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# Determinants of the Adoption of Digital Technologies in Pineapple Production in Southern Benin

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## Abstract

Agriculture is increasingly digital, with increasing use of information technologies and geospatial tools, promoting real-time soil data collection, high-quality soil cultivation, and adequate fertilization, including optimal soil hydration. These digital technologies also simplify many operations, including planning agricultural operations, financing, reporting, and monitoring many operations and agricultural performance. However, very little research has focused on the determinants of the adoption of these digital agriculture practices in Benin. This study fills this gap by using representative data from quantitative surveys of 400 randomly selected pineapple producers to analyze the simultaneous adoption of various digital technologies and the factors determining this adoption in a developing country such as Benin. Using a bivariate probit model, the study shows that the adoption of digital agriculture is significantly influenced not only by sociodemographic and economic variables (producer's education level, access to credit, household size) and access to agricultural advice, but also and above all by producers' perceptions (perception of high usage or purchase costs); the latter plays a crucial role in this adoption. The main policy implications include facilitating producers' access to credit and agricultural advisory services through continuing training to improve producers' technical skills in the use and management of digital technologies.

**Keywords:** Pineapple, digital technologies, adoption, factors, South Benin

## Introduction

Digital agriculture, introduced in the 1990s, refers to technology, and information driven farming that relies on information technologies and geospatial tools (Zhou et al., 2023). Also known as precision agriculture or smart agriculture (Subaeva et al., 2020), it offers several benefits to farmers by transforming production processes, particularly crop development.

This agriculture has several advantages for farmers. It significantly affects the agricultural production process, in particular, crop development. More specifically, it promotes real-time soil data collection, high-quality soil cultivation, adequate fertilization including optimal soil hydration (Nugmanov et al., 2022; Shchemeleva et al., 2021; Xie et al., 2021). By facilitating all of these processes through innovative digital technologies, digital agriculture is positioned as a sustainable strategy that also minimizes costs in inputs, labor, and natural resources (Kashina et al., 2022).

Indeed, agrochemical soil analysis, most often carried out using sensor equipment, makes it possible to assess soil fertility, obtain data on the suitability of the soil for growing a particular crop, optimize the nutritional system and reduce fertilization costs (Kuldybayev et al., 2021). Also, these digital technologies make it possible to simplify many operations, including planning agricultural operations, financing, reporting, monitoring of many operations and agricultural performance (Abiri et al., 2023). All these elements allow digital technologies to optimize agricultural productivity and improve producers' incomes (Ogutu et al., 2014; Lajoie-O'Malley et al., 2020; Xie et al., 2021), while providing greater market transparency (Tadesse and Bahiigwa, 2015).

For example, tools such as guidance technologies (smartphones, social networks) and application technologies (intelligent treatment application machines and irrigation systems) are recognized for their ability to contribute to improving agricultural productivity and sales operations (Hanitravelo, 2020; Balafoutis et al., 2017). However, despite their proven benefits, the adoption of these digital technologies in agriculture remains low due to high costs, lack of knowledge and infrastructure, and uncertainty about economic returns (Feng et al., 2013; Bai et al., 2017). Also, farmers' adoption decisions are strongly linked to their expectations, perceptions, and access to information (Pronti et al., 2020).

Previous studies on technology adoption, particularly irrigation systems, have mostly focused on socioeconomic and geographic factors (Mango et al., 2018; Muluki et al., 2022; Serote et al., 2021; Salazar & Rand, 2016). However, it is widely accepted that the adoption of digital technologies in agriculture must be gradual, thus implying evolutionary dynamics in the determining factors (Pronti et al., 2020). Also, there are no universal factors that explain the adoption of digital agriculture; these factors are generally context-dependent. For example, in a developed country context, the factors influencing producers' decision to adopt digital agriculture generally highlighted are the perceptions of the usefulness and benefits of the technology, lack of expertise, the need to know specific tools to meet high priority needs, the nature of agricultural systems, lack of technical support and lack of technical expertise at different levels (Gabriel and Gandorfer, 2023; Addorisio et al., 2025).

In a developing country context, Hoang Nguyen et al. (2023) and Mhlanga and Ndhlovu (2023) in their respective systematic review came to the conclusion that the adoption of digital agriculture is affected by two types of factors: producer-related factors and those related to their field. Factors related to producers themselves include the producer's age, perceived benefits of the technology, observability, trialability, experience in applying the technology, innovation, risk tolerance, education, level of knowledge of the technology, and perception of the technology's level of complexity. Factors related to the operation concern their size, resource availability, perceived need for technological features, technological compatibility, social influence, competitive pressure, and government support.

Moreover, most studies focus on a single technology at a time – either guidance technologies such as smartphones (Nyagadza et al., 2022; Sennuga et al., 2023) or social media (Anand, 2021), or application technologies such as automatic spraying technologies (Berenstein & Edan, 2017), or smart irrigation systems (Serote et al., 2021) – without taking into account that several technologies can be adopted simultaneously within the same farm. Such analytical approaches might underestimate the interactions, i.e., complementarities or substitutabilities, between digital technologies.

Therefore, understanding and taking into consideration all of these technologies in a single analysis would allow us to better appreciate the complementarities between these tools and their influences on the choice of producers. To address this gap, this study analyzes the simultaneous adoption of multiple digital technologies and the factors influencing their uptake in pineapple production in Benin, providing a comprehensive framework to inform strategies that enhance adoption.

## Methods

### Study and sampling area

This research was conducted in the south of Benin (Figure 1), in the Atlantique department, a region that hosts more than 99% of the country's national pineapple production (DSA, 2019). The municipalities of Zê, Tori-Bossito, and Allada are dominants in the production with 27.73%, 26.3%, and 23.21% of the national production, respectively (DSA, 2019). These municipalities have benefited from numerous agricultural management projects, such as the Entrepreneurship Development Program in the Pineapple Sector (DEFIA) by the Belgian Development Agency (Enabel) (2020-2022), aimed at improving farm management with modern digital tools (Plagbeto, 2020).The sample size of 400 was determined from the Schwartz (1995) formula (Equation 1), taking into account a 95% confidence level (z=1.96) and a margin of error of 2%.

$$\mathbf{N} = \mathbf{Z^2} * \mathbf{p_i}(\mathbf{1} - \mathbf{p_i})/\mathbf{m^2}) \tag{1}$$

Where $i$ denotes the production area, i.e., the Atlantic department in this case. $N$ is the total sample size in the entire study area, in the department $\boldsymbol{i}$; $\mathbf{p_i}$ = proportion of agricultural households producing pineapple in the Atlantique department compared to all agricultural households in this department, estimated at 3.16% (Kpenavoun, 2014).

The distribution of the 400 producers was carried out in a stratified manner between the communes of Zè, Tori-Bossito, and Allada, proportionally to the number of producer households in each commune (Kpenavoun, 2014). Thus, 155 producers were selected in Zè, 149 in Tori-Bossito, and 96 in Allada. The selection of villages was made randomly, favoring villages that are district capitals and those that are easily accessible.

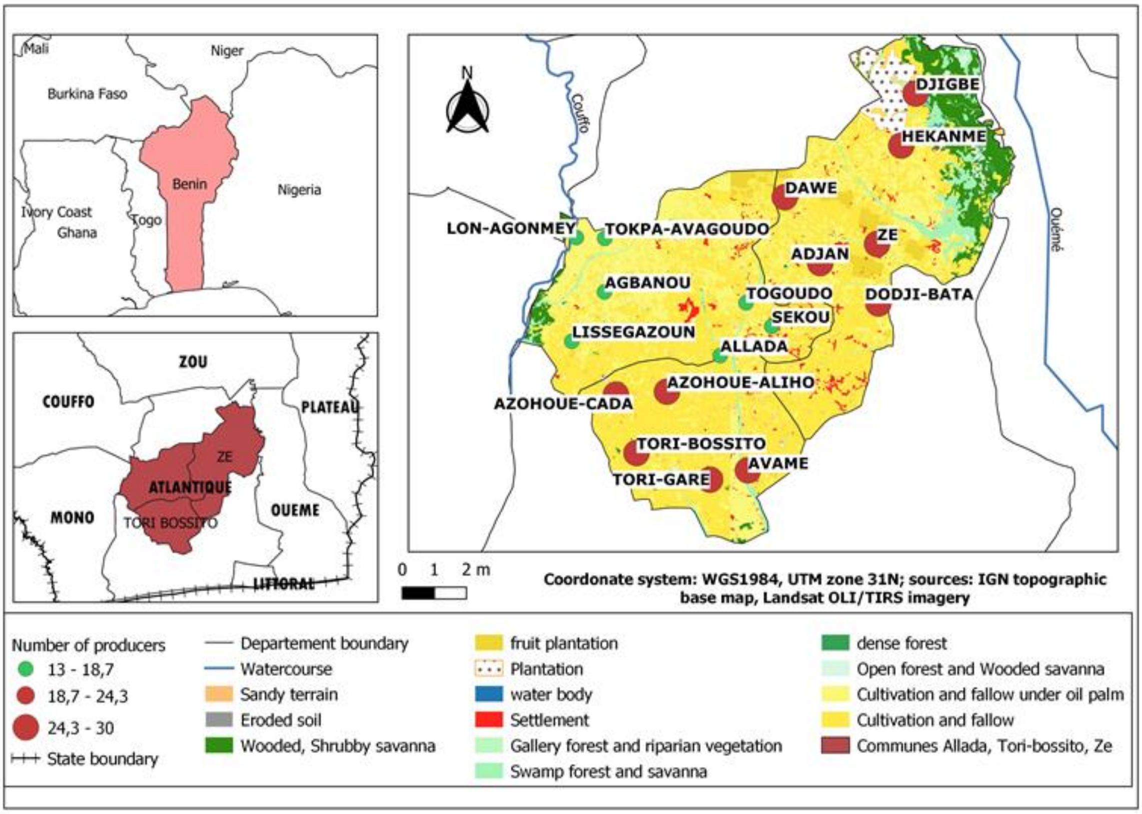



**Figure 1 :** Location of the study environment

## Data collection

Semi-structured interviews and structured questionnaires were used to collect data over the period from April 2nd to 25th, 2024. The data collected include socio-economic and demographic characteristics of the surveyed farmers (age, gender, education, experience, household and farm size, access to credit, organizational membership, and technical training), along with their perceptions of digital technologies regarding accessibility, relevance, and complexity in the production of pineapple. Additional data covered interactions with agricultural advisors, such as the number of consultations, frequency, and the types of information or services received.
This diverse information enables the assessment of producers' access to information, their adoption of digital technologies, and the factors influencing adoption decisions. Data were obtained through semi-structured and structured interviews, through focus groups and individual sessions, ensuring diverse perspectives and reducing bias. It is crucial to clarify that the free consent of each of the 400 producers interviewed was obtained at the beginning of each interview, after a presentation of the study's objectives and the methods of data collection.

## Data analysis

### Reduction of the dimensions of technologies adopted by producers through principal component analysis (PCA)

The study relied on two approaches to analyze the collected data. First, a principal component analysis (PCA) was used to evaluate the digital technologies adopted by pineapple producers. The choice of this approach is justified by its ability to reduce the dimensionality of the input variables and identify significant factors among several others (Kuivanen et al., 2016). Thus, confirming that producers can adopt diverse digital technologies simultaneously, this method is said to be appropriate for reducing this dimensionality by establishing homogeneous groups among them, with heterogeneous groups among themselves.

Drawing on the work of Andati et al. (2022), the utility that a producer derives from adopting smart technologies, such as digital technologies in agricultural production, comprises two components. This is a deterministic component that can be observed (utility function) and a random component, expressed as follows:

$$\mathrm{U_{mn}} = \mathrm{V_{mn}} + \varepsilon_{\mathrm{mn}}$$

The individual pineapple producer is assumed to have a utility function of the form:

$$\mathrm{U_{mn}} = \mathrm{V}(\mathrm{X_m}, \mathrm{Z_n})$$

Where V is the utility function, $X_m$ are the attributes of digital technologies, while $Z_n$ represents the characteristics of the producer. Thus, each pineapple farmer is called upon to choose among various digital technologies to optimize the present value of the benefits of digital technologies on pineapple production over a given period. Therefore, it is estimated that the benefits generated by any digital technology depend on the characteristics of this technology and the socio-economic factors of the producer (Andati et al., 2022 ; Kurgat et al., 2020).

Assuming that the principal components of the study are, $\mathrm{Z_1}$, $\mathrm{Z_2}$…$\mathrm{Z_n}$, they are generated by the linear combination of the variables X as: $\mathrm{Z} = \beta^{\mathrm{T}}\mathrm{X}$
Where $Z = Z_1, Z_2 \ldots Z_p$ is a principal component vector, $\beta^T$ is a coefficient matrix $\beta_{ij}$ with $i, j = 1,2, \ldots, p$

### Justification for using the probit model to identify the factors determining technology adoption

Secondly, to identify the determining factors influencing the adoption of each digital technology, this study adopts a methodology inspired by previous research in agricultural economics (Adekambi et al., 2021; Amare et al., 2018), the rationale for which is outlined in this section. Earlier studies frequently employed binary logistic regression to examine the main determinants of strategies adopted by producers to improve performance (Osumanu et al., 2017; Yabi et al., 2016). However, it is well recognized that farmers' decisions to adopt specific practices to adapt to their environment are not necessarily isolated but may be interdependent with other actions taken on the same farm unit (Amare et al., 2018). In such cases, relying solely on bivariate modeling could limit the integration of relevant data concerning the adoption of interdependent and simultaneous digital technologies.

To address this limitation, the present study employs a bivariate probit (BVP) regression model rather than the classical binary logistic regression approach. The BVP model enables the identification of factors influencing the adoption of digital technologies while accounting for interactions between different technologies. Multinomial models, for instance, become relevant when bivariate response patterns involve more than two possible outcomes (Amare et al., 2018). In this situation, the use of bivariate modelling could restrict the integration of relevant data from the adoption of interdependent and simultaneous digital technologies.

In this context, unlike the classical binary logistic regression approach, the present study uses a bivariate probit (BVP) regression model to identify the factors that influence the adoption of digital technologies while highlighting the interactions between different digital technologies. Indeed, multinomial models are relevant when bivariate response patterns encompass more than two possible outcomes (Amare et al., 2018). This approach has been validated by several recent empirical studies that have sought to circumvent these limitations by developing models that take into account the fact that producers are aware of a set of adaptation strategies and choose the combination that maximizes their expected utility (Adekambi et al., 2021).

In this model (Bivariate Probit), there are two binary dependent variables $Y_{ij}$ and several latent variables $Y_{ij}^*$. These latent variables depend, among other things, on the socioeconomic, demographic, perception and institutional environment (agricultural advice) characteristics of the producer $X_i$. The general expression of this model is as follows (Sileshi et al., 2019):

$$Y_{ij}^* = X_i \beta + \varepsilon_i \tag{2}$$

With

- $i = 1, 2, 3, \dots\dots, N$ designating the number of observations or producers (N= 400)
- $j = 1, 2, 3, \dots\dots, n$ representing the digital technologies adopted by each produce

- $\beta$ is the vector of parameters to be estimated and
- $\varepsilon_i$ the error term resulting from the random disturbance of the soil.
- $X_i$ represents an $K$ exogenous covariance vector (socio-economic, demographic characteristics, perception and agricultural advice received by producers).

The Wald test was used to determine whether the coefficients are simultaneously equal to zero. The Chi2 correlation test was used to test the relevance of the bivariate Probit model. Formally, the model used in this study is written:

$$\begin{aligned} Y_{ij}^{*} = \beta_0 + \beta_1 Age + \beta_2 Exp + \beta_3 Gen + \beta_4 Instr + \beta_5 SizeM + \beta_6\, Cred \\ + \beta_7\, Advant + \beta_8\, Cost + \beta_{10}\, Acce + \beta_{11}\, Compat \\ + \beta_{12}\, Complex + \beta_{13}\, Stru + \beta_{14}\, Vul + \beta_{15}\, Form \\ + \beta_{16}\, Input + \beta_{17}\, Areatot + \beta_{18}\, AreaPine + \mu_i \end{aligned} \tag{3}$$

Furthermore, this study identified twenty (20) digital technologies that producers could adopt, which were reduced by PCA analysis to two components, namely guidance technologies (smartphones, agricultural social networks, Agriwallet) and application technologies (intelligent input application machine and irrigation system).

The dependent variable is the "adoption of a digital technology in each of the two categories of digital technologies, a binary variable (0 = if the individual does not adopt any given technology in the group considered and 1 = if the respondent adopts at least one technology in the group).

$$Y_{ij}^{*} = \begin{Bmatrix} 1\ if\ Y_{ij}^{*} > 0 \\ 0\ else \end{Bmatrix}\ j = 1$$

**Overview of variables included in the models**

The models incorporated a range of variables, their measurement levels, and the expected signs of their influence on the adoption of digital technologies in pineapple production, as summarized in Table 1. The dependent variables are binary, coded as 1 for adoption and 0 for non-adoption (1 = Yes; 0 = No), representing whether a farmer adopted a particular digital technology. The explanatory variables were categorized into four main groups: sociodemographic characteristics, producers' perceptions of digital technologies, access to agricultural advisory services, and farm size. The sociodemographic variables included age, farming experience, gender, education level, household size, and access to credit. The inclusion of these variables was informed by prior studies on the adoption of digital agricultural technologies (Amoussohoui et al., 2024; Ayalew & Girma, 2025; Hailemariam et al., 2024; Rayhan et al., 2023; Ayenew et al., 2020). For producers' perceptions, variables such as perceived advantages, accessibility, compatibility, and complexity were considered, consistent with previous research (Caffaro et al., 2020; Tanos et al., 2024). Variables related to agricultural advisory services, such as contact with technical and financial structures, access to extension services, technical training, and agricultural inputs, were included based on evidence from earlier studies that emphasized their significant role in influencing technology adoption (Amoussohoui et al., 2024; Li et al., 2022; Maula, 2025). Regarding farm size, two variables were used: total cultivated area and area allocated specifically to pineapple production (Kolady et al., 2021; Mwangi & Kariuki, 2015; Schimmelpfennig, 2016). The total area was included to capture the structural effect of farm size on a farmer's capacity to invest in technology, while the pineapple-specific area reflects the influence of crop specialization on adoption decisions. Drawing on these previous works, the study formulated hypotheses regarding the expected direction of influence for each variable, as indicated by the signs in Table 1.

**Table 1 :** Description of variables to be used in the model

| Variables | Description | Abbreviation | Unit | Expected effects |
|---|---|---|---|---|
| **Dependent variables** | | | | |
| $Y_1$ | Guidance technologies | | 0 = No; 1 = Yes | -- |
| $Y_2$ | Application technology | | 0 = No; 1 = Yes | -- |
| **Independent variables** | | | | |
| ***1. Sociodemographic and economic characteristics*** | | | | |
| Age | Producer's age | Age | Year | +/- |
| Experience | Number of years of experience | Exp | Year | +/- |
| Sex | Producer gender | Gen | 0 = Female; 1 = Male | + |
| Education | Educational level | Instr | 0= None; 1= Primary; 2= Secondary; 3 = University | + |
| Household size | Number of people in the household | Size | Discrete Variable (Number) | +/- |
| Credit | Access to credit | Credit | 0 = No; 1 = Yes | + |
| ***2. Producers' perception of digital technologies*** | | | | |
| Benefits | Number of benefits listed | Advant | Discrete Variable (Number) | + |
| Perception | Purchase costs, cost of use, | Cost | Discrete Variable (Number) | + |
| Accessibility | Degree of accessibility | Access | 0 = Not accessible; 1 = Moderately accessible; 2 = Very accessible | + |
| Compatibility | Degree of compatibility | Compat | 0 = Not compatible; 1 = Moderately compatible; 2 = Very compatible. | + |
| Complexity | Degree of complexity | Complex | 0 = Not complex; 1 = Moderately complex; 2 = Very complex. | - |

| Variables | Description | Abbreviation | Unit | Expected effects |
|---|---|---|---|---|
| 3. ***Agricultural advice benefited by producers*** | | | | |
| Structures | Number of structures (technical and financial) with which the producer is in contact | Struc | Discrete Variable (Number) | + |
| Popularization | Agricultural advice | Vul | Binary variable (0 = No; 1 = Yes) | + |
| Technical training | Service provided by the structures | Form | Binary variable (0 = No; 1 = Yes) | + |
| Access to inputs | Other services provided by the structures | Intra | Binary variable (0 = No; 1 = Yes) | + |
| ***4. Operating size*** | | | | |
| Total area | Average total area of farms during previous campaigns (2021-2022; 2023-2024) | Areatot | Continuous variable (Number) | + |
| Pineapple area | Average area reserved for pineapple during previous campaigns (2021-2022; 2023-2024) | AreaPine | Continuous variable (Number) | + |

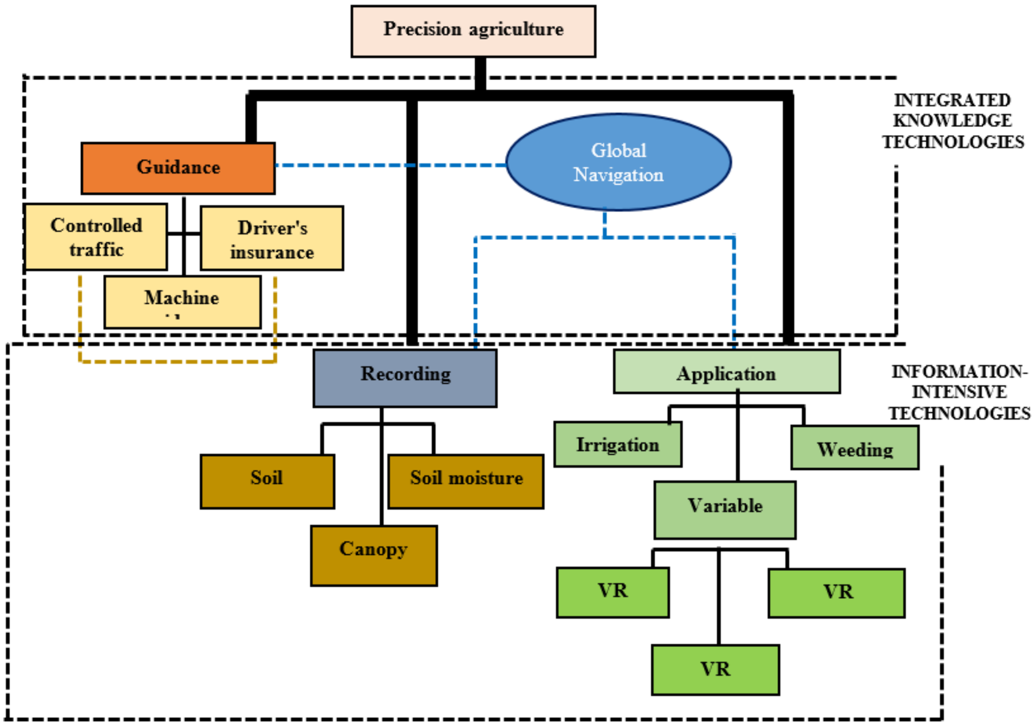
## Theoretical and Conceptual Framework

### Digital Technologies in Agriculture

In the agricultural context, several definitions have been proposed for the concept of digital technology. Initially, some considered digital technologies to be new technologies used for internal or external communication within the production unit (Lio and Liu, 2006; Mazaud, 2017). For others, digital technology encompasses all the technologies used on a farm for precision agriculture, in other words, agriculture aimed at improving the productivity and efficiency of agricultural operations by using ICTs: data acquisition, transfer, and storage technologies, and embedded or remote processing technologies (Bellon-Maurel and Huyghe, 2016).

However, the definition proposed by Schimmelpfennig (2016) is recognized as the most frequently cited when the concept of digital technologies is discussed in an agricultural context. According to the latter, digital technology in an agricultural context encompasses all the tools and technologies whose operation is based on computer science and electronics, and which are capable of being used to collect, store, manage, and analyze agricultural data. However, this definition was subsequently expanded upon by Balafoutis et al. (2017), who, after emphasizing digital tools used to collect, store, manage, and analyze agricultural data, highlighted that these technologies are also used to disseminate information and knowledge about agricultural and environmental practices. The definition proposed by Balafoutis et al. (2017) then allowed for the categorization of digital technologies into three levels based on their use: guidance technologies, recording technologies, and application technologies (Hanitravelo, 2020). Indeed, guidance technologies refer to the entire range of hardware and software used in Decision Support Tools (DSTs), information management, and data storage (Balafoutis et al., 2017). Among other things, Balafoutis et al. (2017) include the use of modern machinery or equipment capable of effectively replacing the producer in certain tasks within this category. As for recording technologies, they represent all the technologies that farmers use to collect farm data. These tools primarily include sensors, GPS, and satellite imagery, which are technologies currently used to monitor the development of plant diseases in some crops (Balafoutis et al., 2017). This category also refers to online platforms used to facilitate commercial transactions between farmers and consumers, sales management systems to manage orders and payments, and customer relationship management software to improve the customer experience (Balafoutis et al., 2017).

Finally, application technologies represent technologies used to assist or replace farmers in implementing decisions made by them. This is the case with smart irrigation systems that allow for the efficient management of crop irrigation based on the actual needs of the plants, thus saving water and reducing production costs (Lameski et al., 2018). Figure 1 summarizes, in accordance with the various proposals, all the digital technologies in agriculture identified by Bellon-Maurel and Huyghe (2016); Schimmelpfennig (2016) and Balafoutis et al. (2017).



**Acceptability of technologies**

The concept of acceptability was first introduced in 1975 by American anthropologist Everett M. Rogers in his book "Diffusion of Innovations." Rogers defined acceptability as the degree to which an innovation is considered consistent with the adopter's existing values, prior needs, experiences, and cultural norms (Rogers, 1975). He explained that acceptability is influenced by five main factors: relative advantage, compatibility, complexity, trialability, and observability. Indeed, the latter perceives acceptability as a subset of compatibility, which refers to the perceived fit between the innovation and the user's values, experiences, and needs. Since then, the concept of acceptability has been widely used in the literature to describe the receptivity of an innovation, product, or service by users or consumers. This is also confirmed by Benbasat and Barki (2007) who defined acceptability as the extent to which a user accepts the use of a technology in order to achieve their objectives.

Furthermore, the concept of acceptability remains complex insofar as it involves two important and closely interdependent approaches (Dubois, Bobillier-Chaumon, 2009). Firstly, it concerns the importance of the innovation system implemented, including its characteristics, which, in order to be "acceptable", must have sufficient adequacy with the user. As a result, one of Everett M. Rogers' conditions arises, namely the question of compatibility of the system with the practices, resources, objectives of potential users and their situation (Dubois, Bobillier-Chaumon, 2009). Moreover, from a functional point of view, the acceptability of the innovation is influenced by the usability characteristics of the system, which in turn call for the ease of their use or their user-friendliness, in other words the ease that users experience in using and mastering the innovation, without requiring complex learning or particular technical expertise.

From these aspects arises the second approach using the user-user relationship which, outside the functional and utilitarian framework, refers above all to the behavior of the individual towards the technology implemented. Considered as a socially situated psychological actor, each person makes the decision to adopt or not a device (technology) implemented under the motivation of his own perceptions towards the said technology. Thus, this raises the need for a reminder of the definition and theory around adoption. The first definitions of the concept of adoption come from the theoretical approaches of "the diffusion of innovations" carried by Rogers (1962) who defines adoption as the desire to exploit the innovation in a continuous manner. He presents the adoption of an innovation as the mechanism of recognition of something as new (an idea, a product or a brand) by an individual or a production unit. For Rogers, this process of adopting an innovation is characterized by five phases: knowledge of the innovation, persuasion, decision regarding its adoption, implementation of the innovation and then confirmation (Cheikho, 2015). Thus, in the context of adopting a new technology, Lapointe (1999) emphasizes that the notion of adoption becomes a little broader insofar as this notion refers to the acceptance, testing, use and internalization of this technology.

Furthermore, the adoption of a technology involves reflection on decisions influenced by multiple factors, which are often interdependent and this over several years (Roussy et al., 2015). As an illustration, Caneva (2019) specifies that the level of adoption of an innovation is influenced by the perception that one has of the innovation concerned. This was also highlighted by Bonnet (2014), when he states that we unconsciously associate what we feel with the cause of our impression or our action, which makes the representations or perceptions of farmers the major elements in the development of their decisions and actions within the farming system. From the perspective of social acceptability, several studies have explored this second behavioral approach of the individual towards technology by developing several models to explain and predict the behavior of individuals when using information and communication technologies.

This is the case of Venkatesh et al. (2016) who proposed a synthesis of research on the acceptance and use of ICTs based on the technology acceptance model. In their capitalization study on the acceptance and use of these technologies, they reached several conclusions according to which, firstly, the perception of the usefulness and ease of use of a technology, contextual factors (culture, age and experience), emotional factors (pleasure and anxiety) constitute the main factors in the acceptance and use of ICTs. These conclusions are corroborated by other studies such as those of Zhu et al. (2019) who indicated the perceived quality of the system, perceived usefulness, perceived ease of use, perceived cultural compatibility, perceived social influence and perceived emotion as the real variables determining the use of information technologies.

In Benin, Hounkpe and Adegbidi (2015), at the end of their studies on the factors that influence the adoption of mobile technologies by farmers, added to the perception of the usefulness of the technology, determined by the benefits it brings to farmers in their work, other factors. These include the socio-economic characteristics of farmers, such as their age, level of education, experience in agriculture, income and access to information and especially other elements such as the characteristics of the mobile technologies themselves, such as their cost, accessibility and reliability and finally the characteristics of the context in which farmers work, such as the availability of electricity and Internet connectivity.

Each of these conclusions allows us to maintain more than 30 years after the Technology Acceptance Model (TAM) proposed by Davis (1986) in his doctoral thesis (Noble et al., 1986), then considered in other articles as the dominant model of acceptability and adoption of digital technologies (Hsiao and Yang, 2011; Atarodi et al., 2018). This model aims to predict and explain the adoption or not of a technology through variables relating to perceptions (perceived usefulness: PU, or perceived ease of use: FUP) and attitudes (A) which will induce behavioral intentions of use. Davis (1986) summarizes this through the diagram below:

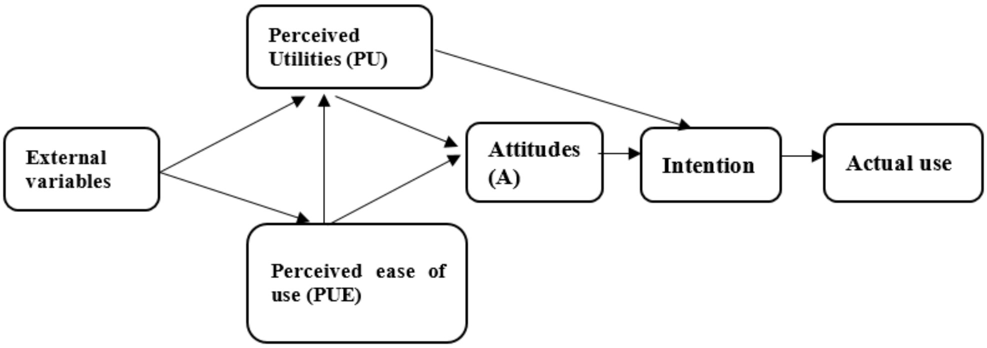



**Figure 2 :** TAM according to Davis (1989)

Based on these elements, this research focuses on the factors of technological acceptance, such Based on these elements, this research focuses on the factors of technological acceptance such as: contextual factors (sociodemographic and economic characteristics), emotional factors (perception of perceived usefulness), perceived ease of use, perceived compatibility and perceived social influence.

## Pineapple production in Benin

Pineapple is the main fruit crop in the south of the Benin Republic, cultivated by about 70% of producers in the Atlantic region, which accounts for 99% of national production (Sossa et al., 2014; DSA, 2019). This region also hosts over 92% of the country's pineapple producers (DSA, 2024), with Zè, Allada, and Toffo ranked among the leading and the top four producing municipalities (MAEP, 2021). Pineapple farming is a priority agricultural sector due to its comparative advantages and economic potential, contributing about 1.28% to national GDP and 4.3% to agricultural industrial GDP (INStaD, 2020).

Despite this importance, production faces major challenges, including low farm productivity (Sossou, 2015). As a result, national output dropped from 374,601 tons in 2018–2019 to 362,964 tons in 2020–2021, a 3.11% decline in total production level (MAEP, 2021). Environmental factors such as climate change and technological constraints further limit the competitiveness of local products on the global markets (FAO, 2023).

In response to these challenges, several digital agricultural solutions have been developed and promoted in the country (Benin), providing services such as agrarian advisory, training, and market information for producers (Gbedomon et al., 2023). For example, Agricef and App céréale offer rapid access to essential agricultural advice, while Agrimétéo provides meteorological information to support production planning. Similarly, Agrotrace serves as a tool for product traceability (Gbedomon et al., 2023). Other digital solutions, such as Agriyara and Jinukun, focus on improving market access by reducing intermediaries between producers and consumers, thereby ensuring better prices for farmers (Gbedomon et al., 2023). Mechanization services have also emerged, with applications like Trotro Civa allowing producers to book tractors through a simple mobile phone interface (Gbedomon et al., 2023). Additionally, monitoring and mapping solutions, including drones and platforms such as Agrimap and Agrosfer Mapping, enable producers to track crop activities and map farms (Gbedomon et al., 2023).

Despite these innovations, only about 54% of the digital solutions identified are currently available on the market, while 30% of them is in prototype or testing phases (Gbedomon et al., 2023). Furthermore, the pineapple sector, which is among the country's priority agricultural sectors, benefits from only 12.5% of these solutions. These include drones such as 4AG and Drone Analyst, as well as technologies designed for broader crop sectors, including Agricef, Ag4all for advisory and pre-financing services, Our Voice for broadcasting messages in local languages, Atingi4AG for online agricultural courses, and Farmer Education for technical training (Gbedomon et al., 2023).

This study seeks to identify the factors influencing the adoption of these digital technologies in Benin's pineapple sector and propose practical recommendations to enhance their uptake. Beyond accessibility, successful adoption depends on producers' acceptance of these tools, emphasizing the importance of understanding concepts such as acceptability within the context of this research.

## Results

### Digital technologies adopted by producers

Analysis of the table shows that in the study area, the smartphone is the most widely adopted digital technology, with an adoption rate of 36.76%. Owning these smartphones also allows producers to adopt other information-sharing technologies, such as agricultural social networks (particularly WhatsApp groups), where moderate adoption is also observed (27.6%). In addition to these two technologies, other producers use input application equipment (pesticides) (20.25%) and an electronic wallet commonly known as an Agriwallet, with a relatively low usage rate (14.6%). Finally, a minority uses smart irrigation systems (8.5%). This suggests limited use of this specialized agricultural equipment, which producers consider expensive to acquire and maintain, potentially hindering its widespread adoption among smallholder farmers.

**Table 2:** Adoption Rates of Digital Technologies on Pineapple Farms

| Types of technologies | Adoption rate |
|---|---|
| Smartphones | 36.75% |
| Agricultural social networks | 27.6% |
| Application equipment | 20.25% |
| Agriwallet | 14.5% |
| Smart irrigation systems | 8.5% |

## Evaluation of digital technologies adopted by pineapple producers

Given that producers are able to adopt numerous digital technologies simultaneously, principal component analysis (PCA) was used to reduce dimensionality by creating homogeneous but heterogeneous groups. Indeed, a total of 16 digital technologies are used by pineapple producers in Benin, based on the literature. Although only 5 of these technologies were most frequently cited by producers in this study, PCA considered the other, unadopted technologies to ensure the most inclusive assessment possible of the digital technologies adopted by producers in these regions.

The principal component analysis (PCA) implemented in this study aims to reduce the complexity of data relating to the adoption of sixteen (16) digital technologies by pineapple producers. The analysis showed that five components accounted for over 98% of the total variance, indicating PCA's strong capacity to summarize information without major loss. The five technologies contributing most to this variance were smart irrigation systems (30.15%), input application machines (22.22%), Agriwallet (20.22%), agricultural social networks (15.19%), and smartphones (10.32%). These five technologies capture most of the variation in adoption behavior and can be considered representative of the overall set of digital tools. They were therefore used to create binary dependent variables for the subsequent econometric analysis, with each variable indicating whether at least one technology in its category was adopted. This dimensional reduction simplifies the statistical model and provides a practical basis for targeting agricultural technology promotion policies toward the most influential digital tools.

**Table 3:** Results of principal component analysis

| Explained component of total variance | Initial eigenvalues | | |
|---|---|---|---|
| | Total | % variance | Cumulative % |
| Smart irrigation systems | 1.256 | 30,145 | 30.145 |
| Input application machine | 3.175 | 22,217 | 52.362 |
| Agriwallet | 2.152 | 20,224 | 72.586 |
| Social networks | 3.823 | 15,185 | 87.771 |
| Smartphones | 4.247 | 10,319 | 98.09 |
| Computers | 0.001 | 0.388 | 98.478 |
| Internet (websites, blogs, etc.) | 0.001 | 0.347 | 98.825 |
| Thorn-A | 0.001 | 0.272 | 99.097 |
| AGRICEF | 0.001 | 0.241 | 99.338 |
| DigitFin | 0.001 | 0.174 | 99.512 |
| Information dissemination device | 0.001 | 0.142 | 99.654 |
| Podcast | 0.001 | 0.124 | 99.778 |
| Trading platforms | 0.001 | 0.082 | 99.86 |
| Sensors | 0.001 | 0.064 | 99.924 |
| GPS | 0.001 | 0.04 | 99.964 |
| Drones | 0.001 | 0.036 | 100 |

## ACP synthesis according to the two technology groups

A summary of the PCA results (Table 4) reveals the predominance of two main dimensions of digital technology adoption. These are the dimension related to the adoption of irrigation systems and input application devices (with a contribution rate of 52.85%) and the dimension of the three other technologies (smartphones, social networks, and agriwallets) with a contribution of 47.15%, thus explaining all the observed variation. This suggests that adoption behaviors are primarily structured around the use of operational tools in the field. These two dimensions also correspond to two of the three categories of digital technologies proposed by Balafoutis and colleagues: guidance technologies (smartphones, social networks, and agriwallets) and application technologies (irrigation systems and input application devices). Table 4 summarizes these PCA results according to the two main dimensions of digital technology adoption: application technologies (52.85%) and guidance technologies (47.15%).

This grouping is essential for the subsequent analyses because it not only mitigates the problems associated with the low adoption rate of these technologies individually but also allows for a better understanding of the determinants of adoption based on the main functions performed by these tools.

**Table 4 :** Summary of the results of the ACP

| Components | Contribution percentage | Digital technologies adopted |
|---|---|---|
| **Application Technologies** | 52.85% | Smart irrigation systems, fertiliser application machines, drones, podcasts, GPS, sensors |
| **Guidance technologies** | 47.15% | Smartphones, Social Networks, Agriwallet, Computers, etc. |

## Factors determining the adoption of digital technologies

### Case of guidance technologies

The bivariate probit model reveals a significant correlation between the residuals of the two equations (p < 0.001; corr = 0.667), confirming interdependence in terms of errors, and justifying the joint estimation of the two categories of digital technologies (Table 5). As regards the factors, the results of the bivariate probit model (Table 5) show that several factors significantly influence the adoption of guidance technologies, namely smartphones, agricultural social networks and the Agriwallet electronic wallet. First, the McFadden's $R^2$ indicates a strong explanatory power of the model (81.3%) and the Durbin-Watson test suggests an absence of serial correlation in the residuals. The Wald chi2 test is also very significant ($p < 0.001$), confirming the overall relevance of the explanatory variables included in the model.

Among socio-demographic and economic factors, education level is a key determinant, with a marginal effect of 0.021 (p <0.05), meaning that a higher education level increases the likelihood of adopting guidance technologies by 2.1%. Membership in a farmers' organization (FO) is also significant, with a marginal effect of 0.243 (p <0.001), suggesting that members are 24.3% more likely to adopt these technologies, partly because they facilitate rapid communication for meetings and information sharing. Conversely, household size has a negative marginal effect of -0.011 (p < 0.05), indicating that larger households are less likely to adopt guidance technologies, likely due to budget constraints and the high cost of smartphones. In addition to these factors, the model also indicates access to credit as a determining factor with a marginal effect of 0.043 ($p < 0.05$). This means that producers with access to credit are 4.3% more likely to adopt this technology, thus highlighting the importance of access to finance in the adoption of guidance technologies. Other sociodemographic and economic variables, such as age, gender, experience, did not show significant effects. This suggests that these factors do not significantly influence the adoption of smartphones at the level of the population of pineapple producers in this department.

However, producers' perceptions of guidance technologies also play a crucial role. High usage cost is significant with a marginal effect of 0.169 ($p < 0.01$), indicating that producers who perceive a high usage cost are paradoxically 16.9% more likely to adopt guidance technologies. This finding therefore demonstrates the recognition of the added value of guidance technologies despite the high usage costs highlighted by adopters. On the other hand, low connection shows a marginal effect of -0.432 ($p < 0.001$), suggesting that producers who have put forward the barrier related to the network or internet connection either given their economic capacity or the specificity of their region are 43.2% less likely to adopt these digital technologies. Paradoxically, a weak connection shows a marginal effect of 0.432 ($p < 0.01$), suggesting that producers who have highlighted network or internet connectivity as a barrier are 43.2% more likely to adopt these digital technologies.

Variables related to agricultural advisory services and technical training, such as extension services, access to inputs, and technical training, did not show significant effects on the adoption of guidance technologies. This could indicate that the perceived benefits of guidance technologies in these areas are not yet tangible enough to influence the adoption decision, or that these services are not sufficiently developed to have a significant impact. Farm size variables, both for total area and for that dedicated to pineapple, did not show significant effects. This suggests that farm size is not a crucial determinant in the adoption of guidance technologies by producers.

These findings indicate that promoting the adoption of guidance technologies among pineapple producers requires strengthening farmer organizations, improving education and credit access, and addressing connectivity issues. Policies should also focus on changing perceptions about cost through subsidies or demonstrations of long-term benefits. By targeting these areas, interventions can effectively enhance adoption, driving innovation and efficiency in the agricultural sector.

**Case of application technologies**

The bivariate probit model for the adoption of application technologies, specifically input application machines and smart irrigation systems, reveals significant factors influencing farmers’ decisions (Table 5). The model demonstrates strong explanatory power, with McFadden's $R^2$ indicating that 91.4% of the variation in adoption is explained by the included variables. The Durbin Watson statistic suggests the absence of residual correlation, further confirming model validity, while the Wald $chi^2$ test (20) is highly significant ($p < 0.001$), validating the overall relevance of the explanatory variables.

Among socio-demographic and economic characteristics, age emerges as a significant factor with a marginal effect of -0.005 ($p < 0.05$), implying that older producers are 0.5% less likely to adopt these technologies. This finding reflects a greater reluctance among older farmers to embrace innovations. Similarly, education level has a negative influence, with a marginal effect of -0.016 ($p < 0.01$), suggesting that a higher level of education decreases the likelihood of adoption by 1.6%. Access to credit also shows a significant positive impact (marginal effect = 0.059; $p < 0.05$), indicating that producers with credit access are 5.9% more likely to adopt application technologies. This finding underscores the importance of financial support in overcoming cost-related barriers to adoption. Other socio-demographic factors such as household size, organizational membership, gender, and experience show no significant effect.

Extension services and technical support play a crucial role in adoption decisions. But paradoxically, producers who benefit from support in agricultural extension are 5.6% less likely to adopt these technologies (marginal effect = -0.056; $p < 0.05$). At the same time, rather than being perceived as a barrier, the model indicates that the perception of high purchase costs significantly improves the likelihood of adoption (marginal effect = 0.736; $p < 0.05$), suggesting that producers who consider purchase prices excessive are 73.6% more likely to adopt these technologies. Farmers report that technical agencies, such as ATDA, often require simultaneous payment for inputs (urea, NPK, herbicides, pesticides) when purchasing application equipment to qualify for a discount, thus compelling them to acquire this equipment despite its perceived cost. Similarly, the perceived high operating costs have a positive influence (marginal effect = 0.217; $p < 0.05$), increasing the probability of adoption by 21.7%. However, faced with these financial constraints, other farmers prefer to turn to organic methods and traditional application techniques, which are more affordable and better suited to their economic resources.

Farm size also plays a role, with a significant positive effect (marginal effect = 0.006; $p < 0.05$), indicating that producers with larger farms are 0.6% more likely to adopt application technologies. This finding reflects the greater need for mechanization among producers managing large farms and possessing greater financial capacity. However, the area specifically dedicated to pineapple cultivation shows no significant effect, suggesting that adoption decisions are more closely tied to overall farm size rather than the size of the pineapple plot.

These findings underscore the need for targeted interventions to enhance the adoption of input application machines and irrigation systems among pineapple producers. Efforts should prioritize improving access to credit and strengthening extension services while addressing perceptions of high purchase and user costs through subsidies, financing options, or cost-sharing schemes. Additionally, providing adequate training and information on the benefits and long-term cost-effectiveness of these technologies could foster greater acceptance and adoption among farmers.

**Table 5 :** Estimation of the results of the bivariate probit model on the adoption of digital technologies

| **Factors** | **Guidance technology** | | | **Application technology** | | |
|---|---|---|---|---|---|---|
| | **Coeff (str error)** | **Marginal effects (AME)** | **P value** | **Coeff (str error)** | **Marginal effects (AME)** | **P value** |
| **Sociodemographic and economic** | | | | | | |
| Age | -0.02 (0.023) | -0.0015 | 0.363 | -0.19 (0.08)* | -0.005 | 0.02* |
| Educational level | 0.3 (0.15) | 0.021 | 0.048* | -0.66 (0.37) | -0.016 | 0.047* |
| Experience | -0.023 (0.02) | -0.0016 | 0.287 | -0.02 (0.05) | -0.001 | 0.63 |
| Membership (OP) | 2.03 (0.4) | 0.243 | 2.96e-07 *** | -0.02 (0.71) | -0.001 | 0.97 |
| Gender (Male) | -0.2 (0.46) | -1.014 | 0.658 | -1.14 (0.83) | -0.038 | 0.17 |
| Household size | -0.16 (0.07) | -0.011 | 0.031* | 0.14 (0.13) | 0.004 | 0.257 |
| Credits | -0.64 (0.4) | -0.043 | 0.011* | 1.61 (0.91)* | 0.059 | 0.046* |
| **Agricultural advice benefited by producers** | | | | | | |
| Popularization (Yes) | -0.34 (0.7) | -0.022 | 0.63 | -2.09 (1.45) | -0.056 | 0.015* |
| Number of structures | 0.42 (0.26) | 0.028 | 0.11 | -0.15 (0.56) | -0.004 | 0.789 |
| Access to inputs | 0.01 (0.4) | 0.001 | 0.97 | 2.66 (1.07)* | 0.144 | 0.013* |
| Technical training | 0.23 (0.5) | 0.017 | 0.64 | -0.72 (0.85) | -0.016 | 0.39 |
| **Producers' perception of technologies** | | | | | | |
| High purchase cost (Yes) | 0.53 (0.54) | 0.037 | 0.33 | 6.64 (1.67) | 0.736 | 7.2e-05 *** |
| High repair cost (Yes) | 0.89 (0.66) | 0.073 | 0.18 | -- | -- | |
| High cost of use (Yes) | 1.92 (0.55)** | 0.169 | 4.36e-04 *** | 3.27 (0.85)* | 0.217 | 1.26e-04 *** |
| Low availability (Yes) | -0.97 (0.47) | -0.075 | 0.04* | -6.47 (1.89) | -0.183 | 6.07e-04 *** |
| Weak connection (Yes) | 3.13 (0.53) | 0.432 | 3.01e-09 *** | -- | -- | |
| Complex method (Yes) | 0.86 (0.68) | 0.067 | 0.21 | 4.87 (1.65) | 0.412 | 0.9 |
| **Operating size** | | | | | | |
| Area of farms | 0.12 (0.16) | 0.008 | 0.437 | 2.15 (1.1) | 0.006 | 0.023* |
| Pineapple area | -0.03 (0.18) | -0.0024 | 0.852 | 0.23 (0.48) | 0.006 | 0.63 |
| **Validity tests** | | | | | | |

| | | |
|---|---|---|
| McFadden's $R^2$ (%) | **0.813** | **0.914** |
| Durbin-Watson | **1.878 (tending towards 2)** | **1.793 (tending towards 2)** |
| Number of observations | 400 | 400 |
| Wald chi2(20) | 427,593 | 368.47 |
| Prob | 7.86e-79*** | 1,872e-18*** |
| **Correlation** | | |
| Corr person | **P<0.000 ; corr = 0.6668** | |

* = p < 0.1; ** = p < 0.05; *** = p < 0.01

## Discussion

The results of the model on the adoption of guidance technologies by pineapple producers show that, in addition to sociodemographic and economic factors, producers' perceptions also play a determining role. Indeed, the positive influence of the level of education and membership in a farmers' organization highlights the importance of education and interaction between producers in the adoption of digital technologies such as smartphones in agriculture. These results are consistent with the studies of Michels et al. (2020) which identify education as a factor that improves producers' ability to understand and use new technologies such as smartphones. As Baumüller (2012) pointed out, the use of a technology requires a certain level of knowledge on how to use it and an ability to manage any associated risks. This is the case with smartphones, where education facilitates understanding of its operation. Thus, cited by producers as the most used technology or means of communication and information, smartphones are useful for producers not only to ensure the sharing of ideas between producers but also to facilitate sales operations (Amessinou 2018). This also echoes the conclusion of Dehnen-Schmutz et al. (2016) who emphasize that this technology remains the device most used daily by producers.

Access to credit has been shown to be a determining factor in the adoption of guidance technologies, highlighting the importance of financial inclusion for the adoption of digital technologies in agriculture (Aker et al. 2016). This result confirms the conclusion of Baumüller (2012) who also identifies access to financial resources and services as another important factor in technology adoption, particularly when financial capital is required to obtain this technology, such as smartphones. However, the results of this study generally contradict the findings of several other researchers who have emphasized that financial resources, often in the form of loans, can be a significant barrier to technology adoption when access is limited (Baumüller, 2012; Poulton et al., 2006). On the other hand, household size has a negative effect on the adoption of this technology. This corroborates the results obtained by Kabbiri et al. (2018). Indeed, often identified (household size) as a factor increasing the risk of poverty (Namegabe et al. 2013), the negative influence of household size thus confirms that budgetary constraints remain serious obstacles to the adoption of technologies including smartphones.

The results also indicate that perceptions of cost of use and low internet availability positively and negatively influence the adoption of guidance technologies, respectively. This partly confirms the findings of Dehnen-Schmutz et al. (2016) who highlight poor access to phone signals and appropriate internet quality ("Poor phone signal, poor broadband connection, therefore slow Wi-Fi") as the main reasons for non-adoption of smartphones in agricultural settings. These findings were also made by Riddlesden and Singleton (2014) who highlighted poor mobile network coverage and poor broadband connectivity as the main problems surrounding smartphone adoption in rural areas of the UK and France. It is in this context that Pongnumkul et al. (2015) conclude that technological applications would be more beneficial if they allowed users to perform tasks offline and then synchronize with appropriate databases once users had access to the Internet. Furthermore, the model indicates that perceptions of high usage costs positively influence the adoption of guidance technologies. This result suggests that producers recognize the added value of guidance technologies despite the costs perceived to be high, which is paradoxically an incentive for adoption, as observed in other studies where the perceived benefits of technologies outweigh the initial costs (Tadesse and Bahiigwa 2015). All of these results also corroborate the findings of Melesse (2018) and Teklewold et al. (2013) who identified all these factors as the main determinants of the adoption of digital technologies in agricultural environments. In light of these observations, to promote smartphone adoption, it is therefore crucial to promote farmer organizations, improve access to education and credit, and invest in rural internet infrastructure. These strategies align with recent recommendations on the importance of systemic interventions to facilitate technology adoption in the agricultural sector (Cirera et al. 2022; World Bank 2020).

With respect to application technologies, the study highlights the influence of several factors in producers' decisions. Age appears to be a barrier, i.e., increasing age decreases the likelihood of producers adopting. This suggests that older producers show great reluctance to adopt new technologies. This finding is consistent with several studies such as Hu et al. (2022); Ayisi et al. (2022) which show that younger producers are often more open to technological innovations in this category compared to older ones. Unlike the adoption of guidance technologies, the level of education significantly increases the likelihood of adopting these technologies. This result contradicts the conclusions of several other studies conducted worldwide (Ruzzante et al., 2021; Riddell and Song, 2017) which established a positive correlation between education level and the adoption of many technologies by farmers. This could be related to the fact that the most educated are younger and have less financial resources compared to older farmers who thus have the resources to adopt application technologies such as irrigation systems.

In addition to these factors, the model also highlights the significant and positive influence of access to credit and farm size. However, for this technology, a positive influence of perceived purchase and operating costs on its adoption was observed. This contrasts with the findings of Hailu et al. (2014), who emphasize that the initial costs of innovative technologies constitute a significant barrier to their adoption. This finding suggests that producers perceive these costs as a necessary investment, with expected benefits in terms of improved productivity, reduced labor burden, or increased operational efficiency deemed far greater than the expenses incurred.

These results thus confirm the importance of sociodemographic and economic characteristics, as well as farm size, in the use of applied technologies, particularly smart irrigation systems (Pronti et al., 2020; Singh et al., 2015; Wheeler et al., 2010).

## Conclusion and Policy Implications

The adoption of digital technologies in the agricultural sector, and the pineapple sector in particular, is essential to modernize and improve the efficiency of agricultural production systems. This study demonstrated that, in addition to the commonly examined sociodemographic and economic factors, producers' perceptions of digital technologies also significantly influence their adoption decisions. This complexity underscores the need for integrated and specific approaches to encourage their large-scale adoption. We considered possible complementarity or substitution between families of digital technologies within the same farm. Our results revealed an interdependence in the adoption of different digital practices for pineapple production in Benin. They indicate that the decision to adopt guidance technologies is partly determined by the decision to adopt application technologies, and vice versa. However, the perception of a high cost of acquiring or using these technologies does not significantly hinder adoption, particularly of smart irrigation systems. Producers who adopt guidance technologies are generally educated, members of a producer organization, and have fewer agricultural resources. Furthermore, the adoption of these technologies is strongly influenced by producers' perception of high usage costs and by the level of internet connectivity in the region. The adoption of application technologies, on the other hand, is strongly influenced not only by the producer's sociodemographic and economic characteristics (age, education level, and access to credit), farm size, and access to agricultural advice, but also by producers' perceptions of these technologies.

Based on the results obtained, it is clear that education, access to credit, and extension services (contact with technical stakeholders) play a crucial role in this technological transition. This underscores the need to invest in continuing education programs for producers to improve their technical skills in using and managing digital technologies. This could involve creating partnerships between financial institutions, farmers' organizations, and government agencies to enable producers to overcome economic barriers. These integrated interventions will accelerate the modernization of the agricultural sector, thereby fostering more productive, sustainable, and resilient agriculture.

**Author contributions**

M.O. conducted the work, collected the data, and wrote the manuscript. S.A. A., R.O.A and J.A.Y. revised the protocol, verified the data collection forms, supervised the processing and analysis of the results, and contributed to the writing of the manuscript.

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