Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-5 |May 2026

Original Researcher Article

Harnessing Ai For Sustainable Agriculture.

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ABSTRACT
The primary goal of this research is to determine how behavioral factors such as perceived utility, ease of use, and environmental consciousness influence AI technology adoption, as well as how AI Technology mediates the relationship between behavioral factors and sustainable organic farming. The study also investigates the moderating influence of government support in the relationship between behavioral characteristics and the adoption of AI technology in sustainable organic agriculture. The study followed a quantitative cross-sectional design. Convenience Sampling is used to identify financial service clients as a sampling unit. The concepts of AI, user innovativeness, understanding of financial services, and government support are measured using a standard questionnaire. To ensure the instrument's validity and reliability, CFA is used. Based on the results, it seems that PLS-SEM is the tool of choice for determining the interrelationships of various variables. This study found significant correlations between behavioural traits, AI adoption in organic farming, and sustainable agricultural techniques, underscoring the importance of individual and external factors in technology acceptance for sustainability. Because of its perceived ease of use, usefulness, and environmental sensitivity, farmers accepted AI. This shows that organic farmers will use AI technology if it is easy, helpful, and eco-friendly. The high correlation between behavioural attributes and AI adoption suggests that farmers' AI adoption is vital to sustainability. AI boosts resource efficiency and chemical use in sustainable agriculture. Government assistance moderates AI adoption and behavioural variables, showing policy initiatives can influence farmers' technology adoption intentions. Government subsidies, training, and incentives help organic farmers employ AI. Mediation research indicates behaviour influences AI adoption and sustainable farming. Positive AI behaviour can lead to sustainability, making AI crucial for sustainable agriculture. The study emphasises behavioural and policy support for AI's impact on sustainable organic farming.
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Keywords: Perceived usefulness, Behavioural factors, sustainable organic farming, PLS-SEM.
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INTRODUCTION:

Research in agricultural economics and agribusiness management has long sought to understand the elements that impact the adoption of AI in agriculture. **(Kallas,2009)** notes that most of the existing research on farmers' adoption of AI in organic farming comes from affluent countries. In organic farming, aiming at sustainability and environmentally friendly practices, the inorganic introduction of AI is slowly being recognized for its ability to improve the processes of pest control, crop surveillance, and distribution of resources. However, it is the behavioural actions of the farmers themselves that tend to make AI successful or not. The decisions of adopting AI would depend on the factors perceived usefulness, ease of use, and trustworthiness of AI technologies, along with awareness and education about AI technologies **(Davis, 1989; Venkatesh et al., 2003).** Social influences and community norms further shape farmers' attitudes, and illiteracy due to cost-benefit analysis and a fear that these are unaffordable or ineffective creates barriers **(Rogers, 2003).** Due to a strong need for alignment between technological advancement and human sustainability goals, it is thought that an understanding of these dynamics is essential when designing interventions meant to encourage AI adoption, particularly in organic farming **(Nagesh & Nagashree, 2022).** As a result, there are few studies that look at what drives developing countries to use AI in organic farming. **(Tereno, 2015).**

The agricultural sector is facing significant challenges in the 21st century that need for innovative solutions. The increasing demand for food production is putting a pressure on agricultural systems, while the global population is expected to reach 9.7 billion by 2050. The demand for agricultural products is on the rise due to several factors, including changing dietary habits, increased urbanisation, and improved economic conditions. But meeting this demand with conventional farming practices has serious ecological consequences, threatening the same ecosystems that support farming. More and more, the environmental impacts of traditional farming methods are becoming apparent and cause for worry. About one-third of Earth's surface is affected by soil erosion, which is caused by over-ploughed fields, over-fertilization with chemical fertilisers, and over-harvesting of the same crop (SWSR Report, 2015). Reducing agricultural efficiency and contributing to global warming, this process releases carbon from the atmosphere. Pesticide and nutrient-laden agricultural runoff has polluted the water supply, damaged marine ecosystems, and creating over 400 oceanic "dead zones" throughout the world. Concerns over pesticide use, habitat loss, and monoculture practices are threatening biodiversity, which threatens food security around the world and the viability of ecosystems.

Awareness of the environment becomes a decisive factor in the adoption of AI in organic agriculture, as it aligns with sustainability principles on which organic methodology goes. Producers who attach more importance to environmental sustainability become more likely to adopt AI technologies that consume fewer resources, fewer applications of chemicals, and increase the level of sustainable farming practices **(Chatterjee et al., 2021).** Applications of artificial intelligence, such as precision agriculture, pest management, and predictive analytics, assist the environmentally conscious farmers in improving the productivity of resources use without compromising soil quality and biodiversity **(FAO, 2021).** In addition to facilitating sustainable agricultural applications, the growing environmental consciousness of farmers makes them receptive to technology that lessen their impact on the environment **(Ramesh et al., 2022).** Interventions in policy and technology that seek to integrate AI into organic farming systems can benefit from a better understanding of and reliance on this ecological consciousness.

Considering these difficulties, organic farming has emerged as a viable substitute for traditional methods. Biological methods are used by organic farmers to increase soil fertility, and synthetic inputs are reduced **(Reganold, 2016).** To promote soil health, increase biodiversity, and decrease pollution, organic farmers forgo using synthetic fertilisers and pesticides. Organic farms have the potential to be more eco-friendly than conventional ones since they sustain 30% higher species variety **(Tuck, S. L., et al, 2014).** Although conventional farming produces more fruit per acre, organic farming has several advantages. Using AI in farming is one creative method. Machine learning, computer vision, smart bots, and big data analytics can revolutionise farming by providing data-driven insights, automating processes, and making the most of available resources.

Organic farming produces less fruit per acre compared to conventional farming, despite the former's advantages. A fresh perspective on farming is introduced by AI. Automation of processes, optimisation of resources, and data-driven insights could all be possible with the use of robotics, computer vision, machine learning, and big data analytics in the agricultural sector. We can end world hunger with the help of AI and sustainable farming. By making farming more environmentally friendly and sustainable, AI can help organic farming thrive. Artificial intelligence (AI) has the potential to improve crop yields in precision agriculture while decreasing environmental, nutrient, and water damage. In order to forecast when crops will be harvested, how to eliminate pests, and how to manage them, machine learning algorithms can sift through mountains of data collected from sensors in the soil, weather stations, and satellite images **(Kamilaris, 2018).** Protecting agricultural lands may be revolutionised by AI. By utilising computer vision and deep learning, pests, insects, and plant diseases may be identified, allowing for more precise and environmentally conscious pest control methods. By reducing the usage of pesticides, this strategy safeguards beneficial creatures and promotes ecological balance. Sustainable farming is based on using organic farming methods, and AI can assist with that.

One of the most important ways to ensure that future generations will be able to feed themselves and live comfortably in rural areas is through sustainable agriculture. The knowledge of ecosystem services is the foundation for this to happen. By improving water and energy management, precision farming, smart farming, and other areas of sustainable agriculture, artificial intelligence is quickly becoming a potent weapon in the agricultural toolbox. **(Kar et al., 2022)**

Precision and sustainability are enhanced by AI-driven agriculture. Artificial intelligence systems can help farmers optimise water saving and irrigation. The use of artificial intelligence (AI)-guided autonomous tractors and harvesters has the potential to greatly decrease the need for human labour in agricultural tasks such as crop harvesting, trimming, and ploughing.

The world's biggest problems are the increasing number of people and the prevalence of hunger. To control issues like pests, diseases that harm crops and livestock, water scarcity, energy instability, and soil fertility, an integrated strategy is required. By adhering to ecological, economic, and social constraints, sustainable agriculture guarantees food production **(Mana et al., 2021)**

Governments of different countries are increasingly recognizing the excellent potential of AI in agriculture and accordingly providing various types of support to make AI integration into organic farming easier. This includes financial grants for AI products, funding for research that encourages innovations in agricultural AI, and trainings to enhance the digital literacy of farmers (FAO, 2021). Furthermore, policy frameworks are in place for data security and open data platforms, thus increasing farmers' easier access to AI-based insights **(World Bank, 2022).** The governments collaborate and make contributions to companies like private technology companies and agricultural organizations to create AI-based solutions. These include precision pest management and soil health monitoring, organized around organic farming needs **(NITI Aayog, 2021).** The objective of such initiatives is to reduce the digital gap among rural regions and encourage fair access to AI technologies in tandem with sustainability objectives.

In this regard the main objective of the study is to identify how the behavioural factors such as Perceived usefulness, Ease of use and environmental consciousness will impact adoption of AI Technology and how AI Technology mediates between behavioural factor and Sustainable organic Farming. Government support is also looked at as a moderator in the study. The goal of this research is to find out how government subsidies affect the connection between farmers' actions and the use of artificial intelligence in environmentally friendly organic production.

2.Theoretical Framework and Hypotheses

From past decade the question how, behaviour is determined by Attitude is Centre of research interest. The goal of this study is to investigate the determinants of behavioral factors that influence AI adoption in organic farming. The TPB and the TAM are two ways that we might establish our theoretical framework. Assuming that humans act in accordance with three separate but interrelated constructs, the TPB derives from the TRA **(Fishbein & Ajzen, 1975)** Beliefs about the expected outcomes of a behaviour, which influence our attitude towards that behaviour; beliefs about social norms and the motivations to conform to them, which can lead to feelings of social pressure or subjective norm; and beliefs about the controls over behaviour, which can either help or hinder it **(Ajzen, 1991)** . Concern for the environment influences people's actions in a positive way, according to the available data. **(Willock et al.,1999), Vogel (1996), and Lynne et al. (1988)** are just a few of the many studies that have looked at the attitude-behaviour relationship on farms and shown that attitude theory may be used to explain conservation behaviour. Scientists have found a strong correlation between organic farming and farmers' green concerns. One of the most important ways to ensure that future generations will be able to feed themselves and live comfortably in rural areas is through sustainable agriculture. The knowledge of ecosystem services is the foundation for this to happen. By improving water and energy management, precision farming, smart farming, and other areas of sustainable agriculture, artificial intelligence is quickly becoming a potent weapon in the agricultural toolbox. **(Kar et al., 2022).** When it comes to sustainable farming techniques and increased precision, AI-driven agriculture is crucial. Algorithms powered by artificial intelligence can help farmers better manage irrigation and save water. Furthermore, AI enables the automation of agricultural labour-intensive operations like ploughing, crop harvesting, and trimming with the use of self-driving tractors and harvesters led by AI technology, drastically cutting down on human involvement. Cost and risk of transitioning to a new farming method, developing strategies to sell specialised products, and access to necessary information and technology are some of the major challenges that farmers encounter when trying to switch to organic farming practices, according to the research **(Greene, 2003)**

We model two constructs perceived ease of use and perceived usefulness as latent variables in our framework to predict behavioural intention drivers to adopt or continue using technologies for organic farming. Additionally, we consider sustainable farming practices and government support for organic farming in our model.

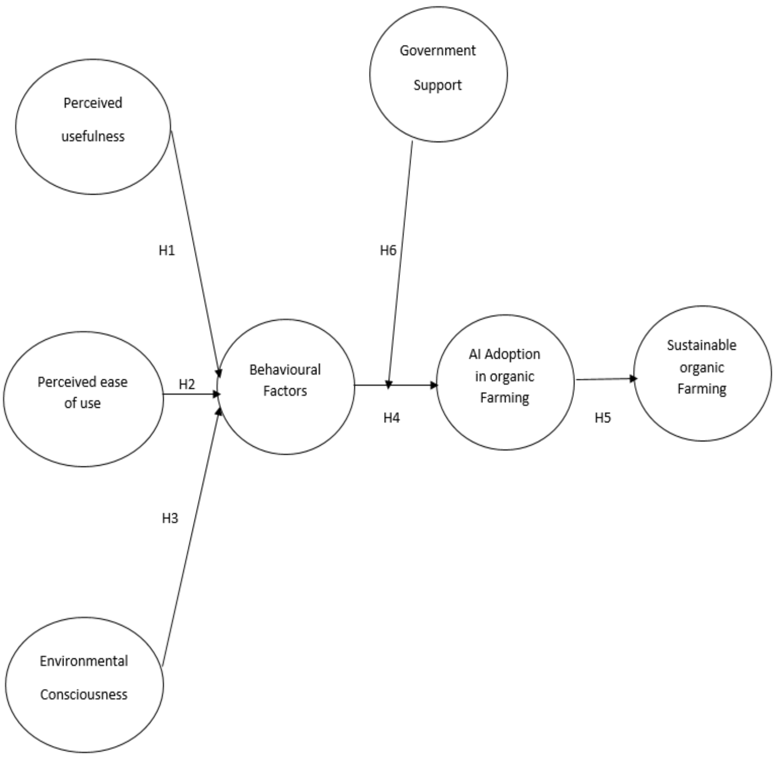

Figure 1: Research Model

In this section, we present our research model, constructs, and linkages based on the logic of the TPB and TAM to explain farmers' intentions towards organic production. Our hypotheses are based on the literature on the influence of perceptions.

2.1Perceived Usefulness

That which an individual thinks "will enhance her/his job performance" is known as "perceived usefulness" (Davis 1989). Behavioural intention to use (BI) of the technology of interest is believed to be directly predicted by PU in the TAM framework (Park, et al., 2014). The significance of social effects and perceptual processes cannot be overstated when trying to comprehend benefit evaluation. Since organic farmers presumably prioritise financial gain from the transition over behavioural propensity and creation of the intended application takes place. Financial and non-financial gains would result from organic farming [70]. Research indicates that farmers view organic farming as a profitable alternative to conventional farming, which may encourage conversion. Organic produce prices are higher to compensate for decreased yields in organic cultivation.

Price premiums may boost farmers' incomes. Certified organic farming is perceived as more beneficial by farmers who raise their income. Organic farming can enhance market access and corporate ties **(Karipidis et al., 2009)**. Organic farming lowers health hazards for farmers and consumers due to pesticide use, in addition to economic benefits. Organic farms not only improve health but also promote sustainability and productivity for future generations through increased soil fertility and variety. Within this literature, we assess the perceived benefits of organic farming as key drivers of farmers' adoption behaviour. An individual's subjective assessment of how well a certain system or technology (in this case, AI tools) helps them do their work or complete activities more easily is what we mean when we talk about perceived usefulness. It demonstrates how people think the technology will help them get things done more quickly, easily, or effectively (Wicaksono & Maharani, 2020; Davis, 1989).

2.2Perceived Ease of use: Perceived ease of use refers to an individual's perceived level of simplicity, effortlessness, or intuitiveness when engaging with a certain technology or system (AI tools in the current study). It indicates how much people believe that utilizing the technology will involve little effort, complexity, or cognitive load. This perception encompasses factors such as the simplicity of system operation, ease of learning, and user-friendly interface design **(Li, 2023).** Davis (1989) who proposed the theory of Technology Acceptance Model (TAM) has formulated simpler characteristics of technology, namely perceived usefulness (PU). According to **(Zeithaml et al., 2002) ,** PEU is the extent to which an innovation is user- and comprehension-friendly. Prior research has shown that PEU is an important consideration when deciding to implement new agricultural technologies **(Aubert et al., 2012).** Even though TAM is the theory of adoption, it has received insufficient attention.

2.3 Environmental Concern: As per the research conducted by **(Štreimikiend' and Baležentis, 2014),** the term "environmental concern" is used to describe the degree to which individuals are cognisant of, and willing to help address, environmental problems. According to **(Schlegelmilch et al., 1996),** being environmentally conscious entails maintaining an optimistic view and taking actions that reduce environmental impacts. According to **(Alibeli and Johnson, 2009),** the degree to which an individual care about the environment is proportional to their knowledge of environmental problems and their motivation to take action to address them. Therefore, environmental awareness can be described as the extent to which an individual is knowledgeable of environmental issues and motivated to take action to resolve them. Whether or not consumers purchase eco-friendly goods is significantly influenced by their level of environmental concern. According to **(Arısal and Atalar, 2016),** environmental concern influences the intention to buy eco-friendly products. Organic products and unique agricultural food products are more likely to be purchased by eco-conscious consumers, according to studies **(Nguyen et al., 2019) and (Wang et al., 2019).**

2.4 Behavioural factors

Behavioural factors refer to the psychological, cognitive, social, and emotional characteristics involved in shaping the decision-making behaviours of individuals within specific contexts. These factors involve attitudes, perceptions, beliefs, and habits; social influences and personal motivations, which together indicate how individuals respond to innovations and change **(Ajzen, 1991).** In agriculture, behavioural elements, in this case, influence the uptake of technologies such as artificial intelligence because these impact the perception of usefulness, user-friendliness, and congruence toward their values among farmers, according to **(Rogers, 2003).**

2.6 AI Adoption in organic Farming

The integration of AI technologies with organic farming practices refers to the process through which agricultural producers enhance decision-making, optimize resource utilization, and improve productivity while being under principles of eco-friendliness and sustainability. This integration involves the use of AI instruments for precision agriculture, pest control, assessment of soil health, and yield forecasting concurrent with the fundamental tenets of organic farming **(FAO, 2021).** Technological awareness, environment, perceived usefulness, and socio-economic factors have played a significant role in the adoption process **(Chatterjee et al., 2021).**

2.7 Government Support

It must do, in general, with support directed toward the adoption of technology in agriculture-the ways governments support policy and development initiatives and provide resources to make sophisticated technologies like Artificial Intelligence, precision agriculture tools, and Internet of Things systems available and useful for farming. There are many forms: financial incentives, subsidies, education, infrastructure, and other support to promote farmers to adopt it. It begins with an initiative to make innovations accessible and functional for farmers **(World Bank, 2022).** The government interventions have been targeted at increasing productivity, sustainability, and resilience in agriculture through concerns such as financial constraints, low technical literacy, and inadequacies in infrastructure **(FAO, 2021).** From the above theoretical framework hypothesis are stated below

2.8 Hypothesis of the Study

H_1: Perceived usefulness has a considerable favorable impact on behavioral characteristics.

H2: Perceived ease of use has a significant positive effect on behavioural factors

H3: Environmental consciousness has a substantial positive impact on behavioural characteristics.

H4: Behavioral considerations have a substantial favorable effect on AI adoption in organic agriculture.

H5: AI use in organic farming has a substantial positive impact on sustainable farming practices.

H6: The Moderation effect of government support and behavioural factors has a significant positive effect on AI adoption in organic farming

3.Methodology

The still-emerging area of artificial intelligence deployment in organic agriculture warrants an exploratory study approach to better understand the behavioural elements that influence technology acceptance. A cross-sectional study is perfect for examining the correlation between AI adoption and behavioural traits like environmental concern and perceived usefulness. This is because there was only ever one instance when the data was gathered. Current trends and their impact on sustainable agriculture can be better understood with a bird's-eye view of farm attitudes and practices.

Based on the findings of a comprehensive survey that enquired about farmers' intentions regarding organic farming, this research was conducted. The data was collected by an extensive survey of farmers in Bangalore District. This study's findings came from a comprehensive survey of one hundred farmers that were spread out across the districts of Bangalore. All the data needed was derived from direct, in-person conversations with organic farms. Researchers can get quick and cheap data from accessible organic farmers via convenience sampling, thus it's a good choice. Researching how people utilise AI in areas where farmer registrations are not yet mandatory can benefit from this approach. As a result, researchers can swiftly collect opinions from the organic agricultural community and get preliminary data. A questionnaire was used to collect the most fundamental data required to understand the study's context. A range of questions were added to assess farmers' ideas, attitudes, and intentions to obtain insight into their decision-making process. The questions ranged from "strongly disagree" (1) to "strongly agree" (5). Each component's measuring items were based on prior research on related issues. The statements that are utilised to measure the study model's latent variables were delivered to respondents in Appendix A, Table Al.

The data used to estimate the structural model were analysed using structural equation modelling (PLS-SEM) methods and Smart PLS 4 statistical software. According to **(Hair et al., 2021),** structural equation modelling (SEM)-PLS, a variance-based technique, is a suitable tool for exploratory research that aims to find essential driving factors. The PLS-SEM model is great for complex models since it allows for small sample numbers and is variance-based. Additionally, the PLS-SEM does not presume anything on the distributions of the indicators. examining the measuring tools' correctness and reliability is the first step in assessing and interpreting PLS models. The second step is examining the structural model, which displays the relationships between the constructs. After the study model was loaded into Smart PLS, the software's PLS algorithm and bootstrapping methods were triggered. **(Henseler et al., 2009).**

4. Data Analysis and Results

4.1 Sample Statistics

The demographic characteristic of the respondents reflects some very important information regarding the profile type of the participants. The mean age for the respondents is 52.23 years, with a standard deviation of 1.84, reflecting an older and more homogeneous population. Participants, on average, have had 32.48 years of experience in farming, which again represents a considerable level of experience and familiarity with agricultural practices. An average household size of 2.96, with a standard deviation of 0.83, also indicates that household sizes are small and relatively uniform, thereby exhibiting experience and an established character of the farming households in research.

Table 1: Sample Statistics

Demographic Characteristics		
Variables	**Mean**	**Std dev**
Age	52.23	1.84
Farming Experience	32.48	1.84
Household Size	2.96	0.83

4.2 Assessment of the Measurement Model

The model's stated constructs are measured via attributed observable objects. Prior to evaluating the measurement model, we conducted confirmatory factor analysis to establish which items were appropriate for each latent variable. Appendix A shows the findings of the factor loadings. If an item had an outer loading of less than 0.7 in the confirmatory factor analysis, we eliminated it from the latent variables and did not include it in subsequent analyses. This was done to achieve maximum internal uniformity and dependability. Following that, we used Cronbach's alpha (CRA) and composite reliability (CR) to ensure internal consistency and construct reliability (Hair et al., 2014). To ascertain the convergent validity of the measures, we assessed the average variance extracted (AVE) in accordance with the Fornell and Larcker criterion **(Fornell & Larcker, 1981).** Initially, we ensured that each item had a substantial load on its own build (CRA > 0.70).

On the other hand, the CR for each construct must be 0.7 or higher (Nunnally, 1994). Also, the AVE must be 0.5 or higher because, on average, it accounts for almost half of the indicator variance (Fornell & Larcker, 1981). The results showed that all items had substantial loadings of 0.70 or higher on their respective constructions.

Every construct has a CR rating above 0.70 and an AVE above 0.50. To assess discriminant validity, we looked for constructs with squared correlations less than their corresponding AVEs. Despite the lack of findings, data analysis revealed no evidence of multicollinearity or cross-loading (collinearity statistics; VIF < 3.5, tolerances < 1).

Table 2. Measurement information of the constructs

	N	CRA	CR	AVE
Construct	**Items**	**(>=0.7)**	**(>=0.7)**	**(>=0.5)**
Perceived usefulness	4	0.82	0.894	0.738
Perceived Ease of use	4	0.754	0.845	0.576
Environmental Consciousness	3	0.851	0.931	0.871
AI Adoption in Organic Farming	4	0.8	0.883	0.715
Sustainable Farming practices	4	0.833	0.889	0.666
Government Support	3	0.775	0.871	0.693

4.3 Assessment of the Structural Model

The hypothesised relationships in the proposed research model were assessed using the structural model (refer to Figure 1). Significance, direction, and size of effect (f^2) of a particular predictor construct, statistically significant t-values associated with path coefficient estimates, and R^2 are all signs of a well-designed structural model that allows one to understand the complex interrelationships between the independent and dependent variables. **(Hair et al., 2014).**

Sustainable Organic Practices, an endogenous variable, has a variance explained (R^2) of 0.491. **(Hair et al., 2014)** discusses PLS models. recently regarded R2 values of 25% as somewhat poor, 50% as moderately substantial, and 75% as very strong. The results were deemed satisfactory when the complexity level of the research model was considered along with the exploratory nature of the investigation. We discovered a medium effect for conventional farmers' perceptions of usefulness (>0.15) and a significant effect for perceived ease of use (>0.35) when determining the predictive relevance, f^2. Environmental Consciousness was determined to have an effect size of 0.103, which is close to the medium effect size. **(Cohen, 1988)**

Using 5000 samples, the Smart PLS bootstrapping method was used to assess both the hypothesised effects and group differences. Below, you may find and assess the outcomes of the path coefficient, significance, and P-value computations.

Table3: Results of the hypothesis

Hypothesis/ Paths	**Path Coefficient (Beta)**	**T statistics**	**P values**	**HS**
PEUSFN -> BF	0.4	17.988	0.000	Accepted
PEUSE-> BF	0.356	13.31	0.000	Accepted
ENVCONC-> BF	0.386	10.81	0.000	Accepted
BF -> AIADOP	0.245	2.332	0.020	Accepted
AIADOP -> SFPRAC	0.701	11.341	0.000	Accepted
GOVSUP x BF -> AIADOP	0.102	1.964	0.050	Accepted

Source: Authors' own calculation. HS = Hypothesis support (hypothesis rejected or accepted). PEUSFN: Perceived Usefulness, PEUSE: Perceived ease of Use, ENVCONC: Environmental Consciousness, BF: Behavioural Factor, AIADOP: AI Adoption in Organic Farming, SFPRAC: Sustainable Practices in Organic Farming, GOVSUP: Government Support.

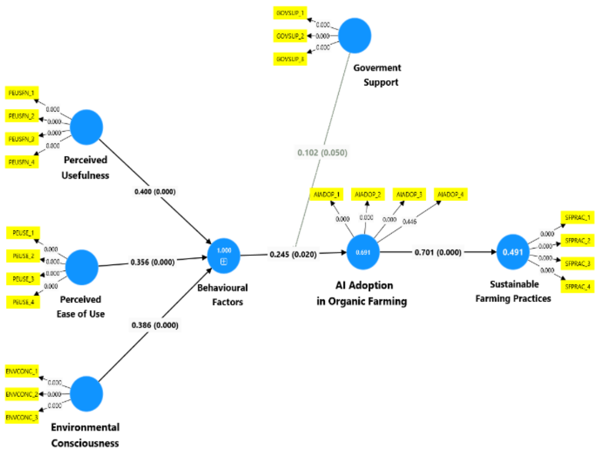

Figure 2: Structural Model

4.4 Model Estimation and Hypothesis Testing

The model's path coefficients and hypotheses define each path. Results of the model estimation, which constitute the evaluation of the hypotheses, are displayed in Table 3. Strong influence is defined as a route coefficient value greater than 0.35, moderate impact as a value greater than 0.15, and weak influence as a value greater than 0.02 (Cohen, 1988). An examination analysis shows a statistically significant, positive association between perceived usefulness and behavioural determinants at a beta coefficient of (β = 0.4). This means that as the perceived utility of AI technologies increases, so too do the factors of behaviour that contribute to the adoption of AI. The value of the T-statistic (T = 17.988) surpasses the critical limit of 1.96, thereby validating the significance of this association at the 5% significance level. In addition, the P-value (P = 0.000) offers compelling evidence against the null hypothesis, further emphasizing the importance of perceived usefulness as an essential factor influencing behavioural elements within the framework of AI adoption in organic agriculture **confirming Hypothesis 1.**

The correlation is statistically significant between perceived ease of use and behavioural factors, as suggested by the beta coefficient at 0.356, indicating a moderate positive influence. The critical value was surpassed by the T-statistic of 13.31. This finding confirmed the practical significance of the relation. Moreover, the P-value of 0.000 offers significant support against the null hypothesis, and thus, perceived ease of use significantly influences the development of behavioural factors in organic farming when it comes to AI adoption confirming **hypothesis 2.**

The statistical link between environmental awareness and behavioural determinants shows a value of beta-coefficient at 0.386. This is an intermedium positive influence. The T-statistic of 10.81 is more than the critical value, hence the strength and validity of the correlation are upheld. The P-value of 0.000 offers strong evidence against the null hypothesis; thus, a case can be made that environmental awareness does indeed have a significant influence on behavioural determinants of AI adoption **confirming hypothesis 3.**The results of the analysis suggest that behavioural factors significantly and positively affect AI adoption in organic farming (β = 0.245, t(DF) = 2.332, p = 0.020). The calculated t-statistic is above the critical value so that it is significant at 5%. The positive beta coefficient also suggests that improvements in behavioural factors correlate with the increase in the likelihood of adoption of AI with organic farming. The p-value is 0.020, also extra evidence in support of the hypothesis that this association is not due to random variation **confirming hypothesis**

4. Thus, the outcomes of the structural model show that AI adoption significantly contributes to sustainable farming practices (β = 0.701, t(DF) = 11.341, p = 0.000). A high t-statistic suggests that there is a strong correlation between the degree of AI adoption and sustainable practices. Additionally, a large positive beta coefficient points out that enhanced AI adoption goes with a significant development in sustainable farming methodologies. The p-value of 0.000 indicates that the observed relationship is exceedingly statistically significant **confirming hypothesis 5.**

The study evidence that governmental support acts as a moderator towards the association of behaviour factors with the AI adoption in organic farming (β = 0.102, t(DF) = 1.964, p = 0.050). Since the beta coefficient is positive, governmental support motivates the role of behavioural factors in AI adoption. The t-statistic also attests that at a level of 5%, the moderator effect is statistically significant while the p-value is exactly 0.050 **confirming hypothesis H6**.

5. Discussion and Results

We examined 100 organic farmers in the Bangalore district. Previous research has shown that behavioural drivers greatly affect farmers' attitudes towards adopting or sustaining organic farming practices. Our findings support the proposed linkages between the TPB and TAM for reorienting farming techniques in the Bangalore region. The study's objective was to determine the factors influencing behavioural intention towards organic farming and its impact on sustainable practices. To measure intention, we used endogenous variables from the TPB **(Ajzen, 1991)** and TAM **(Davis, 1985)**, which are fundamental theoretical principles for understanding adoption decision-making.

The result of hypothesis 1 supports the fact that there is a significant positive relationship with behavioural variables; one who thinks AI technologies have the potential to be useful will likely have positive attitudes towards behaviour related to their adoption. This is in accordance with previous studies that suggest that the perceived usefulness is a critical factor for technology adoption **(Davis, 1989; Venkatesh et al., 2003).** This implies, therefore that the nature of advantages from using artificial intelligence must always come forth in ways that change behaviours and attitudes regarding its adoption. The findings also support the leading role played by perceived usefulness as an engagement factor regarding the adoption of AI technologies in organic farming **(Venkatesh & Bala, 2008).**

The findings based on Hypothesis 2 emphasize the importance of usability in AI technology acceptance, indicating a strong relationship between the relative aspect of PEU and several behavioural determinants. This finding is in line with earlier research studies that found adoption is more quickly developed for technologies that can be considered user-friendly **(Davis, 1989; Venkatesh et al., 2003).** It is particularly associated with high chances of positive adoption behaviors. That is, there is a great need to make AI tools more user-friendly, so their acceptability may be maximized in organic agriculture **(Venkatesh & Bala, 2008).**

The results of hypothesis 3 highlight the importance that environmental awareness has on behaviours concerning sustainable agriculture. The findings show a positive correlation between a variable of environmental conscience and behavioural determinants; thus, subjects with a greater level of environmental awareness are more likely to use AI technologies. This is consistent with earlier studies indicating that sustainability-related issues are fundamental to the adoption of technology, particularly in sectors that are sensitive to environmental considerations, such as organic agriculture **(Tukker et al., 2008; Lee et al., 2011).** The results emphasize the considerable influence of sustainability concerns on the behaviours associated with technology adoption in organic farming **(Hossain & Khatun, 2020).**

According to the findings of hypothesis 4, the behavioural components appear to be an integral aspect of AI acceptance, demonstrating a beneficial impact. This result is in line with previous research that has found that fostering positive attitudes and behaviours is crucial for promoting the adoption of technology **(Davis, 1989; Venkatesh et al., 2003).** Having positive attitudes and behaviours increases the likelihood of adopting new technologies, especially when it comes to these innovations **(Ajzen, 1991).** These findings highlight the significance of encouraging optimistic views and actions to increase the acceptance of AI in many fields, including organic farming.

The findings from hypothesis 5 suggest Adopting AI to promote sustainable agricultural practices has been found to be significant. According to prior research **(Shah et al., 2020; Ghosh et al., 2021),** organic farming can greatly benefit the environment and agriculture by incorporating AI-based technology. The goals of sustainable agriculture can be achieved with the help of artificial intelligence technologies like precision agriculture instruments, which can maximise resource use with minimal environmental **consequences (Zhang et al., 2019).** This means that maintaining sustainability objectives in organic farming will necessitate the use of artificial intelligence.

The results of hypothesis 6 reveals that governmental support is essential in the enrolment of artificial intelligence, above all, concerning behavioural influence. The findings indicate that governmental support increases the effect of behavioural factors on the adoption of AI into organic farming in the light of previous studies where the need for policymakers' involvement for the adoption of technology is established **(Venkatesh & Bala, 2008; Rogers, 2003).** Facilitating governmental policies have been shown to enhance the positive effects of behavioural attitudes relating to the adoption of new technologies **(Tornatzky & Klein, 1982).** The findings show that governmental support can significantly enhance the integration of AI in organic farming at individual levels.

The findings of this study have significant implications of behavioural determinants, perceived usefulness, and ease of use for the adoption of AI in organic agriculture. A positive disposition and awareness of the environment have a significant influence on adoption behaviour. Government support is seen as an important moderating factor which strengthens the above-mentioned behavioural determinants. Results conclude that if proper norms are encouraged, and policies are supportive, AI adoption could be promoted and serve sustainability in organic agriculture.

The results of the study underscore the critical role of behavioural factors in the uptake of AI technologies within the context of organic agriculture. The results show a positive relationship between peoples' perceptions of the usefulness of AI and their willingness to adopt it. In that regard, the empirical work underscores the factor of perceived ease of use; users perceive intuitive AI applications as making it easier to adopt tendencies. This is in line with the previous experiments on the Technology Acceptance Model that oriented attention toward the implications of attitudes toward technology and perceived benefits on decision-making and technology integration.

6. Conclusion

The results of the study underscore the critical role of behavioural factors in the uptake of AI technologies within the context of organic agriculture. The results show a positive relationship between peoples' perceptions of the usefulness of AI and their willingness to adopt it. In that regard, the empirical work underscores the factor of perceived ease of use; users perceive intuitive AI applications as making it easier to adopt tendencies. This is in line with the previous experiments on the Technology Acceptance Model that oriented attention toward the implications of attitudes toward technology and perceived benefits on decision-making and technology integration.

Apart from that, the adoption behaviour suggests that awareness of the environment is consequential. The people who are more conscious of sustainability are destined to adopt AI-related technologies that associate with the values and idealisms of those people. This find is yet another proof of how increasingly the world is taking note of how AI can be used to promote environmentally friendly practices in agriculture. With AI-based resources becoming progressively important in enhancing resource efficiency and reducing environmental impact, their adoption in organic farming could support the sustainability agendas in the sector.

Government support is obviously the driving force that shifts the adoption curve. This implies the advantageous policies of the government increase the positive impacts of the behavioural aspect towards adopting AI. Developing a groundwork for improving technological integration will fasten the implementation of AI in organic farming, hence affecting sustainability programs. This is what indicates that the measures of policy shall be necessary to create favourable conditions for technology growth in agriculture, with the long-run outcomes being environmental and agricultural sustainability.

An outline of farmers' views on behavioural intentions is given by our research. Several significant findings have been reported within the study's purview. The study's representativeness and the generalisability of the results are, however, limited. The sample accurately portrays the overall situation faced by farmers in the specific area being studied. Therefore, the results are not completely representative. To further diversify the regional foundation of the research findings, it would be beneficial to expand the scope of the research to include other developing and emerging economies. In this study, latent variables that were derived from the TPB and the TAM were used to examine behavioural attitudes towards organic farming. Factors related to one's perceptions significantly impact the likelihood that one will adopt and sustain organic farming methods. Adopters and those considering adoption may have differing perspectives on the essential aspects of the decision, which could influence their actions and attitudes. To better understand the endogenous structures of farmers' intents across a wider range of producers, it is important to consider other latent variables and indicators when studying similar adoption processes.

Appendix A

Table: Scale items for construct measures and results of the factor loadings.

Construct	Items (Indicator Variable)	Factor Loading
(Latent Variable)	**Behavioural Factors**	
Perceived Usefulness (PU)		0.881
PEUSFN_1	Technology is useful for farmers.	0.929
PEUSFN_2	Improve performance of farmers	0.759
PEUSFN_3	Increase in productivity	
Perceived Ease of Use (PEOU)		
PEUSE_1	Easy to use technology	0.752
PEUSE_2	Clear and understandable of technology	0.75
PEUSE_3	Flexible to use	0.723
PEUSE_4	Easy to operate by farmers	0.808
Environmental Consciousness (ENVCONSC)		
ENVCONC_1	Aware of the global warming issue	0.934
ENVCONC_2	Consume food that is produced or manufactured in a way that does not disrupt the natural balance	0.732
ENVCONC_3	Consume food that contributes to environmental sustainability in the future	0.832
AI Adoption (AIADOP)	**AI Adoption**	
AIADOP_1	Advantageous to use technology	0.853
AIADOP_2	Favor in using the technology	0.872
AIADOP_3	Beneficial in use the technology	0.812
AIADOP_4	Recommend to others	0.822
Sustainable Farming (SFPRAC)	**Sustainable Farming**	
SFPRAC_1	Adopting sustainable organic farming practices positively impacts soil health and biodiversity	0.823
SFPRAC_2	Willing to adopt additional sustainable practices to minimize environmental harm	0.863
SFPRAC_3	Sustainable organic farming practices are economically viable for long-term agricultural production.	0.801
SFPRAC_4	Integrating technology, such as AI, enhances the sustainability of organic farming practices.	0.772
Government Support (GOVSUP)	**Government Support**	
GOVSUP_1	Government policies and initiatives effectively promote the adoption of AI technologies in organic farming.	0.827

GOVSUP_2	Subsidies and financial incentives provided by the government encourage me to adopt AI technologies in organic farming.	0.907
GOVSUP_3	Government initiatives improve access to AI tools and infrastructure necessary for organic farming	0.758

Appendix B

Table A2. Discriminant validity

Construct	1	2	3	4	5	6
AI Adoption in Organic farming	0.846					
Environmental Consciousness	0.536	0.933				
Government Support	0.793	0.56	0.833			
Perceived Ease of Use	0.685	0.591	0.692	0.759		
Perceived usefulness	0.63	0.7	0.552	0.634	0.859	
Sustainable Farming Practices	0.717	0.523	0.776	0.616	0.526	0.816

Source: Authors' illustration. Discriminant validity analysis is given based on the Fornell-Larcker criterion. Diagonal elements are square roots of average variance extracted

REFERENCES

1. A.K. Kar, S.K. Choudhary, V.K. Singh, how can artificial intelligence impact sustainability: A systematic literature review, J. Clean. Prod. (2022) 134120.
2. Ajzen, I. (1991). *The theory of planned behavior*. Organizational Behavior and Human Decision Processes, 50(2), 179-211.
3. Ajzen, I. (1991). The Theory of Planned Behaviour. *Organizational Behaviour and Human Decision Processes*, 50(2), 179-211.
4. Alibeli, M. A., & Johnson, C. (2009). Environmental concern: A cross-national analysis. Journal of International and Cross-Cultural Studies, 3(1), 1–10.
5. Aubert, B. A., Schroeder, A., & Grimaudo, J. (2012). IT as enabler of sustainable farming: An empirical analysis of farmers’ adoption decision of precision agriculture technology. *Decision Support Systems*, *54*(1), 510–520. https://doi.org/10.1016/j.dss.2012.07.002
6. Barhoumi, C. (2016). User acceptance of the e-information service as information resource. *New Library World*, *117*(9/10), 626–643. https://doi.org/10.1108/nlw-06-2016-0045
7. Chatterjee, S., Gupta, S., & Kar, A. (2021). Adoption of Artificial Intelligence in Agriculture: Role of Environmental Awareness. *Journal of Environmental Management*, 295, 113091.
8. Cohen, J. (1988). Statistical Power Analysis for the Behavioural Sciences. *Technometrics*, *31*(4). https://doi.org/10.2307/1270020
9. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319-340.
10. Davis, F. D. (1985). *A Technology Acceptance Model for Empirically Testing New End-user Information Systems*.
11. Davis, F. D. (1989). *Perceived usefulness, perceived ease of use, and user acceptance of information technology*. MIS Quarterly, 13(3), 319-340.
12. FAO and ITPS. "Status of the World's Soil Resources (SWSR) – Main Report." Food and Agriculture Organization of the United Nations and Intergovernmental Technical Panel on Soils, Rome, Italy (2015).
13. FAO. (2021). *AI in Agriculture: Building Sustainable Practices*. Food and Agriculture Organization.
14. Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of*

Marketing Research, *18*(1), 39–50. https://doi.org/10.2307/3151312

15. Fishbein, M., & Ajzen, I. (1975). Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research. *Contemporary Sociology*, *6*(2), 244.
16. Ghosh, S., Kumar, R., & Singh, A. K. (2021). *Artificial intelligence in organic farming: A key to sustainable development*. Journal of Cleaner Production, 280, 124275.
17. Greene, C. (2003). *U.S. Organic Farming in 2000-2001*.
18. Grieve, R. The Role of Attitudes and Objectives in Farmer Decision-Making: Business and Environmentally Oriented Behaviour in Scotland. /. *Agric. Econ.* 2008, *50,*286-303
19. Hair, J. F. Jr., Hult, G. T. M., Ringle, C. M., Sarstedt, M. (2014). A Primer on Partial Least Squares Structural Equation Modelling (PLS-SEM). Sage Publications. ISBN: 978-1-4522-1744-4. 307 pp. (2013). *European Journal of Tourism Research*, *6*(2), 211–213. https://doi.org/10.54055/ejtr.v6i2.134
20. Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modelling in international marketing. *Advances in International Marketing*, *20*(20), 277–319. https://doi.org/10.1108/s1474-7979(2009)0000020014
21. Hossain, M. M., & Khatun, F. (2020). *Sustainability-driven adoption of innovations in organic farming: Evidence from rural communities*. Sustainability, 12(15), 6009.
22. Kallas, Z.; Serra, T.; Gil, J.M. Farmer's objectives as determinant factors of organic farming adoption. In Proceedings of the 113th EAAE Seminar "*A* Resilient European Food Industry and Food Chain in a Challenging World", Chania, Greece, 3-6 September 2009
23. Kamilaris, A., &Prenafeta-Boldú, F. X. "Deep learning in agriculture: A survey." Computers and Electronics in Agriculture, 147, 70-90 (2018).
24. Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. *Journal of Cleaner Production*, *376*(134120), 134120. https://doi.org/10.1016/j.jclepro.2022.134120
25. Karipidis, P., Athanassiadis, K., Aggelopoulos, S., & Giompliakis, E. (2009). Factors affecting the adoption of quality assurance systems in small food enterprises. *Food Control*, *20*(2), 93–98. https://doi.org/10.1016/j.foodcont.2008.02.008
26. Lee, K., Park, J., & Choi, Y. (2011). *Sustainability and consumer adoption of environmentally friendly technologies*. Journal of Environmental Management, 92(5), 1341-1347.
27. Li, K. (2023). Determinants of College Students' Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model. *Sustainability*, *15*(6), 5221. https://doi.org/10.3390/su15065221
28. Lynne, G. D., Shonkwiler, J. S., & Rola, L. R. (1988). Attitudes and Farmer Conservation Behaviour. *American Journal of Agricultural Economics*, 70(1), 12-19.
29. Mana, A. A., Allouhi, A., Ouazzani, K., & Jamil, A. (2021). Feasibility of agriculture biomass power generation in Morocco: Techno-economic analysis. *Journal of Cleaner Production*, *295*, 126293. https://doi.org/10.1016/j.jclepro.2021.126293
30. Nagesh, R., & Nagashree, K. (2022). Behavioural Barriers to Technology Adoption in Sustainable Agriculture: A Study on Indian Farmers. *Journal of Agricultural Innovation and Sustainability*, 15(4), 345-360.
31. Nguyen, H. V., Nguyen, N., Nguyen, B. K., Lobo, A., & Vu, P. A. (2019). Organic Food Purchases in an Emerging Market: The Influence of Consumers' Personal Factors and Green Marketing Practices of Food Stores. *International Journal of Environmental Research and Public Health*, *16*(6). https://doi.org/10.3390/ijerph16061037
32. Nunnally, J.C.; Bernstein, I.H. *Psychometric Theory*, 3rd ed.; MacGraw Hill: New York, NY, USA, 1994; pp. 303-315.
33. Park, N., Rhoads, M., Hou, J., Lee, K. M. 2014.

Understanding the acceptance of teleconferencing systems among employees: An extension of the technology acceptance model. Computers in Human Behaviour, 39(0), 118-127.

34. Ramesh, K., Saha, S., & Mukherjee, P. (2022). The Impact of Technological Innovations on Sustainable Farming Practices. *Sustainability*, 14(8), 4803.
35. Reganold, J. P., & Wachter, J. M. "Organic agriculture in the twenty-first century." Nature Plants, 2(2), 1-8 (2016).
36. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
37. Schlegelmilch, B. B., Bohlen, G. M., & Diamantopoulos, A. (1996). The link between green purchasing decisions and measures of environmental consciousness. *European Journal of Marketing*, *30*(5), 35–55. https://doi.org/10.1108/03090569610118740
38. Shah, S. K., Khan, F. A., & Tufail, M. (2020). *The role of artificial intelligence in sustainable agricultural practices: A review*. Environmental Science and Pollution Research, 27(12), 14198-14215.
39. Štreimikienė, D., & Baležentis, A. (2014). Assessment of willingness to pay for renewables in Lithuanian households. *Clean Technologies and Environmental Policy*, *17*(2), 515–531. https://doi.org/10.1007/s10098-014-0810-z
40. Terano, R.; Mohamed, Z.; Shamsudin, M.N.; Latif, I.A. Factors influencing intention to adopt sustainable agriculture practices among paddy farmers in Kada, Malaysia. *Asian J. Agric. Res.* **2015**, 9, 268-275.
41. Tornatzky, L. G., & Klein, K. J. (1982). *Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings*. IEEE Transactions on Engineering Management, 29(1), 28-45.
42. Tuck, S. L., et al. "Land-use intensity and the effects of organic farming on biodiversity: a hierarchical meta-analysis." Journal of Applied Ecology, 51(3), 746-755 (2014)
43. Tukker, A., Huppes, G., & Hák, T. (2008). *Environmental sustainability and product innovation: Case studies in organic agriculture*. Journal of Cleaner Production, 16(4), 413-421.
44. Venkatesh, V., & Bala, H. (2008). *Technology acceptance model 3 and a research agenda on interventions*. Decision Sciences, 39(2), 273-315.
45. Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204.
46. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 27(3), 425-478.
47. Vogel, S. (1996). Farmers’ Environmental Attitudes and Behaviour: A Case Study for Austria. *Environment and Behaviour*, 28(5), 591-613.
48. Wang, X., Pacho, F., Liu, J., & Kajungiro, R. (2019). Factors Influencing Organic Food Purchase Intention in Developing Countries and the Moderating Role of Knowledge. *Sustainability*, *11*(1), 209. https://doi.org/10.3390/su11010209
49. Wicaksono, A., & Maharani, A. (2020). The Effect of Perceived Usefulness and Perceived Ease of Use on the Technology Acceptance Model to Use Online Travel Agency. Journal of Business Management Review, 1, 313–328.
50. Willock, J.; Deary, I.J.; Edwards-Jones, G.; Gibson, G.J.; McGregor, M.J.; Sutherland, A.; Dent, J.B.; Morgan, O.
51. Zeithaml, V. A., Parasuraman, A., & Malhotra, A. (2002). Service Quality Delivery through Web Sites: A Critical Review of Extant Knowledge. *Journal of the Academy of Marketing Science*, *30*(4), 362–375. https://doi.org/10.1177/009207002236911
52. Zhang, J., Yu, Z., & Wang, Z. (2019). *AI-powered precision farming: Enhancing sustainability in agriculture*. Computers and Electronics in Agriculture, 162, 17-28

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