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Institutional Credit Access and Farmers' Willingness to Adopt Affordable AI-Enabled Smart Farming Solutions for Improving Horticultural Productivity in Karnataka

Veerabhadra C[1*] & Prof. A. Senthil Kumar[2]

[1]Research Scholar, ISBR Research Centre, Bengaluru, Karnataka, India.
[2]Research Supervisor, ISBR Research Centre Bengaluru, Karnataka, India.

[*]Corresponding Author: veerabhadranaagu@ gmail

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Abstract

Smart Farming (AISF) using Artificial Intelligence (AI) technologies has shown great potential to enhance the quality of farm decisions, the efficiency of use of resources, risk management and horticultural productivity, however the uptake of these technologies by farmers will largely depend on the economic viability of the technology and farmer perceptions of its usefulness. This study proposes an approach to the finance-to-adoption issue, which connects the concepts of Institutional Credit Access (ICA), Perceived Affordability of AI enabled solutions (AFF), Willingness to Adopt (WAI) and Perceived Horticultural Productivity Improvement (PHPI). The study is carried out in economically significant commercial horticulture area and the use of AI is emerging in Kolar district, Karnataka. The method applied is quantitative, cross sectional and deductive with research design that is adapted to the Research Onion. The analytical sample comprises the horticultural farmers of the study taluks of Kolar, Malur, Mulbagal and Srinivaspur comprising 78 farmers. A 16 item 5 point likert inventory is used to measure ICA, AFF, WAI and PHPI. The strongest structural relationship is between AFF and WAI (β≈.33), positive relationships is found between ICA and AFF (β≈.09), WAI (β≈.18) and PHPI (β≈.08). Additionally, there is a positive association between WAI and PHPI (β≈.18). A positive coefficient chain suggests an indirect finance-to-productivity pathway, in which ICA can be expected to have an impact on the PHPI via better AFF and better WAI. The study adds by bringing up the concept of institutional finance as an upstream enabler and the proximal economic mechanism between access to credit and farmers' readiness to adopt AI and expected horticultural outcomes as AFF

Keywords: *Artificial Intelligence, Institutional Credit Access, Affordability, Smart Farming, Technology Adoption, Horticulture, Kolar, Structural Equation Modelling.*

Introduction

The roles and processes of information and management in agriculture are changing due to the impact of AI. This is a modern AISF, combining the domains of ML, IoT sensors, remote sensing, computer vision, predictive analytics/decision support systems, offering improved crop monitoring, irrigation, pest identification, crop yield prediction, input planning and market planning. However, adopting AI is not only about having access to physical equipment but also data access, connectivity, software services, digital capability and financial strength – qualities that are not shared by all of the preceding

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waves of farm mechanisation (Liakos et al., 2018; Wolfert et al., 2017; Miller et al., 2025). This implies access economics is an important part of the continuing process of agriculture digitisation.

India is a case of special interest to think about this transition in. The agriculture sector is faced with a series of challenges, such as climate risk, resource constraint, market inefficiencies, fragmented land holdings, etc., which create a need to tackle them to ensure the sector continues to play its role in generating employment for about 42% of India's population and about 18% of the Gross Domestic Product (GDP), as per the World Economic Forum (WEF, 2025). At the same time, GoI has been pushing forward on developing a digital agricultural ecosystem. The National Farmer ID as on February 2026 has reached 7.63 crore Farmer ID and estimated 23.5 crore crop plots have been surveyed under the Digital Agriculture Mission and the AI-based pilot for forecasting the onset of monsoon has reached 3.88 crore farmers in 13 States (GoI, 2026a). The developments suggest that the use of AI was not just an ancillary part of Indian agriculture, but has become a part of the public agricultural service delivery.

AISF is a special significance to horticulture. The second advance estimates of GoI for 2025-26 predicted the country's horticulture production to be around 377.776 million tonnes on 30.151 million hectares (GoI, 2026b). The management of horticultural crops is extremely sensitive to the timing and quality of irrigation, nutrient application, pest and disease control, harvest timing and market coordination. This value can be achieved by cutting down losses due to weather or crop disease, and by making resources more efficient, via AI based crop diagnostics, weather intelligence, smart irrigation and market advisory, as the examples of Gebbers& Adamchuk (2010), Talaviya et al. (2020), and Wu et al. (2026) demonstrate.

The horticultural strategic setting in Karnataka is Kolar district. Horticulture is an important component of the farming system and of the main crops, mango, sapota, guava and vegetables occupy up to 64% of the cultivable land in Kolar District Administration (2026). In addition, Kolar has a strong association with farming of mango, tomato, floriculture and market oriented vegetable crops. Data-driven irrigation, pest surveillance, assessing crop health and market intelligence are some of the benefits that could be gained from such production systems, but access to these technologies is not evenly distributed amongst all farmers.

A major economic obstacle is, in particular, the fact that AISF is not free. Digital solutions might have all sorts of requirements, whether they're more costly or not, such as a smartphone, stable data communications, subscription fees, compatible equipment, service charges, training and complementary investments. In this issue, agriculture finance is right in the heart of the debate on adopting AI. The effects of liquidity and credit constraints on new technology investment have been a well-known result of classical agriculture economics (Feder et al., 1985). The credit rationing theory also provides a rationalization of the exclusion of otherwise willing borrowers from formal finance due to information asymmetry and collateral constraints and lender risk assessment (Stiglitz & Weiss, 1981). A recent meta-analysis of 52 studies revealed that access to agricultural credit has average positive correlations with the adoption of different technologies, and is highly heterogenous across technologies, regions and institutional settings (Pandurangan et al., 2026). Implication: ICA is not a prerequisite of adoption but is more a facilitating condition.

In this background, the study will look at a sequential process in developing a sequential framework: ICA – AFF – WAI – PHPI. It contributes to literature in the other ways: Agricultural finance is integrated with the use of behavioural theory on technology adoption; Agricultural finance is treated as an independent mediating variable; and it is tested in a horticulture intensive area where the technological opportunity is high but the adoption of technology is still in its budding stage. Furthermore, the framework establishes links between financial inclusion, access to innovation and efficient use of agricultural resources, highlighting the importance of the study in the context of sustainability in agriculture supported by AI.

Research Objectives

- To examine whether ICA influences farmers' perceived AFF of AISF solutions.
- To test the mediating effects of AFF and WAI, including the serial indirect pathway from ICA to PHPI.

Review of Literature

- **Literature Analysis and Synthesis**

A review of the literature shows a trend of traditional interpretations of agricultural innovation to a more holistic perspective of digital and AI incorporation. The early agricultural-economics research indicated that decisions to adopt would be affected by liquidity, risk, and information and institutional characteristics; and credit-rationing theory would explain why even apparently good borrowers might face financial constraints as a result of the asymmetry of information between the borrowers and the lenders (Feder et al., 1985). The studies support the economic foundation of the ICA in this model: “technology adoption” needs to be a part of the farmer's access to formal finance.

Behavioural theories lie on the second level. The perceived usefulness and perceived ease of use of technology have been shown to be antecedents of technology acceptance (Davis 1989), perceived behavioural control of technology has been found to be a key antecedent of technology intention (Ajzen 1991), relative advantage, compatibility and complexity have been found to influence technology acceptance (Rogers 2003), and performance expectancy, facilitating conditions have been found to influence technology intention (Venkatesh et al., 2003). These theories, put together, imply that, if an innovation is technically feasible, it will not be picked up if a farmer believes that the cost of the investment is too high. Theoretically, this brings together these two concepts, and makes it possible to view AFF as a separate entity instead of the general usefulness or the 'facilitating' conditions.

Support for the economic mechanism is provided from the empirical PA research. All of these studies (Tey and Brindal, 2012; Pierpaoli et al., 2013; Lowenberg-DeBoer and Erickson, 2019; Thompson et al., 2019) reveal that the likelihood of adoption is related to the expected economic return, the technology cost, farm structure, and perceived benefits. These concerns are furthered in the more recent AI literature with the addition of data services, technical capability, and institutional coordination of the digital infrastructure. While infrastructure and implementation costs are known to be barriers to smart sensing as identified by Miller et al. (2025), the researchers of Huda et al. (2026), Shitaye et al. (2026) and Alkhwaldi et al. (2026) show that socio-technical and economic factors are important in the adoption of AI.

The mechanism is also not well understood from the finance literature. The findings from Rayhan et al. (2023) suggest that rural credit would be good facilitator for adopting agricultural technology, and Pandurangan et al. (2026) showed that there is a positive relationship between pooled credit and adoption of agricultural technology in 52 studies. But the latter study reported a very high degree of heterogeneity indicates that credit does not work the same way for all technologies and situations. In the context of AISF the question would be whether the amount of institutional finance available is affordable for the farmer in providing the relevant service, device or digital package? This is the place where the ICA→AFF→WAI sequence comes in handy.

Lastly, the productivity literature provides a list of the reasons why AISF may be attractive for horticultural farmers. Crop-health monitoring using ML, IoT, computer vision and precision systems (Liakos et al., 2018; Talaviya et al., 2020; Miller et al., 2025) may include potential areas of support for crop-health monitoring. In addition, Wu et al. (2026) demonstrate that the economic value of PA is not only determined by the benefits of investing and operating, but also by the benefits of resource-efficiency and productivity. Hence, in the current study, the behavioural outcome WAI is split from PHPI since many farmers may believe that with AI, farming productivity may rise but not have enough experience to witness the productivity increase.

- **ICA and AFF: Hypothesis Development**

The actual capacity of farmers to avail formal agricultural finance in the form of banks, Regional Rural Banks, co-operative institutions and government-supported credit mechanism and the formal channel. From the point of view of a credit rationer, access depends on the demand, information given by the lender, the collateral, and the risk of repayment and the cost of the transaction. These limitations are compounded in the agricultural sector through weather risk, the volatility of agricultural output, seasonality and imperfect agricultural accounting.

Feder et al. (1985) showed that liquidity and credit constraints can cause the postponement and/or non-adoption of productivity enhancing technologies. This mechanism is still documented in modern times. Agricultural credit constraints have been found to be both demand-side and supply-side

constraints (Balana and Oyeyemi, 2022) and rural credit has been found to be relevant to technology adoption (Rayhan et al., 2023). In the Pooled Relationship, estimated in this Synthesis of 52 Studies by Pandurangan et al. (2026), there is a positive relationship between access to credit and the adoption of technology, and the heterogeneity was very high. This heterogeneity implies that even if plenty of credit is available, technology adoption may not take place unless credit is used to finance the specific economic cost of the technology.

There are both direct and indirect costs associated with AISF. Smartphones and data plans and subscriptions may be needed for digital advisory services, while sensor-based or automated systems need to be installed, maintained and supported. From the above, it is clear that for PA to be economically viable the efficiency and productivity gains must be at least equal to the investment and operating costs; as emphasized by Wu et al. (2026). Thus, the key step in making technology more economically feasible to the eye is the first step to be taken, the perceived economic feasibility. This leads to H1.

H1: ICA has a positive and significant effect on AFF of AISF solutions.

- **AFF and WAI: Hypothesis Development**

AFF is a term used to describe farmers who feel the cost of installing and operating an AISF solution is acceptable, given their expected benefits, and their financial capacity. This is not an outright "low price" interpretation. The one technology may be very costly, but if the financial needs can be eased by flexible finance, shared services, subsidy or credible return expectations, then the impact is not that great.

TAM has put emphasis on perceived usefulness and ease of use and TPB has put emphasis on perceived behavioural control (Ajzen, 1991; Davis, 1989). Likewise, facilitating conditions are believed to be one of the factors of technology use (UTAUT) (Venkatesh et al., 2003). Farmers have an opportunity to gain from AFF for increasing their perceived behaviour control by tackling a practical question: can my farm afford and operate this technology? The economic feasibility argument also backs up this thought, as it determines compatibility and perceived relative advantage (Rogers, 2003).

The empirical approach has been continuously conducted in PA adoption studies and the determinants of PA have been found to be investment cost and expected economic returns (Tey & Brindal, 2012; Pierpaoli et al., 2013; Thompson et al., 2019). That is the idea that is developed in the recent research related to the development of the AI. Financial constraints are cited as one of the reasons that hinders the adoption of AI by Alkhwaldi et al. (2026); affordability and socioeconomic conditions are mentioned as constraints in smallholder environment by Shitaye et al. (2026); Institutional and infrastructural conditions are mentioned as constraint in South Asian context by Huda et al. (2026). Thus, farmers with the idea of affordability for AISF would exhibit a higher WAI.

H2: AFF has a positive and significant effect on WAI AISF solutions.

- **WAI and PHPI: Hypothesis Development**

WAI reflects behavioural intention to use, invest in and frequently implement AISF to make horticultural decisions. Advantages of such adoption could be improved crop monitoring, yield prediction, pest and disease identification, planning of irrigation, input use efficiency and market intelligence. These functions have been shown to be possible with the potential of AI and ML applications (Liakos et al., 2018; Talaviya et al., 2020; Miller et al., 2025).

In terms of both TAM and UTAUT, the expectation of performance improvement is the key aspect of technology acceptance. For agriculture, performance expectancy could be increased production, decreased loss, increased input efficiency, decreased operating cost or increased profitability, etc. Thompson et al. (2019) show the farmer perceptions of PA benefits to depend on the benefits expected in terms of yield and cost, and Wu et al. (2026) link PA with resource efficiency and economic performance. Depending on other institutional factors, Monica et al. (2026) also show the potential of AI to help achieve climate-smart productivity and efficiency, but with different effectiveness.

The outcome is intentionally presented under the name of PHPI – Potential Handling of Information Services for the Future – and is not really productivity, since many of the persons who were sampled aren't using AISF at all, or using it very light. The hypothesis is thus related to the relationship between behavioural willingness and perceived potential productivity benefit.

H3: WAI has a positive and significant effect on PHPI.

- **Mediating Role of AFF**

A direct ICA→WAI relationship is a relationship between a formal financial and an immediate adoption intention. This is a more or less hypothetical assertion. The input credit for seasonality may be available, but not specific to a digital subscription, sensors and complementary and advisory technology. The expectation of the mechanism of credit to the behavioural intention is therefore through financial feasibility.

This formula is one that will expand the farmer's resource capacity to improve AFF and the improvement in AFF will improve WAI. The model is an integration of the credit rationing theory with TPB and UTAUT: financial access reduces an external resource constraint while AFF increases perceived control and facilitating conditions..

H4: AFF mediates the relationship between ICA and WAI.

- **Mediating Role of WAI and Serial Mediation**

Productivity does not result from AFF. Only when a financial feasibility results in willingness and use is value created. Hence, it is proposed that the behavioural mechanism that links AFF to PHPI is WAI. The logic is comparable to that of UTAUT which creates conditions and PEX are drivers of BIO and use, and to DOI which favourable perceptions are the drivers of adoption decisions.

The overall mechanism is thus suggested to be a serial mechanism. ICA gives an enabling financial condition, AFF determines if the solution is seen as financially feasible, WAI captures the behavioural response and PHPI captures expected farm level benefit. This is better than a lean response, because it specifies a trajectory of economic and behavioural activities that might lead to technological value in the financial medium..

H5: WAI mediates the relationship between AFF and PHPI.

H6: AFF and WAI sequentially mediate the relationship between ICA and PHPI (ICA→AFF→WAI→PHPI).

Conceptual Framework Development

The conceptual structure is based on the economic and behavioural logic from the literature, and combined into a serial pathway.

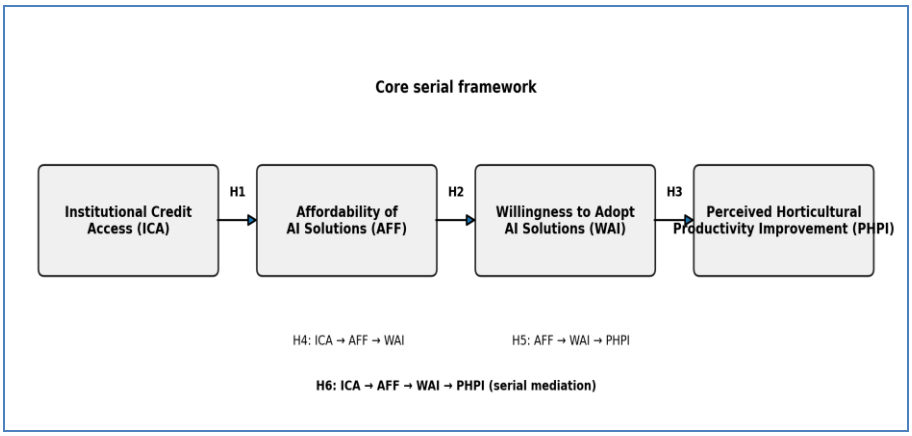


Figure 1: Proposed Conceptual Framework

Research Methodology

- **Research Design**

The study design used in the study is based on the Research Onion suggested by Saunders et al. (2019). The deductive form of theory development is used. The methodological choice is mono-method quantitative because the aim of the study is an empirical one which is to estimate the strength, direction and significance of relationships between the four constructs (mono-method quantitative).

- **Study Area and Sampling Frame**

The study is carried out in Kolar district of Karnataka. The district was chosen due to its significant dependence on horticulture for economic activities and the presence of commercial crops like mango, tomato, vegetables and flowers which present an attractive opportunity for AI-driven crop monitoring, irrigation recommendations, pest identification and market insights. The analytical sample consists of 4 taluks namely Kolar, Malur, Mulbagal and Srinivaspur which are relevant to the Horticulture.

- **Sample Size Determination**

The sample size was determined by using Cochran's (1977) formula for proportions:

$n_0 = Z^2pq / e^2$

Using the conservative values of p=.50, q=.50, Z=1.96, and e=.10, the conservative number of respondents to use is n_0=96.04. The analytical data set consists of 78 cases that are suitable for analysis, and is treated as a pilot/exploratory sample with the conservative assumption of p=.50. As an example, Cochran's formula requires a minimum sample of approximately 72 people with a proportion of people using the AI at about .25 and a 5% error margin (confidence level of 95%). The final empirical paper should identify which planning assumption was actually made during the fieldwork, and shouldn't be a matter of being forced to use the planning assumption because that is what was necessary to obtain the desired sample.

Another aspect of the early stages of AISF diffusion in the study setting is the relatively small size of the pilot sample. While there is a high level of exposure to a variety of digital technologies and smart farming, so far, only 25.6% of the respondents report using an AI/smart farming tool. The sample of users of WAI, rather than of users of AI, was used in this pattern to support the study focus.

- **Research Instrument and Construct Operationalisation**

The research instrument has two parts. Information on the respondent and farm profile is gathered in Section A, including taluk, crop category, age, gender, education, land holding, farming experience, annual farm income, institutional-credit exposure, smartphone use and use of digital-farming tools. AI awareness, training, and use of AI/smart farming tools are also captured in Section A. The variables were chosen to provide the background of the interpretation of the adoption environment in Kolar district.

There are 16 reflective statements in section B that are rated by using a 5-point Likert rating scale from 1=Strongly Disagree to 5=Strongly Agree. The four items of ICA are being evaluated for ICA (access to formal agricultural credit), ICA2 (manageability of procedures), ICA3 (sufficiency of credit for technology investment) and ICA4 (manageability of repayment terms). The construct is supported by literature on Agriculture credit and Innovation (Feder et al., 1985; Balana & Oyeyemi, 2022; Rayhan et al., 2023; Pandurangan et al., 2026).

- **Plan of Statistical Analysis**

Data analysis is an iterative measurement and structure process. SPSS ver 25 and AMOS Ver 28 are used for the study

Results and Analysis

- **Structural Model Assessment**

Table 1: SEM Model-Fit Indices

Index	Observed	Guideline
χ^2	104.611	Lower relative to df; non-significant desirable
df	98	—
p	.305	>.05
χ^2/df	1.067	<3.0
CFI	.990	>.95
TLI	.988	>.95
RMSEA	.030	<.06/.08
SRMR	.072	<.08

Overall overall fit in the structural model is good. The model's $\chi^2(98)=104.611$ ($\chi^2/df=1.067$) indicates a small disagreement with the model as a function of number of degrees of freedom. The values of CFI = .990 and TLI = .988 are much higher than the traditional .95 index, RMSEA = .030 is very close to .05, which is the standard for a very small error of approximation, and SRMR = .072 is lower than .08. Taking both indexes together, the four-construct structure seems to be a good model for the observed pattern of covariances (Hu & Bentler, 1999; Hair et al., 2019).

Table 2: Standardized Structural Path Coefficients

Hyp.	Path	Standardized β	Structural interpretation
H1	ICA → AFF	.09	Positive; upstream credit-to-affordability pathway
—	ICA → WAI	.18	Positive direct contribution to adoption willingness
H2	AFF → WAI	.33	Positive and strongest structural relationship
—	ICA → PHPI	.08	Positive direct relationship with expected productivity
—	AFF → PHPI	.01	Positive but comparatively small direct relationship
H3	WAI → PHPI	.18	Positive adoption-to-productivity relationship

All structural coefficients in the AMOS are in the same direction: finance to adoption to productivity. The correlation that is highest is between AFF and WAI (β≈.33). The result indicates that the farmers with a positive attitude towards the financial management of AISF are also more prepared to implement the solutions to AISF. From a practical point of view, therefore, the relevance of a technology for diffusion, rests on a farmer's ability to see the technology as affordable, which is further influenced by institutional finance, and AFF thus has a central behavioural role in the model.

ICA is positively related to AFF (β≈.09), WAI (β≈.18) and PHPI (β≈.08). The ICA (ICA→AFF) coefficient is smaller than the AFF (AFF→WAI) coefficient, but it is still positive because ICA is at the beginning of the serial mechanism, that has a substantive importance. Institutional finance is thus seen not only as a credit-to-productivity linkage, but also as an upstream enabling resource through which the impact of institutional finance can be felt through the affordability and the behavioral-adoption phase.

Also, there is a positive coefficient between WAI and PHPI (β≈.18). This is consistent with the hypothesis of a positive relationship between behavioural readiness to use AISF and an increase in yield improvement, loss reduction, efficient input use and economic returns. This direct relationship (AFF→PHPI) is relatively weak (β≈.01), further supporting the conceptual premise that affordability is likely to impact productivity mainly because it promotes adoption, and not to alter productivity perceptions without the adoption.

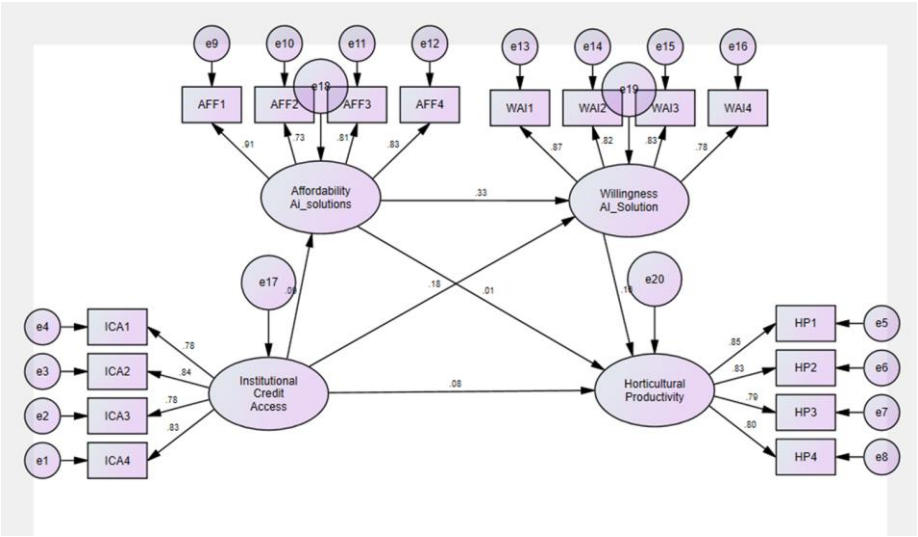


Figure 2: Original AMOS Structural Model Output with Standardized Path Coefficients

The original AMOS analysis image is shown in Figure 2. The measurement loadings are significantly high, and the structural part has positive loadings for the proposed relations. The structural path AFF→WAI is the most pronounced with a score of ~ .33, followed by ICA→WAI and WAI→PHPI (~ .18 each). The ICA→AFF link (approximately .09), ICA→PHPI (approximately .08) and AFF→PHPI (approximately .01) are still positive, and thus the logic of the serial framework is maintained.

- **Indirect and Serial Pathway Assessment**

Table 3: Directional Indirect Effects Derived from Standardized Path Coefficients

Hyp.	Indirect Path	Approx. Standardized Indirect Effect	Interpretation
H4	ICA → AFF → WAI	.030	Positive indirect pathway to WAI through AFF
H5	AFF → WAI → PHPI	.059	Positive indirect pathway to PHPI through WAI
H6	ICA → AFF → WAI → PHPI	.005	Positive serial finance-to-productivity pathway

The indirect effects in Table3 are produced by multiplying the rounded standardized coefficients as shown in the AMOS diagram. ICA has an indirect positive effect on WAI (via AFF) of ~.030 (.09 x .33). This pathway is conceptually significant as it illustrates a more direct economic pathway that institutional finance can affect on the willingness to adopt – when credit access enhances financial feasibility, affordability strengthens willingness to adopt.

There is positive indirect relationship between AFF and the WAI with a value of correlation coefficient: .059 (0.33 x 0.18). The size of this pathway is bigger than the direct pathway AFF→PHPI in the AMOS model. The pattern confirmed that affordability is significant when it comes to adoption willingness and that, willingly putting up behaviour, is the gateway to making economic sense of AI solutions for improved productivity.

The overall standardized coefficient product for the serial pathway ICA - AFF - WAI - PHPI is positive and is about .005 for the product (.09 x .33 x .18). The direction is, although modest, theoretically important, because improved financial access results in more affordable AISF, leading to increased farmers' willingness to adopt AISF, which will support expected horticultural productivity. Apart from this strict serial route, there are a number of positive indirect routes from ICA to PHPI in the model, for instance, ICA→WAI→PHPI. With the rounded diagram coefficients the indirect contribution of ICA (the sum of the four diagram coefficients) is about .039 and the direct plus indirect contribution of the model-implied is about .119.

Conclusion Limitations and Future Research

Conclusion

This study aims to create an integrated framework for finance-to-adoption in horticultural farmers in Kolar district involving the interaction of the three factors namely, ICA, AFF, WAI and PHPI. Measurement results support the stability of the four-construct structure, reliability of all measures, the convergent and discriminant validity of all measures, as well as the overall good SEM fit. From the AMOS model, it is found that all relationships given in the model have positive values, where the highest value is for the AFF→WAI relationship.

The result of the analysis corroborates the staged interpretation of the adoption of AISF. Upstream enabling resource is translated to perceived economic feasibility (FAIF) by AFF, financial capacity is translated by AFF to farmers' behavioral readiness in the use of AISF (WAI), and the expected benefits in terms of yield, loss reduction, input efficiency and economic return is represented by PHPI. The chain of positive ICA→AFF→WAI→PHPI thus indicates an indirect channel for institutional finance to contribute to the realization of a digital transformation towards productivity.

The key policy stipulation is that institutional credit should be made available for farmers, and more affordable for the adoption of specific AISF solutions. If the cost barrier is reduced by financing and in this way a channel opens for farmers to be more inclined to accept, then they can benefit from improved productivity and sustainability of their agricultural operations, especially in horticulture.

Limitations

- The current sample size (N=78) is a pilot sample, which is smaller than the recommended sample size (Nc=~96) obtained by using Cochran's rule (p=.50 and e=.10). It is therefore important to take care when interpreting the structural estimates and larger field sample should be used to estimate.

Scope for Further Research

The model should be replicated in a larger number of farmers, who have a high chance of being selected in the first place and then further research should be conducted in farmers from Kolar district and neighboring horticultural districts of the district with careful selection of farmers. Multi group analysis can then be used to compare these farmers of fruit, vegetable and flowers with the farmers with small and semi-medium (medium) size farms. Comparing current users of AI, potential users and non-users would be of significant value.

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