Factors influencing pneumatic precision corn planter adoption in the Philippines: An empirical study using the Technology Acceptance Model (TAM) and Partial Least Squares Structural Equation Modeling (PLS-SEM)

Duan P. Mary Rose[1], Gonzales G. Gamaliel[1], Papaya Iway Harold Jay[1], Buot Pisao Amadito Jr.[1], Montebon Defensor Vincet Rhey[1], Moya S. Emmanuel[1], Mata Dumanacal Marlon[1*]

[1]Cebu Technological University-Danao Campus, Danao City, Philippines
[*]Corresponding author: marlon.mata@ctu.edu.ph

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ABSTRACT

This study applies the Technology Acceptance Model (TAM) to evaluate the factors influencing the adoption of pneumatic precision planters in corn farming in the Philippines. Data from 393 farmers were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the relationships between Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioral Intention (BI), and three extended TAM constructs: Compatibility (CO), Observability (OB), and Personal Innovativeness (PI). The model was validated for reliability and discriminant validity, with the Average Variance Extracted (AVE) ranging from 0.664 to 0.823. Statistical significance was observed in ten out of twelve hypothesized relationships, indicating a high likelihood of adoption. This study extends TAM by incorporating external factors such as CO, OB, and PI, offering a deeper understanding of how these variables influence farmers' perceptions of the technology's usefulness and ease of use. The findings suggest that, for successful adoption, policymakers should focus on enhancing the visibility of the technology's benefits, ensuring compatibility with existing farming practices, and promoting openness to innovation through targeted education and support. The results highlight the need for practical interventions, such as educational programs and demonstration projects, which could significantly improve technology adoption, productivity, and sustainability in Philippine agriculture.

1. Introduction

Corn is a widely cultivated crop grown in over 170 regions globally. While global corn production is slightly declining, the consumption rate is outpacing production, increasing demand for this essential crop (USDA, 2021). In the Philippines, corn, also known as maize, is considered a critical staple, ranking second only to rice in importance. It is one of the top crops worldwide regarding harvested area (Ramirez-Cabral et al., 2017). The corn industry plays a significant role in the Philippine economy, contributing approximately 100 billion pesos annually and supporting around 1.8 million farmers growing white and yellow maize.

White maize is an alternative staple, while yellow maize is primarily used for animal feed (Naval & Dolojan, 2020).

Corn production in the Philippines has steadily increased, reaching more than eight million metric tons in 2022, slightly lower than the 8.29 million metric tons produced the previous year (Statista, 2023). This growth in production highlights the need for increased automation to meet rising demand. The country must embrace larger, more advanced machinery typically used in developed countries to achieve this. Precision planting techniques are an effective strategy for boosting maize yield (Li et al., 2016), and a key tool for this is the pneumatic precision corn planter.

A pneumatic precision planter is a mechanized seeding device equipped with a fertilizer applicator that uses vacuum pumps to place individual corn seeds accurately. These planters are critical in modern agriculture, enabling precise planting while reducing energy consumption, labor, and costs (Xing et al., 2017). Proper seed placement is essential for optimizing crop yield, with the primary objective of pneumatic precision planters being to ensure accurate seed spacing and depth to maximize plant population and yield (Yang et al., 2016).

Li et al. (2016) support that precision planters, originally developed in more advanced countries, were introduced to developing nations in 2016. However, their adoption has been limited in some regions due to differences in cropping systems, geographical conditions, and environmental factors. Precision planters must be adapted to suit the local agricultural environment to overcome these challenges. This can be achieved through policy support, research funding, and local researchers' encouragement. Namjoo et al. (2016) designed a pneumatic precision planter for corn that demonstrated precision and efficiency across various soil surface conditions, including tilled, no-till, and wheat residue, offering a potential solution to local challenges.

Despite advancements in other countries, pneumatic precision planters have not been widely adopted in the Philippines, hindering agricultural competitiveness and sustainable growth. This research aims to assess the factors influencing the adoption of pneumatic precision planters in the Philippine corn farming sector. By examining these factors, the study offers insights into how the country can leverage mechanization to boost corn production and enhance agricultural efficiency, which is crucial for long-term growth in the farming sector.

A key contribution of this study is its extension of the Technology Acceptance Model (TAM) (Davis, 1986) to understand the adoption of pneumatic corn planters, a critical innovation in Philippine agriculture. While TAM has been widely applied to technology adoption in various fields, limited research has focused on agricultural technologies in the Philippines. This study fills that gap by incorporating additional factors - Compatibility (CO), Observability (OB), and Personal Innovativeness (PI) - that influence technology adoption in other contexts but have been underexplored in agriculture. By adapting TAM to the Philippines' specific agricultural, economic, and social conditions, the study provides a more comprehensive framework for understanding technology acceptance. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the study offers robust insights for policymakers, researchers, and practitioners aiming to improve technology adoption and mechanize Philippine agriculture.

The remainder of this paper is organized as follows: Section 2 presents the theoretical background, hypotheses development, and literature review. Section 3 outlines the research methodology and data collection process. Section 4 discusses the analysis of the study's findings, while Section 5 presents the study's conclusions. Finally, Section 6 offers recommendations for policymakers and future research in this field.

Aim of the study

This study aims to examine the factors influencing the adoption of pneumatic precision corn planters in the Philippines, using the Technology Acceptance Model (TAM) and integrating external variables such as Compatibility (CO), Observability (OB), and Personal Innovativeness (PI). The study seeks to assess how these factors interact with the core TAM constructs - Perceived Usefulness (PU), Perceived Ease of Use (PEU), and Behavioral Intention (BI) - to shape farmers' perceptions and adoption decisions. By employing Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS4, the study aims to validate the relationships between these factors and provide a comprehensive understanding of the mechanisms driving technology acceptance in the agricultural sector.

In addition, the study offers practical insights for policymakers and agricultural practitioners, particularly in regions with lower levels of mechanization. It aims to recommend tailored strategies to enhance awareness, accessibility, and adoption of precision farming technologies, considering socio-economic factors such as educational levels, farm size, and cultural preferences for community-based decision-making. By promoting the compatibility of the technology with existing practices, demonstrating its observable benefits, and fostering openness to innovation, the study aims to inform policies that support the adoption of pneumatic precision planters, ultimately improving agricultural productivity and sustainability in the Philippines.

2. Discussion

The Technology Acceptance Model (TAM) is preferred over models like the Unified Theory of Acceptance and Use of Technology (UTAUT) for agricultural technology adoption studies due to its simplicity, flexibility, and focus on core constructs such as Perceived Usefulness (PU) and Perceived Ease of Use (PEU). Developed by Davis in 1986, TAM's two main factors have proven to be strong predictors of technology adoption, especially in agricultural contexts where socio-economic, environmental, and technological factors play a crucial role. This focused framework allows for an in-depth analysis of the primary drivers influencing adoption.

While UTAUT includes additional constructs like Social Influence and Facilitating Conditions, its complexity makes it less suited for studies with a smaller sample size or those targeting a limited set of factors. In contrast, TAM's emphasis on PU and PEU allows for a more targeted approach to understanding adoption decisions. It is a precise and actionable model for examining farmers' willingness to adopt new technologies, such as pneumatic precision planters.

Recent studies on adopting agricultural technology have further validated TAM's effectiveness. For instance, Kumar et al. (2021) used TAM to study drone adoption for precision agriculture in India, finding that both PU and PEU significantly influenced farmers' intentions to use drones. Similarly, Agarwal et al. (2020) explored mobile-based agricultural advisory services in India and discovered that PU was the most significant factor driving adoption. These findings demonstrate TAM's continued relevance in agrarian settings, where perceived benefits and ease of use are pivotal in adoption decisions.

Partial Least Squares Structural Equation Modeling (PLS-SEM) has gained traction in agricultural technology studies, effectively analyzing complex relationships between multiple variables. PLS-SEM allows researchers to simultaneously examine various interrelationships, making it ideal for studies with multidimensional data. For example, Müller et al. (2021) applied PLS-SEM to study precision irrigation adoption in Pakistan, finding PU and Facilitating Conditions to be significant predictors. Similarly, Zhang et al. (2022) used PLS-SEM in Europe to examine smart farming adoption, highlighting Compatibility and Social Influence. These studies illustrate PLS-SEM's value in capturing nuanced relationships between adoption factors.

TAM's simplicity and focus on key adoption factors make it an ideal model for agricultural studies, while PLS-SEM provides a robust tool for analyzing complex data relationships. Together, these frameworks enable a deeper understanding of how farmers adopt new technologies like pneumatic precision planters, ultimately contributing to enhanced agricultural productivity.

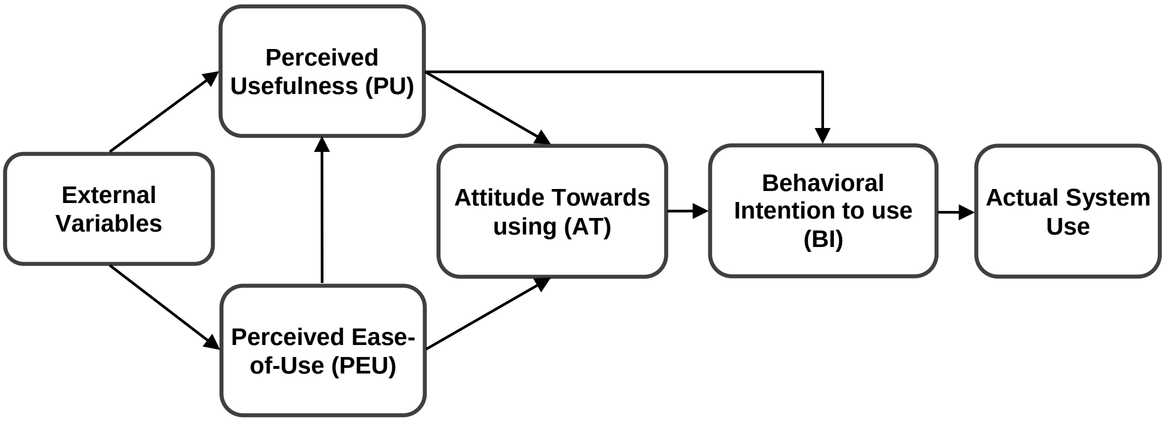
2.1. Theoretical background

Technology Acceptance Model (TAM). The proposed research model of this study was theoretically grounded in the framework of the TAM. Davis (1986) originally formulated the TAM as a theoretical framework to evaluate proposed technologies before implementation. TAM has been widely applied to business, healthcare, education, and agriculture to predict and understand technology adoption. Researchers and practitioners use it to analyze the factors influencing users' willingness to adopt new technologies, essential for crafting strategies that boost technology acceptance and facilitate successful implementation. The theory suggests when users are presented with a new technology, there will be several determinants that will affect their choice of ways how and time to use it, mainly Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitude Towards use (AT), and Behavioral Intention to use (BI).

As Davis et al. (1989) described, PU and PEU are the primary predictors of behaviors related to technology adoption. PU pertains to the perception of how a specific technology can enhance job performance, while PEU reflects the belief that the technology is not overly complicated to use. The study says PEU affects PU. As the technology becomes more accessible, it will increase users' perceived usefulness (Venkatesh & Bala, 2008). The system's actual usage is dictated by BI, which is indirectly affected by PEU and directly influenced by PU. AT is influenced by both PU and PEU, with PEU exerting an indirect influence on PU. According to TAM, external factors can also be leveraged, potentially exerting an indirect influence on system usage through their impact on PU and PEU (Davis, 1989). Figure 1 illustrates the structure of the TAM model.

Figure 1

Technology Adoption Model



Note. The data are from "Perceived usefulness, perceived ease of use, and user acceptance of information technology" by F. D. Davis, 1989, *MIS Quarterly, 13*(3), pp. 319-339 (https://doi.org/10.2307/249008)

Innovation Diffusion Theory (IDT). TAM emphasized the significance of user attitudes and behaviors regarding new technologies, often overlooking the impact of their features and social factors. It is suggested that external variables be incorporated based on IDT principles to overcome this limitation. IDT was developed to elucidate the factors influencing individuals' decisions to adopt or reject innovations based on their beliefs. According to IDT, the decision-making process for innovation adoption involves five stages: knowledge, persuasion, decision, implementation, and confirmation (Rogers, 1995). The author notes that the innovation's attributes shape the acceptance and decision-making processes, which are assessed through factors like relative advantage, compatibility, complexity, trial-ability, and observability.

The Proposed Extended TAM Structure. A study has demonstrated that compatibility, observability, and trial-ability together explain the variance in (PU) and (PEU) (Yuen et al., 2020). Furthermore, another study highlights that Personal Innovation (PI) is a significant factor influencing PU, PEU, and, ultimately, Behavioral Intention (BI) (Lee, 2019). Given these insights, the study extended the TAM by incorporating three external variables drawn from previously tested variables in existing studies, namely the following: Compatibility (CO), Observability (OB), and Personal Innovativeness (PI). The aim is to identify the factors influencing the intention to adopt pneumatic corn planters in the maize agricultural sector of the Philippines.

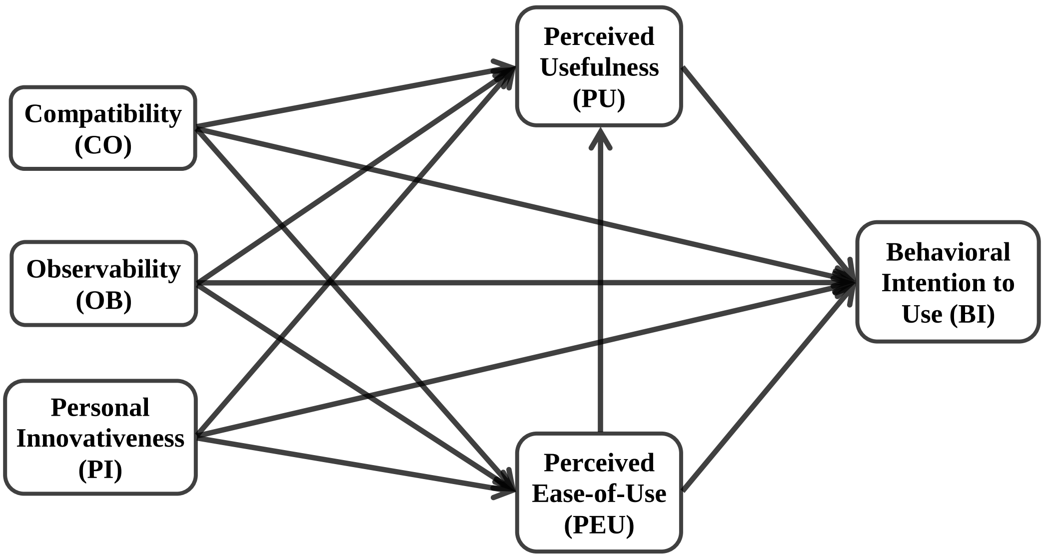
Compatibility. Compatibility is the degree to which an innovation is recognized as consistent with the existing values, past experiences, and needs of potential adopters. Potential adopters will decline the adoption of the innovation if it is incompatible with the values and norms of a social system (Sharifzadeh et al., 2017).

Observability. Observability is an important characteristic that directly influences all inner or dependent variables. According to Davis (1989), this variable is one of five general innovation attributes identified by Rogers (1983). It affects potential adopters' perceptions of innovations and the rate of adoption (Moore & Benbasat, 1991; Rogers, 1995). Visibility and result demonstration as parts of the observability of precision agriculture technologies provide the opportunity to see their results (Schepers & Wetzels, 2007).

Personal Innovativeness. Personal innovation demonstrates an openness to embracing new technology. A study characterized it as an open mindset. In contrast, a study defined it as the degree of intention to accept new technology more quickly than other members of the social structure toward a change (Rogers, 1995). PI has considerable effects on perceived utility, PEU, and eventually acceptance of new technology, according to a study about determining the elements that influenced users' adoption of new technologies. Additionally, TAM was used to evaluate how self-efficacy and PI affect PEU and PU. The results showed that PI significantly influences PEU and PU (Agarwal & Prasad, 1998; Davis, 1989).

Figure 2

Theoretical Framework (Proposed Research Model)



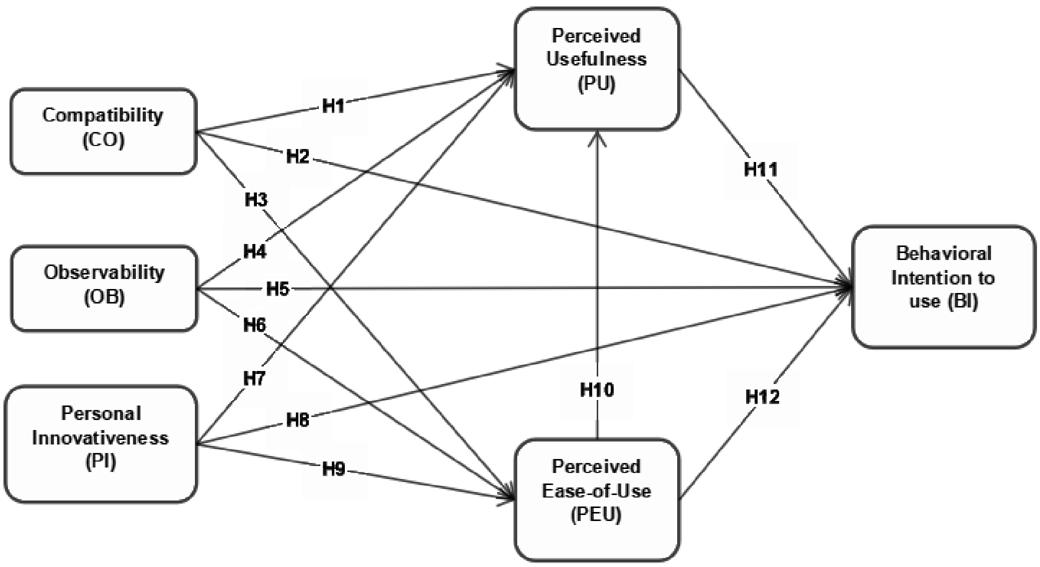
Note. The authors

2.2. Hypotheses development

With the newly developed extended TAM illustrated in Figure 3, the proposed hypotheses for this study are presented below.

Figure 3

Proposed Extended TAM Hypotheses



Note. The authors

CO measures the degree of harmony between an innovation and an individual's current technical and social context (Wang et al., 2018). The innovation faces resistance from potential adopters when it does not align with the values and norms ingrained in a particular social system (Sharifzadeh et al., 2017). A high degree of unity indicates that potential adopters would require fewer adjustments to their habits or less effort when integrating an innovation. The perceived compatibility of the system acts as an influencing factor, prompting us to investigate its effects on (PU), (PEU), and (BI). Consequently, we have developed our initial hypothesis:

H1: Compatibility is positively associated with perceived usefulness

H2: Compatibility is positively related to behavioral intention to use

H3: Compatibility is positively associated with perceived ease of use

In the context of IDT, observability comprises two fundamental concepts: result demonstrability - emphasizing the transparent display and communicability of the outcomes of innovation adoption - and visibility - highlighting the ease of enabling social learning via observation (Moore & Benbasat, 1991). The first concept implies that as the ease of communicating or demonstrating the advantages of adopting innovation to others increases, so does the probability of its widespread adoption (Venkatesh & Davis, 2000). On the other hand, visibility is defined by how individuals can observe and learn from others who have embraced an innovation. The greater the exposure to an innovation, the more likely it is to be adopted by potential users (Yuen et al., 2018). The perceived observability of the system acts as an influencing factor, and this study aims to explore its effects on PU, PEU, and BI. In line with this, we proposed that:

H4: Observability is positively associated with perceived usefulness

H5: Observability is positively related to behavioral intention to use

H6: Observability is positively associated with perceived ease of use

Personal innovativeness indicates a readiness to adopt emerging technologies. One study characterizes it as representing an open mindset. In contrast, another defines it as the degree of inclination to swiftly embrace new technology compared to other members within the social structure toward a change (Rogers, 1995). Additionally, TAM was employed to assess the influence of self-efficacy and PI on the perceptions of ease of use and usefulness. The results indicated that PI significantly influences both constructs (Davis, 1989). The influence of the system's PI is a significant factor, and our objective is to examine its impacts on PU, PEU, and BI. Consequently, the following hypothesis was suggested:

H7: Personal Innovativeness is positively associated with perceived usefulness

H8: Personal Innovativeness is positively associated with behavioral intention to use

H9: Personal Innovativeness is positively associated with perceived ease of use

TAM has been empirically demonstrated to be a reliable and extensively used model, evaluated in various circumstances, and potentially has broader applicability. This research utilizes a modified TAM structure and suggests the fundamental TAM model of the constructs: a) perceived usefulness, b) perceived ease of use, and c) behavioral intention to use (King & He, 2006). Accordingly, the following hypotheses were presented:

H10: Perceived ease of use is positively associated with perceived usefulness

H11: Perceived usefulness is positively related to behavioral intention to use

H12: Perceived ease of use is positively associated with behavioral intention to use

2.3. Related literature

Global corn production and consumption are projected to increase, mainly driven by the growing demand for feed and food, with feed usage accounting for 68% of this rise (OECD, 2021). In the Philippines, where maize production is significant, labor shortages during peak planting and harvesting seasons are common challenges (Cruz et al., 2018), and mechanization in corn production remains low (Dela Cruz & Garcia, 2014). Using larger machinery, such as pneumatic precision planters, common in more developed countries, could help improve productivity. These planters ensure uniform seed spacing, promote consistent root growth, and offer precise seed control with minimal damage, but their adoption in the Philippines is still limited. This study explores the factors influencing the adoption of pneumatic precision planters using the Technology Acceptance Model (TAM) (Davis, 1986).

Research has shown that several theoretical models and frameworks can simplify the understanding of factors influencing technology adoption in the agricultural sector. Notably, the IDT and the TAM are among these frameworks. The TAM is the foundational structure used to construct the research framework for this study. Given the objective of this research, which is to assess corn farmers' intentions to adopt new technology, the TAM is appropriate. The TAM, which builds upon the Theory of Reasoned Action, asserts that behavioral intention can predict individual behavior. Additionally, the TAM proposes that behavioral intentions, attitudes, PU, and perceived ease of use of technology directly or indirectly impact the actual usage of the technology (Davis, 1989).

Rezaei-Moghaddam and Salehi (2010) found that observability, trialability, and attitude toward use positively influence the intention to adopt precision agriculture technologies, using Structural Equation Modeling (SEM) to assess their model. SEM includes the structural model, which tests relationships between latent variables, and the measurement model, which is often used for Confirmatory Factor Analysis (CFA) of questionnaire data. In a similar study by Rezaei et al. (2020), an extended Technology Acceptance Model (TAM) was used to examine factors affecting Iranian farmers' adoption of Integrated Pest Management (IPM) with external constructs like social influence and compatibility. Likewise, Sharifzadeh et al. (2017) extended TAM2 to study farmers' adoption of biological control for rice stem borers, highlighting the positive impact of Perceived Usefulness (PU) on farmers' behavioral intention to use the technology.

The framework for this study was constructed based on established research problems derived from the aforementioned existing literature and empirical studies. This comprehensive approach ensures the research is grounded in a robust theoretical foundation and addresses relevant gaps identified in previous studies.

3. Methods

This study adopts a modified version of the Technology Acceptance Model (TAM) (Davis, 1986) to examine the factors influencing the adoption of pneumatic precision planters in Philippine maize farming. The research focuses on six key constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioral Intention (BI), Compatibility (CO), Observability (OB), and Personal Innovativeness (PI). These constructs are essential in understanding the factors affecting adoption. The study targets 300 maize farmers across the diverse agro-climatic regions of Luzon, Visayas, and Mindanao, ensuring a broad representation of demographic profiles, farm sizes, and operational contexts. The data collection method involves distributing in-person and online questionnaires to reach a wide geographical area and capture various farmer experiences. The questionnaires are available in English, Filipino, and Bisaya, aligning with the theoretical framework and measuring the identified constructs on a 7-point Likert scale. Data analysis uses Partial Least Squares Structural Equation Modeling (PLS-SEM), a robust technique for analyzing complex relationships among observed and latent variables. This method allows the simultaneous examination of multiple variables, validating the proposed model and testing hypotheses. The analysis identifies the significance of each construct in the adoption process, providing valuable insights into the adoption dynamics of pneumatic precision planters. A licensed statistician validates the reliability of the research instrument, and the data is processed using SmartPLS software (version 4.1.0.2) to ensure its reliability. Ethical considerations, including informed consent and data privacy, are strictly followed to maintain the study's integrity. This methodology offers a comprehensive framework for understanding the factors influencing the adoption of precision farming technologies in Philippine agriculture.

3.1. Sampling

The measurement items for each construct in this study were adapted from validated scales in previous research, as outlined in Appendix A - online version. To better understand the factors influencing mechanization adoption in Philippine maize farming, the study employs a modified Technology Acceptance Model (TAM) (Davis, 1986), incorporating constructs such as Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioral Intention (BI), Compatibility (CO), Observability (OB), and Personal Innovativeness (PI). This framework provides a comprehensive view of the adoption process. The research targets various maize farmers across Luzon, Visayas, and Mindanao, considering varying agro-climatic and socio-economic conditions. A sample of at least 300 farmers is selected to represent different farm sizes and operational contexts, ensuring a broad range of experiences. Collaboration with local agricultural agencies ensures the study's relevance and that ethical guidelines, including informed consent and data privacy, are strictly followed.

3.2. Data distribution and collection

The research began with a comprehensive review of existing literature on pneumatic corn planter adoption in the Philippines, integrating TAM with external variables to provide a complete view of adoption dynamics. Data was collected through in-person and online questionnaires across various regions of the Philippines, ensuring a diverse and representative sample. In-person visits to maize farms provided reliable data, while online distribution via Google Forms extended geographic reach. The questionnaires, available in English, Filipino, and Bisaya, assessed six constructs (CO, OB, PI, PU, PEU, and BI) using a 7-point Likert scale. Measurement items ranged from "strongly disagree" to "strongly agree" (Venkatesh et al., 2012), with sections covering demographic details and questions aligned with the theoretical framework. A licensed statistician validated the accuracy and reliability of the research instrument.

3.3. Data analysis

The collected responses underwent sophisticated analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM), which evaluates multiple variables and indicators simultaneously, validates the proposed model, and assesses hypotheses. This analysis identified the significance of each variable in the adoption process. PLS-SEM is suitable for analyzing complex relationships between observed and latent variables, integrating factor analysis, path analysis, and regression analysis. This method provided insights into the fundamental structure of the model, enabling a comprehensive understanding of the phenomena under study (Neuberg, 2003). The SmartPLS software, version 4.1.0.2, was used in this study.

3.4. Profile of the respondents

Four of 397 respondents were excluded due to consent issues, leaving 393 for analysis. The majority were female, reflecting significant female involvement in corn farming. Most respondents were aged 18 - 25, likely due to the online nature of the survey, attracting younger, tech-savvy participants. Geographically, Region 7 had the highest representation, while the National Capital Region had the lowest. Nearly half had college degrees, suggesting openness to new technologies. Most had less than five years of experience in maize farming, possibly due to seasonal or secondary income. Respondents held various roles in the sector, including farm workers and agronomists. Farm terrain varied, with many using flat land suitable for machinery. Most owned 01 - 02 hectares, indicating small to medium-scale operations. Most were unfamiliar with pneumatic precision planters, citing cost and availability issues, highlighting the need for more accessible agricultural technologies.

Table 1 illustrates the percentage breakdown of the respondents' profiles.

Table 1

Profile of the Respondents

Category	Number of Respondents	%
SEX		
Male	171	0.4351
Female	222	0.5649
AGE		
66 years old and above	23	0.0585
56 - 65 years old	38	0.0967
46 - 55 years old	41	0.1043
36 - 45 years old	36	0.0916
26 - 35 years old	36	0.0916
18 - 25 years old	219	0.5573
REGION		
Region 1	19	0.0483
Region 2	14	0.0356
Region 3	30	0.0763
Region 4-A	11	0.028
Region 5	24	0.0611
Region 6	22	0.056

Category	Number of Respondents	%
Region 7	119	0.3028
Region 8	14	0.0356
Region 9	08	0.0204
Region 10	29	0.0738
Region 11	20	0.0509
Region 12	15	0.0382
Region 13	15	0.0382
NCR	04	0.0102
MIMAROPA	22	0.056
CAR	18	0.0458
BARMM	09	0.0229
EDUCATIONAL ATTAINMENT		
College Graduate or Higher	72	0.1832
College Undergraduate	188	0.4784
High School Graduate	60	0.1527
High School Undergraduate	24	0.0611
Elementary Graduate	27	0.0687
Elementary Undergraduate	22	0.056
How many years have you been involved in the corn farming industry?		
26 years and above	33	0.084
21 - 25 years	14	0.0356
16 - 20 years	18	0.0458
11 - 15 years	34	0.0865
06 - 10 years	58	0.1476
Less than 05 years	236	0.6005
Which role do you currently hold on your farm or in the corn farm industry?		
Farm Worker	117	0.2977
Farm Manager	15	0.0382
Landowner/Landlord	25	0.0636
Farmer and Landowner	115	0.2926
Tenant Farmer	42	0.1069

Category	Number of Respondents	%
Equipment Operator	02	0.0051
Agronomist	57	0.145
Sales and Marketing	20	0.0509
How many corn farms do you have?		
more than 04	12	0.0305
03	21	0.0534
02	43	0.1094
01	173	0.4402
N/A (None)	144	0.3664
What type of landscape or terrain characterizes the farm where you work?		
Plain of Flat Terrain	213	0.542
Sloped or Mountainous Terrain	90	0.229
N/A	90	0.229
What is the approximate size of your corn farm?		
More than 04 hectares	09	0.0229
03 - 04 hectares	16	0.0407
01 - 02 hectares	167	0.4249
1/2 - 01 hectares	91	0.2316
Less than half a hectare	104	0.2646
N/A	06	0.0153
Have you ever used a pneumatic precision planter to plant corn on your farm?		
Yes	68	0.173
No	325	0.827

Note. The authors

4. Results

The demographic profile of the respondents, as shown in Table 1, provides essential context for the findings of this study, offering insights into factors like gender, age, education, farming experience, and use of pneumatic precision planters. This breakdown helps to understand the diversity within the sample and its potential influence on technology adoption. Notably, many respondents are college undergraduates (47.8%) with less than five years of farming experience, suggesting a need for targeted educational programs catering to different education levels and focusing on practical technology benefits. The profile also reveals that many farmers operate smaller farms, which may present financial barriers to adopting high-tech machinery, highlighting the need for accessible financing options or subsidies.

The study's findings have practical implications for policymakers and practitioners in the Philippines. With the low adoption of pneumatic precision planters, raising awareness and providing incentives to encourage adoption is crucial, particularly in regions with lower mechanization. Considering Filipino farmers' socio-economic and cultural factors, such as their preference for community-based decision-making and peer influence, adoption strategies should leverage local leaders and word-of-mouth promotion. Additionally, understanding the demographic profile of respondents can help design training programs tailored to different educational backgrounds and farming experiences, ensuring greater acceptance of new technologies. By addressing these factors and offering financial support, policymakers can develop more effective strategies to boost adoption and improve agricultural productivity and sustainability.

4.1. Measurement model assessment

The PLS-SEM method was engaged in the study to determine the causal relationships between exogenous (dependent) and endogenous (independent) variables. PLS-SEM is a prominent multivariate analytical approach used to provide theoretical frameworks. This technique allows for the simultaneous analysis of both the measurement and structural models, thereby enhancing result accuracy (Barclay et al., 1995). PLS-SEM analysis presents sequential parallel testing of the outside measurement and inner structural patterns and determines the existence of reflective and formative latent variables (Fornell & Bookstein, 1982). The proposed model encompasses reflective means; hence, the first criterion for assessing the model is toanalyze the measures' reliability and validity (Hair et al., 2017).

The measurement model assessment findings showed that all indicators were convergent and credible, as presented in Table 2. The permitted factor loading for each item was 0.60; outer loading more than 0.6 was considered acceptable, and factors with loading values less than 0.60 were neglected. No indicators were excluded in this probe since they all passed the threshold. The final study included 30 measurement markers. The coaxial validity of the measurement model was determined by assessing the Average Variance Extracted (AVE) value. The appropriate AVE threshold value was 0.50, and composite reliability was more than 0.70, indicating that the concept had adequate convergent validity (Fornell & Larcker, 1981). All constructs exhibited good convergent validity, with values between 0.664 and 0.823.

Furthermore, this study's Cronbach's Alpha (α) values ranged from 0.87 to 0.946. Hence, the measurement items were all reliable, with all constructs achieving Cronbach's Alpha (α) threshold value of 0.60, which was deemed a valid and satisfactory index (Ursachi et al., 2015). Apart from the standard Cronbach's Alpha, composite reliability was utilized to evaluate the construct measures' internal consistency. Composite Reliability (CR) scores ranged from 0.907 to 0.959. These findings pointed to excellent reliability values. The CR threshold value of 0.70 (Hair et al., 2017) was achieved.

Table 2

Measurement Model Assessment Results

	Convergent validity		Construct Reliability				Convergent validity		Construct Reliability		
	Loadings	AVE	α	CR (rho_a)	CR (rho_c)		Loadings	AVE	α	CR (rho_a)	CR (rho_c)
BI1	0.880	0.771	0.926	0.926	0.944	**PEU1**	0.833	0.664	0.870	0.877	0.907
BI2	0.863					**PEU2**	0.876				
BI3	0.897					**PEU3**	0.651				
BI4	0.880					**PEU4**	0.825				
BI5	0.870					**PEU5**	0.868				
CO1	0.836	0.705	0.895	0.898	0.923	**PI1**	0.759	0.693	0.889	0.896	0.918
CO2	0.869					**PI2**	0.885				
CO3	0.857					**PI3**	0.822				
CO4	0.823					**PI4**	0.881				
CO5	0.811					**PI5**	0.808				
OB1	0.843	0.719	0.901	0.905	0.927	**PU1**	0.900	0.823	0.946	0.947	0.959
OB2	0.890					**PU2**	0.921				
OB3	0.885					**PU3**	0.914				
OB4	0.863					**PU4**	0.908				
OB5	0.750					**PU5**	0.895				

Note. The data are from "SmartPLS 4" by C. M. Ringle, S. Wende, and J. M. Becker, 2022 (https://www.smartpls.com)

The discriminant validity in this study was evaluated using the Fornell and Larcker criterion and the Heterotrait-Monotrait criterion. The AVE of the constructs demonstrating discriminant validity was significantly higher than the squared correlation of each latent variable (Fornell & Larcker, 1981). In Table 3, bolded values highlight the square roots of the AVE, whereas non-bolded numbers show the intercorrelation value between constructs. The table presented that all off-diagonal values are much lesser than the square roots of AVE, indicating that the Fornell and Larker requirement was satisfied.

The SmartPLS algorithm function generated the HeterotraitMonotrait (HTMT) criterion output. HTMT is the ratio of between-trait to withintrait correlations (Fornell & Larcker, 1981). Discriminant validity problems arise when HTMT levels are exceedingly high. Henseler et al. (2015) proposed a threshold value of 0.90 for structural models that are conceptually comparable. An HTMT score higher than 0.90 indicates a lack of discriminant validity. Table 4 displays the valid HTMT values for each construct, all of which were less than 0.9. The HTMT values presented in the table vary from 0.716 to 0.897.

Table 3

Fornell and Larcker Criterion Results

	BI	**CO**	**OB**	**PEU**	**PU**	**PI**
BI	**0.878**					
CO	0.697	**0.840**				
OB	0.802	0.702	**0.848**			
PEU	0.798	0.643	0.773	**0.815**		
PU	0.842	0.699	0.769	0.751	**0.907**	
PI	0.751	0.646	0.752	0.737	0.685	**0.832**

Note. The data are from "SmartPLS 4" by C. M. Ringle, S. Wende, and J. M. Becker, 2022 (https://www.smartpls.com)

Table 4

Heterotrait-Monotrait Criterion Results

	BI	CO	OB	PEU	PU	PI
BI						
CO	0.758					
OB	0.876	0.776				
PEU	0.890	0.726	0.871			
PU	0.897	0.751	0.832	0.829		
PI	0.823	0.716	0.835	0.838	0.738	

Note. The data are from "SmartPLS 4" by C. M. Ringle, S. Wende, and J. M. Becker, 2022 (https://www.smartpls.com)

The measurement model's reliability and validity tests were completed and met successfully. Therefore, all of the items used to measure constructs in this study were reliable and suitable for estimating parameters in the structural model.

4.2. Structural model

The structural model was analyzed through the coefficient of determination (R2) and path coefficients in PLS. The initial principle was to determine each endogenous latent variable's R2, which assesses the relationship between a latent variable's explained variance and the overall variance (Sarstedt et al., 2014). The acceptable R2 values of 0.75, 0.50, and 0.25 correspond to significant, moderate, and modest levels of prediction accuracy (Hair et al., 2011; Henseler et al., 2009).

Table 5

R Square of Endogenous Variables in SEM

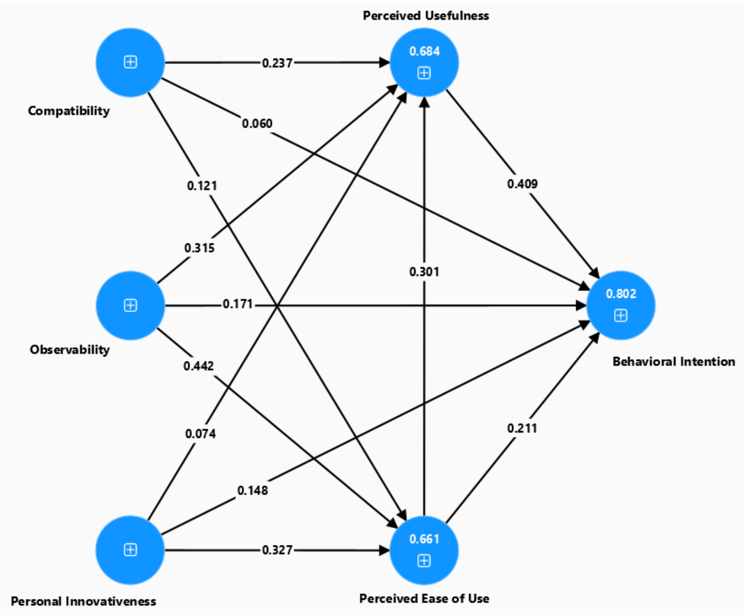
	R-square	**R-square adjusted**
BI	0.802	0.800
PEU	0.661	0.658
PU	0.684	0.681

Note. The data are from "SmartPLS 4" by C. M. Ringle, S. Wende, and J. M. Becker, 2022 (https://www.smartpls.com)

Table 5 depicts the R^2 of the structural model used in this study. BI explained the highest degree of variation, with an R^2 of 0.8 (80%). Moreover, PEU has a moderate prediction accuracy of 0.658 (65.8%), as does PU at 0.68.1 (68.1%). The following principle is to investigate the path coefficient value, which estimates the correlation intensity between the two latent variables, by assessing the path coefficients, algebraic sign, magnitude, and significance.

Figure 4

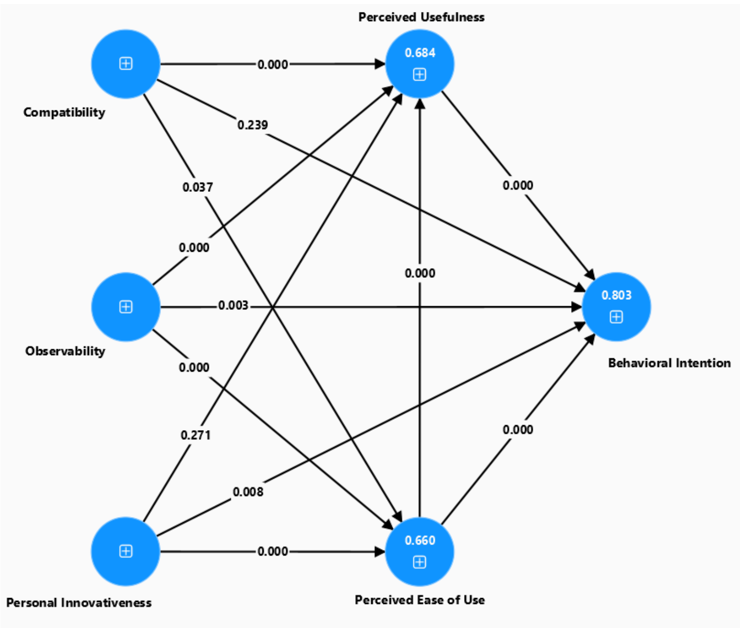
Path Coefficients



Note. The data are from "SmartPLS 4" by C. M. Ringle, S. Wende, and J. M. Becker, 2022 (https://www.smartpls.com)

Figure 5

Significance of Relationship



Note. The data are from "SmartPLS 4" by C. M. Ringle, S. Wende, and J. M. Becker, 2022 (https://www.smartpls.com)

The majority of hypotheses (H1, H3, H4, H5, H6, H8, H9, H10, H11, and H12) were supported in this study, except two (H2 and H7). The corresponding significant values are presented in Table 6.

Table 6

Path Coefficient Results

	Original Sample (O)	T value	P values	Decision
CO -> BI	0.060	1.176	0.239	Not supported
CO -> PEU	0.121	2.083	0.037	Supported
CO -> PU	0.237	4.170	0.000	Supported
OB -> BI	0.169	2.930	0.003	Supported
OB -> PEU	0.443	5.949	0.000	Supported
OB -> PU	0.314	4.655	0.000	Supported
PEU -> BI	0.211	3.927	0.000	Supported
PEU -> PU	0.301	5.075	0.000	Supported
PU -> BI	0.412	7.846	0.000	Supported
PI -> BI	0.147	2.658	0.008	Supported
PI -> PEU	0.326	5.471	0.000	Supported
PI -> PU	0.074	1.100	0.271	Not Supported

Note. The data are from "SmartPLS 4" by C. M. Ringle, S. Wende, and J. M. Becker, 2022 (https://www.smartpls.com)

Further, the effect size (f2) values were calculated using the PLS algorithm as shown in Table 7, which estimated 0.02 (minor), 0.15 (medium), and 0.35 (substantial) effects on the correlation between independent and dependent variables (Hair et al., 2017). A score less than 0.02 indicates that independent constructs do not influence a dependent construct.

Table 7

f-Square Result

	BI	CO	OB	PEU	PU	PI
BI						
CO	0.008			0.021	0.083	
OB	0.040			0.204	0.092	
PEU	0.070				0.097	
PU	0.267					
PI	0.040			0.128	0.006	

Note. The data are from "SmartPLS 4" by C. M. Ringle, S. Wende, and J. M. Becker, 2022 (https://www.smartpls.com)

The f^2 data indicated that CO did not affect BI (f^2 = 0.008) but had a minor effect on PEU (f^2 = 0.021) and PU (f^2 = 0.083). Meanwhile, OB has a minor impact on BI (f^2 = 0.040) and PU (f^2 = 0.092) but has a medium effect on PEU (f^2 = 0.204). PEU had minimal impact on BI (f^2 = 0.070) and PU (f^2 = 0.097). PI had a minor effect on BI (f^2 = 0.040) and PU (f^2 = 0.006) but a medium impact on PEU (f^2 = 0.128). PU had a medium effect on BI (f^2 = 0.267). These findings were consistent with the rest of the study.

4.3. Findings

The PLS-SEM (Partial Least Squares Structural Equation Modeling) analysis conducted using SmartPLS4 confirmed that the outer loadings of the measurement model were satisfactory, validating the reliability of the indicators used for the latent constructs. The constructs demonstrated good convergent validity, as evidenced by the Average Variance Extracted (AVE) values, and discriminant validity was confirmed through the Heterotrait-Monotrait (HTMT) ratio, ensuring the distinctiveness of the constructs. The Fornell-Larcker criterion was also met, providing further confidence in the structural equation model's validity and the results' reliability.

Regarding relationships between constructs, the study found a positive correlation between Compatibility (CO) and Perceived Usefulness (PU), supporting hypothesis H1. This result aligns with previous studies, including Chau and Hu (2001), which emphasized that compatibility with existing farming practices influences the perceived usefulness of technology. Similarly, CO was positively correlated with Perceived Ease of Use (PEU), supporting hypothesis H3. The compatibility of the technology with farmers' values and practices enhanced their confidence in using the machine, making it seem easier to operate.

However, while CO positively influenced PEU, it did not directly affect behavioral intention, rejecting hypothesis H2. Instead, CO indirectly influences behavioral intention, mediated by PU and PEU, consistent with previous studies by Rezaei et al. (2020) and Kurkinen (2012). This suggests that compatibility affects adoption intentions not directly but through its impact on perceived usefulness and ease of use. Moreover, Observability (OB) significantly impacted PU, PEU, and behavioral intention, reinforcing the importance of visible benefits in encouraging adoption.

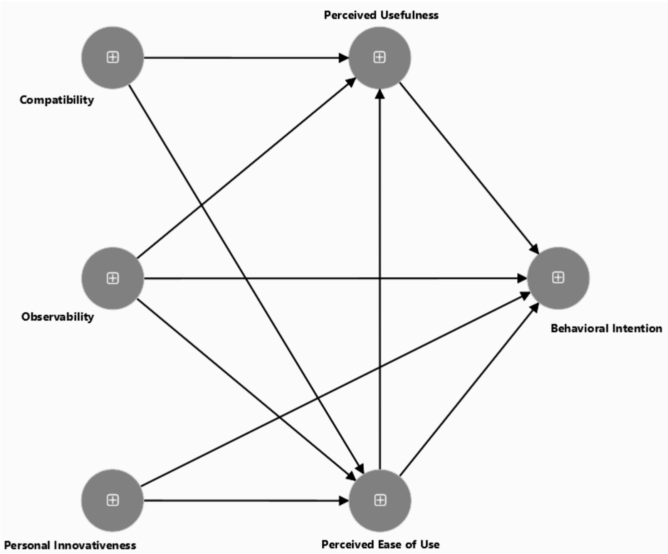
Personal Innovativeness (PI) also played a key role, positively influencing PEU and behavioral intention, supporting hypotheses H8 and H9. Innovativeness enhanced farmers' perceptions of ease of use and their likelihood of adopting the technology, although it did not directly impact PU. This suggests that innovative individuals are more open to new technologies but do not necessarily perceive them as more useful. The study also found that PEU positively influenced both PU and behavioral intention, supporting hypotheses H10 and H12 highlighting the importance of user-friendliness in the adoption process.

The study confirmed the significant positive relationship between PU and behavioral intention, indicating that the perceived usefulness of the technology directly influences farmers' intentions to adopt it. The f-square analysis further supported these findings by demonstrating that the variables in the model had significant relationships, reinforcing the overall robustness and validity of the model. This comprehensive validation ensures that the study's conclusions provide a reliable understanding of the factors influencing the adoption of pneumatic precision planters in Philippine maize farming.

Final Structure Equation Model. Final Structure Equation Model. Figure 6 exhibited the final structural equation model based on the path coefficients table, which revealed the significant and insignificant correlations among latent variables. The model only demonstrated a qualitative interpretation of possibly positive relationships between latent variables.

Figure 6

Final Structure Equation Model



Note. The data are from "SmartPLS 4" by C. M. Ringle, S. Wende, and J. M. Becker, 2022 (https://www.sm artpls.com)

5. Conclusion

This study examined the factors influencing the adoption of pneumatic precision planters in the Philippines using the Technology Acceptance Model (TAM) and incorporating external variables: Compatibility (CO), Observability (OB), and Personal Innovativeness (PI). Based on 393 valid responses, the analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to test 12 hypotheses, of which 10 were supported. The findings validated TAM as a relevant framework for understanding agricultural technology adoption, particularly in the context of pneumatic precision planters in the Philippines.

The results highlighted that farmers in the Philippines were generally open to adopting new farming technologies. OB and PI were key factors in shaping their intention to use pneumatic precision planters. While CO did not directly impact adoption intentions, OB emerged as the most influential external variable. This underscored the importance of social influence from trusted figures like agricultural authorities and pioneering farmers, which could significantly encourage the adoption of new technologies. These findings were valuable for policymakers aiming to enhance the adoption of agricultural technology.

The study also emphasized the role of younger farmers (aged 18 - 25), who were more open to adopting new technologies due to their digital fluency. Policymakers were advised to empower agricultural extension agents and provide targeted training programs to bridge socio-economic barriers, especially for less resource-rich farmers. Additionally, the regional diversity of Philippine agriculture required context-specific strategies to address local challenges, ensuring that interventions were tailored to farmers' unique needs. These insights were crucial for crafting effective policies to modernize Philippine agriculture and promote the widespread adoption of advanced farming technologies.

6. Recommendations

A tailored approach considering socio-economic factors is essential to boost the adoption of pneumatic precision planters in the Philippines. This includes policies addressing farmers' unique educational levels, farm sizes, and decision-making preferences. Targeted education and training should cater to diverse academic backgrounds, with hands-on training for farmers with lower formal education and more technical instruction for college-educated farmers. Demonstrating the technology's usefulness and ease of use through field days, workshops, and demonstration projects is crucial. Financial barriers can be alleviated through low-cost financing and subsidies while promoting the compatibility of these planters with traditional farming methods, which is key to increasing adoption. Social influence plays a significant role in decision-making, so leveraging trusted local leaders and "champion" farmers can encourage wider use. Engaging younger, tech-savvy farmers through digital literacy programs and social media campaigns can further speed adoption. Policymakers should also consider regional differences and tailor strategies to address challenges faced by farmers in remote areas while showcasing observable benefits through case studies and testimonials to enhance confidence. Finally, fostering a culture of innovation by celebrating early adopters and emphasizing long-term benefits will help drive broader adoption of precision farming tools.

Future research on adopting pneumatic precision planters in Philippine agriculture should focus on several key areas. Longitudinal studies can track adoption patterns and their long-term effects on productivity, efficiency, and sustainability. The role of social influence from peer groups, agricultural extension agents, and community leaders should be explored to understand how networks impact adoption decisions. Research on cost-effective solutions, such as low-cost financing and subsidies for small-scale farmers and the influence of cultural and regional differences, is also needed. Additionally, examining how digital tools like mobile apps and farm management software integrate with pneumatic planters and affect adoption could provide valuable insights. Studies on farmers' digital literacy and the relationship between personal innovativeness and sustainability could help promote environmentally sustainable practices. Finally, understanding the impact of weather variability and factors driving perceived usefulness can aid in developing more resilient farming technologies. Addressing these gaps will refine strategies for enhancing agricultural productivity and sustainability in the Philippines.

Limitations of the study

As with any survey research about a less well-known population, it is crucial to recognize potential limitations. The validity of the results was impacted by response biases or inaccuracies brought about by the dependence on self-reported data. Furthermore, the study's concentration on the Philippine corn sector limited the conclusions' generalization to other contexts. Moreover, the results were partially influenced by the difficulty in accessing specific groups of farmers, agronomists, or professionals in related sectors with restricted access to resources. However, despite these limitations, the overall validity and implications of the study's findings remain intact.

NO CONFLICT OF INTEREST STATEMENT

All authors declare that they have no conflict of interest.

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