https://doi.org/10.1108/IJEM-02-2023-0066
41. Jasimuddin SM, Mishra N, A. Saif Almuraqab N. Modelling the factors that influence the acceptance of digital technologies in e-government services in the UAE: A PLS-SEM approach. Production planning & control. 2017 Dec 10;28(16):1307-17. https://doi.org/10.1080/09537287.2017.1375144
42. Hanna RD, Alyouzbaky BA. Investigating factors affecting Bitcoin adoption using the technology acceptance model in Iraq. foresight. 2025 Mar 10. https://doi.org/10.1108/FS-05-2022-0061
43. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. European business review. 2019 Jan 14;31(1):2-4. https://doi.org/10.1108/EBR-11-2018-0203
44. Raghavendra, Suvarni, Deeksha. Factors influencing teachers' use of digital learning resources in Dakshina Kannada, India: a UTAUT2 analysis. International Journal of Management, Technology, and Social Sciences. 2025;10(1):193-217. https://doi.org/10.5281/zenodo.15378850
45. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS quarterly. 1989 Sep 1:319-40. https://doi.org/10.2307/249008
46. Shmueli G, Sarstedt M, Hair JF, Cheah JH, Ting H, Vaithilingam S, Ringle CM. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. European journal of marketing. 2019 Jun 25;53(11):2322-47. http://dx.doi.org/10.1108/EJM-02-2019-0189
47. Diyin Z, Bhaumik A. The Impact of Artificial Intelligence on Business Strategy: A Review of Theoretical and Empirical Studies in China. International Journal of Advances in Business and Management Research (IJABMR). 2025 Mar 12;2(3):9-17. https://doi.org/10.62674/ijabmr.2025.v2i03.002