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Faculty of Tropical AgriSciences

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Agri-Food system business analysis and impact assessment on rice value chain in West Africa-Nigeria

DISSERTATION THESIS

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Declaration

I hereby affirm that I have done this thesis entitled "**Agri-Food system business analysis and impact assessment on rice value chain in West Africa-Nigeria**" independently except for jointly authored publications that are included. In the case of such publications, my specific contributions to each chapter have been clearly stated at their respective beginnings. Furthermore, I affirm that proper acknowledgement has been provided within this thesis for any references made to the works of others, I also ensure that this work has not been and is not being submitted for any other degree to this or any other university. All the sources have been quoted and acknowledged by means of complete references and according to Citation rules of the FTA.

In Prague, August 26th, 2024.

Rico Lionel Senanmi Amoussouhoui

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Abstract

The adoption of digital agricultural technology within the rice sector of developing countries has garnered considerable attention. While the literature widely demonstrates the positive impact of adopting such technology, there remains an unanswered question concerning its sustainable adoption. Given the low education level, limited e-literacy, unfamiliarity with digital tools, and inadequate infrastructure and information among smallholder farmers, ensuring a high and sustainable adoption of digital technologies poses a significant challenge. To address these barriers, this study proposes a paid extension service approach designed across various business profiles. This research aims to analyze the overall adoption of digital agricultural technologies, comprehend the factors driving farmers' adoption, introduce the new adoption approach, and test its efficacy with rice farmers through a field experiment. This study utilizes a digital extension technology developed by the AfricaRice Center and its partners to deliver personalized advice to rice farmers. Conducted in Nigeria, the study involved a sample size ranging from 1440 to 1560 rice farmers. The primary findings of the systematic review indicate that various types of digital agricultural technologies have been introduced and adopted over the last decade. However, challenges persist regarding the adoption rate and its sustainability. Our research uncovered that not only are farmers willing to pay for extension advice delivered through digital tools, but this approach also presents a profitable opportunity for the service provider as an agribusiness promoter, serving as an indirect adoption option. The pre-experiment study indicates that nearly half of the sample population preferred the option of cash payment after rice harvest, with a suggested rate of US$9.70/hectare, while the optimum price stood at US$14.50/hectare. Subsequently, the experimental evidence substantiated these initial findings. It revealed that over 61 percent of the participating rice farmers embraced and paid for the designated business profiles. Moreover, our findings indicate that the paid extension service, entailing cash payment after harvest at a rate of US$13/hectare, emerged as the most widely adopted option. Notably, cash payment also yielded the highest economic impact. Our study not only presents a practical solution for the sustainable adoption of digital agricultural technology but also provides empirical evidence of its adoption and its influence on farmers' economic and technical performance.

Keywords: Digital agricultural technologies; Rice; Smallholder farmers; Adoption approach; Extension service; Nigeria.

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Abbreviations

ANCOVA	Analysis Of Covariance
ASI	**A**fricarice - **S**AED (The Senegal Extension Authority for The Development of the Senegalese River Valley) - **I**SRA (The Senegalese National Agricultural Research Institute)
ATE	Average Treatment Effect
AVE	Average Variance Extracted
BM	Business Model
BMC	Business Model Canvas
BP	Business Profile
CARI	Competitive African Rice Initiative
CGIAR	Consortium Of International Agricultural Research Centers
CHAID	Chi-Square Automatic Interaction Detection Algorithm
CI	Confidence Interval
DAT	Digital Agricultural Technology
DCE	Discrete Choice Experiment
EE	Economic Efficiency

ES	Effect Size
GIS	Geographic Information System
HIC	High Income Countries
HTMT	Heterotrait-Monotrait
ICC	Intra-Cluster Correlation Coefficient
ICT	Information Communication Technology
ICT4D	Information Communication Technology for Development
IDI	Identically Distributed Independence
IFAD	International Fund for Agricultural Development
IIA	Irrelevant Alternatives
ILO	International Labour Organization
IPM	Integrated Pest Management
IRR	Internal Rate of Return
IT	Information Technology
ITT	Intention To Treat
LGA	Local Government Areas
LMIC	Low- or Middle-Income Country
MNL	Multinomial Logit
MXL	Mixed Logit Model
NGO	Non-Governmental Organization
NPK	Nitrogen, Phosphorus, and Potassium
NPV	Net Present Value
OLS	Ordinary Least Squares
PAD	Precision Agriculture Development
PCC	Partial Correlation Coefficient
PESTEL	Political, Economic, Social, Technological, Legal, And Environment
PLS-SEM	Partial-Least Square Structural Equation Modelling

PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT	Randomize Control Trial
REML	Restricted Maximum Likelihood
RUT	Random Utility Theory
SSA	Sub-Saharan Africa
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
WOS	Web of Science

Introduction

Despite its importance, the rice sector in many African countries lags behind in terms of productivity and efficiency compared to other regions of the world. The challenges facing the rice sector in Africa are multifaceted. They include low yields due to outdated farming practices, inadequate access to high-quality seeds and inputs, inefficient water management, and post-harvest losses. Moreover, climate change exacerbates these challenges by increasing the frequency and intensity of extreme weather events such as droughts, floods, and erratic rainfall patterns, which directly impact rice production.

Digital agricultural technology encompasses a wide range of innovations and tools aimed at improving agricultural productivity, efficiency, and sustainability. These technologies include precision farming techniques, remote sensing, geographic information systems (GIS), drones, mobile applications, and data analytics. In the rice sector, digital technologies offer opportunities to optimize production processes, manage resources more effectively, and mitigate the impacts of climate change. Precision farming, for example, enables farmers to apply inputs such as water, fertilizers, and pesticides with greater accuracy, thereby minimizing waste and environmental pollution. Remote sensing and GIS technologies provide valuable insights into soil health, crop growth, and pest infestations, allowing farmers to make informed decisions and take timely actions. Drones equipped with multispectral cameras can monitor large rice fields and identify areas requiring attention, such as water stress or disease outbreaks. While digital extension technologies are designed to provide personalized and more efficient production and post-production recommendations to farmers to boost agricultural output.

The adoption of digital agricultural technology in the rice sector of developing African countries is gaining momentum, albeit at varying rates across different regions and countries. Several factors influence the adoption process, including access to technology, infrastructure, education, financial resources, and policy support. In some countries, initiatives led by governments, non-governmental organizations (NGOs), and private sector stakeholders have promoted the adoption of digital agricultural technology through capacity building programs, demonstration projects, and subsidized access to digital tools and services. For example, mobile-based applications providing weather forecasts, market prices, and agronomic advice have been deployed to reach smallholder rice farmers in remote areas. However, challenges remain in scaling up the adoption of digital agricultural technology in the rice sector. Limited access to affordable technology and internet connectivity in rural areas, low digital literacy among farmers, and insufficient institutional support and extension services are significant barriers. Moreover, the high upfront costs of digital technologies and concerns about data privacy and security deter some farmers from embracing these innovations.

Despite the challenges, Consultative Group for International Agricultural Research (CGIAR) center AfricaRice developed a digital extension tool called RiceAdvice. RiceAdvice is an open-source Android application which is designed to provide personalized recommendations to rice farmers. The recommendations include a nutrient management plan, appropriate production schedules and calendar. Several studies have been conducted to assess the acceptability of the technology, farmers' willingness to use it as well as the impact of the adoption on rice yield and food security. However, the question of sustainable adoption is still not answered, and that is why our study was initiated to first design a solution for the sustainable adoption of RiceAdvice, and second to test the proposed solution by assessing its impact on farmers' economic efficiency and rice production profitability.

Objectives

Main objectives

Develop an indirect approach for the sustainable adoption of the agricultural extension technology RiceAdvice. The solution is expected first, to bypass the direct adoption barriers such as limited access to digital technology, the low e-literacy of farmers, and limited adequate infrastructure; second, to increase the indirect use of the technology; and third, to have a positive and significant impact on farmers' economic efficiency and rice production profitability.

Specific objectives

- Conduct a systematic and meta-analysis on the adoption of agricultural digital technology.
- Design an indirect adoption approach through a business model framework and evaluate its profitability sensitivity.
- Identify farmers' preferred adoption options among theoretical business profiles implying paid extension services and analyze the determinant factors.
- Analyze farmers' behavior in the adoption of paid extension services.

- Assess the impact of adopting paid extension services on the farmers' economic efficiency and rice production profitability.

1. Adoption of ICT4D and its determinants: A systematic review and meta-analysis

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Abstract

Various Digital Agricultural Technologies (DAT) have been developed and implemented around the world. This study aims to estimate the overall adoption rate and identify the determinant factors for a better adoption perspective after decades of innovation and dissemination. A systematic review was conducted on published studies that reported adoption rates and determinant factors using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. We used meta-regression and the partial correlation coefficient to estimate the effect size and establish the correlation between socioeconomic characteristics and the adoption of various technologies reported. Fifty-two studies with 32400 participants met the selection criteria and were included in the study. The results revealed an overall pooled adoption rate of 39%, with the highest adoption rates in developing countries in Africa and South America. Socioeconomic factors such as age, education, gender, and income were found to be the main determinants and should be considered when designing technology for sustainable adoption. The study also found that young farmers were more susceptible to adoption. Moreover, farmers with higher income levels and educational attainment are more likely to use technology linked to agricultural production, market access, and digital advising, implying that high-income farmers with more education are more tech-savvy. However, this does not exclude low-income and low-educated farmers from adopting the technologies, as many models and strategies with socioeconomic considerations were developed. It is one of the reasons behind the underlying enthusiasm for digital agricultural adoption in low and middle-income countries.

Keywords: Agriculture 4.0, Digital Agricultural Technologies, Meta-analysis, Adoption

1.1. Introduction

The rapid growth of the world population, climate change, and its negative impact on the environment and food security have been significant challenges faced by global agriculture in the last 50 years [1,2]. Information and Communication Technology (ICTs) has provided new opportunities and alternatives for economic development in various sectors, including agriculture, by allowing farmers to reduce constraints and improve their value chain [3,4]. In recent decades, Digital Agricultural Technologies (DAT) have offered diverse opportunities to address challenges and enhance farmer resilience [2,5] including smart devices, intelligent systems supported by interconnected networks, and cloud computing [6]. This provides small, medium, and industrialized farm holders with an intelligent solution to transform conventional agricultural systems [7,8]. These innovations are expected to lead to the fourth agricultural revolution (Agriculture 4.0), which aims to improve agricultural development, offer better ecosystem services, and establish a future for reliable and sustainable agriculture [9,10]. Even though there is still an open discussion in the literature regarding the meaning of digital technologies, this study focuses on the most common definition of DAT, which includes smart devices, big data, and precision agricultural technologies [2,11]. It implies technologies such as global positioning systems, remote sensing, smart devices, robotics, and cloud-based decision support tool software. DAT positively impacts agricultural development by increasing productivity, resource efficiency, and climate change resilience [12]. In addition, it can enhance the whole value chain productivity and help manage unpredicted situations such as the

COVID-19 pandemic [13]. Due to their levels of education, better access to credit, and higher purchasing power, high-income countries (HICs) are hypothetically more likely to use digital technologies. In contrast, many digital agricultural innovations are being developed and introduced in low- and middle-income countries (LMICs). Still, due to weak infrastructure, limited digital literacy, poverty, and other reasons, few farmers have adopted DAT thus far. This is one of the reasons why the literature is more focused on LMICs regarding DAT adaptation [13]. Indeed, adopting DAT in LMICs is a new, promising perspective regarding its economic, social, and environmental impact [13,14]. Alternatively, the adoption of communication tools for agricultural purposes is growing [15] through the use of communication channels such as WhatsApp, Twitter, Zoom, and YouTube to share information [16], as well as Android software developed for this purpose. The growth of DAT is considered a pillar for the Agriculture 4.0 revolution, given the expected impact, especially in developing countries where agriculture is the pith of economic development [17–19]. DAT does not imply necessary or only precision machines but tools such as digital devices, applications, and other digital platforms accessible through smartphones for agricultural purposes [20].

Some initiatives have emerged in Africa, such as the RiceAdvice technology developed for rice farming [21]. In East Africa, where the digital agricultural initiative started in Africa, approximately 60% of farmers use digital technology [22]. The former Technical Center of Agricultural and Rural Cooperation (CTA) estimated that approximately 10% of farmers and pastoralists in sub-Saharan Africa use some digital service [20].

The literature has shown that DAT can positively impact yields, productivity, food security, and rural incomes [21,23,24]. However, despite the numerous promised advantages and interests, there are challenges and risks linked to accessibility, such as the cost of the technologies, limits when considering local ecological knowledge, and the complexity of the technologies [25,26]. These challenges explain the low adoption of precision agricultural technologies registered in the past years [27,28] especially in developing countries. Among these challenges, literature has focused more on accessibility, a preliminary step to adoption. The expected impact of DAT can be achieved if most farmers adopt them.

We found similar studies in the literature, but they show some limitations and do not quantitatively focus on the adoption rate and determinants. Through a literature review performed only on Web of Science, Shang et al. [29] worked on adopting DAT but did not use the Cochrane guidelines or PRISMA protocol. Benyam et al. [25] used Scopus, Web of Science, ScienceDirect, Connected Papers, Google Scholar, and Google to analyze a global trend, adoption opportunities, and barriers of DAT regarding food loss and waste prevention and reduction. Abbasi et al. [30] accessed the digitization of the agricultural industry, and Porciello et al. [31] studied digital agriculture services in low and middle-income countries. Although Benyam et al. [25], Abbasi et al. [30] and Porciello et al. [31] used a systematic review approach, a meta-analysis of the adoption rate and determinants was not done.

Nevertheless, there is a lack of information on the global adoption of DAT and the determinant factors. The study should determine the adoption level globally for each technology type and highlight the socioeconomic determinants that drive adoption. First, the global level of adoption would tell us how the technologies are being adopted and at which level. Second, what are the socioeconomic factors that drive adoption? This information would enable us to determine which type of technology has more potential in the future and which socioeconomic characteristics to consider when designing a tailor-made technology that is more likely to be adopted. To our knowledge, no study has provided extensive information on this matter that would guide future efforts and investments to target better and improve accessibility and adoption of DAT. To fill this literature gap, this study aims to conduct a systematic review, and a meta-analysis of the published research papers related to the adoption of DAT to answer the following research questions:

(i) To what extent do farmers adopt DAT? What is the overall adoption rate of DAT worldwide?

The answer to these questions would provide a global view of DAT's adoption rate and technology type. This information will help technology developers, policymakers, and development partners develop better strategies and policies.

(ii) Does the adoption rate vary by socioeconomic characteristics such as age, education, gender, income, and publication year?

We first search for a correlation between socioeconomic factors and the adoption rate to understand and identify the factors that drive adoption. We also search for a correlation between publication year and the adoption rate to appreciate the trend of research related to adoption over time.

(iii) How do small studies affect the estimated overall adoption rate?

This research question aims to evaluate the effect of a small study on the overall adoption rate to check if it affects the overall result and controls the bias.

(iv) What is the correlation between the effect size (ES) of socioeconomic characteristics and the characteristics of DAT?

A better understanding of these issues may help promote and ensure farmers' sustainable adoption of DAT. This is a first step toward agricultural sustainability and economic growth. This study proposes a critical and comprehensive review using empirical studies. Note that the uniqueness and novelty of the study can be summarized in three lines. To the best of our knowledge, this is the first study to estimate the global adoption rate and effect size of DAT and the determinants of their adoption, using a systematic review, a meta-analysis, and the partial correlation coefficient (PCC) approach. Even though the literature has broadly addressed studies on the adoption of specific digital agricultural technology, to ensure a sustainable adoption of the technology, it is essential to analyze the adopter's behavior based on their socioeconomic characteristics and explore how the individual socioeconomic characteristics affect the adoption of a technology or another. This is an important outcome of designing more suitable technologies and developing an adequate adoption approach. Based on each continent's socioeconomic realities, our study provides the first in-depth analysis of the adoption of DAT and their potential contribution to development. We provided a quantitative overview of the adoption of DAT, categorized the different types of technologies, and identified the key factors that drive their adoption. Above all, our research's theoretical contribution to literature is twofold. This research contributes to understanding the adoption of ICT4D and the scientific knowledge in systematic review applied to adopting new technologies.

In addition, our study collects and analyzes quantitative data on technology adoption and its determinants and conducts a systematic review using the well-known PRISMA protocol. Furthermore, we collect and categorize various DATs worldwide. This distinguishes and differentiates our paper, which provides policymakers, technology developers, and development institutions with more quantitative information.

1.2. Materials and Methods

Article identification strategy

We performed a systematic review following the Cochrane guidelines [32] and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol [33]. The aim was to identify quality research papers on adopting DAT. We were interested in evaluating how farmers adopt digital agricultural technology and digital technology/devices not designed for agriculture but used for agricultural purposes. Based on a recent study examining the relevant and suitable academic search system for systematic review [34]. The Web of Science (WoS) and Scopus search engine databases were used as the sources of information. Only peer-reviewed articles were selected. The search focused on the last 20 years to have the maximum number of published papers fitting the criteria. The keywords used to identify the papers were: Adoption of digital agricultural technology; Adoption of digital farming technology; DAT; Agriculture digital technology adoption; ICT adoption of agriculture; Determinant adoption of ICT agriculture; Determinant adoption of digital technologies agricultural; Determinant adoption of digital farming technologies; and Agriculture 4.0 adoption. Figure 1.1 presents the PRISMA flowchart describing the data collection process following the systematic review protocol. The final sample of 52 studies (focusing on the adoption and determinants of DAT) with 67 adoption rates were recorded when including the studies with more than one technology.

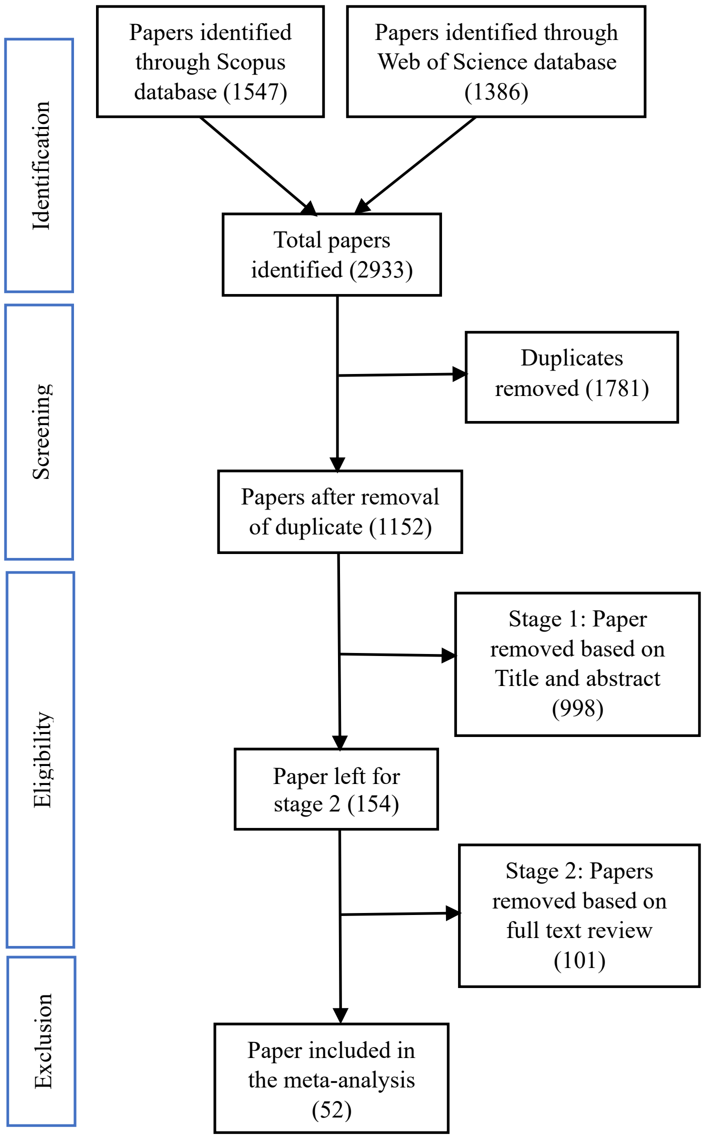

Figure 1. PRISMA diagram of the paper collection.

Article eligibility

The review results highly depend on the quality of the papers used for the meta-analysis. To ensure the quality of the selection, we used the following strategy. First, we reviewed the titles and abstracts of the papers obtained using the keywords in the search engines. If the abstract was not explicit enough, we read through all the content. We defined inclusion and exclusion criteria (Table 1.1) for selecting relevant articles that we used for the meta-analysis.

Table 1.1. Article selection criteria.

Criteria	Inclusion	Exclusion
Language	English	Other languages
Peer-review and publication status	Fully peer-reviewed and published	Not fully peer-reviewed or unpublished
Topic	Related to the adoption of DAT	ICT tool adoption by farmers, Agricultural extension in general, Private agricultural extension in general
Evaluation of determinants of DAT adoption	Yes	-
Methodology	Quantitative data and econometric methods	-
Sample size	Random samples with a minimum size of 30	-
Review type	-	Qualitative review on agricultural extension

Article classification

DAT involves using different digital technologies for various reasons and uses. We first adopted the classification by Abbie [35] (Table 1.2), which provides a classification for the LMIC.

Table 1.2. Classification of Digital Agricultural Technologies by Abbie.

Access to services		Access to markets		Access to assets
Digital advisory	Agri digital financial services	Digital procurement	Agri e-commerce	Smart farming
Agri VAS	Credit and loans	Digital records	Inputs	Smart shared assets
Smart advisory	Input financing	Digital records with payments	Outputs	Equipment monitoring
Weather information	Credit scoring	Digital records with traceability	Inputs and Outputs	Livestock and fishery management
Pest and disease management	Crowdfunding	Digital records with payments and traceability		
Product verification	Insurance			
Record keeping	Digital agri wallet			
	Savings			
	Accountability tool			

Source: Abbie [35]

However, this classification does not necessarily consider high-income countries. It does not fit with all types of technologies registered, for example, when a smartphone or a phone is used for agricultural purposes. Therefore, studies were categorized into three groups considering the nature of the technology and its location. The first group is the technology field, which refers to the field in which/for which the technology is used, with two options: Crop production and livestock. The second group is the type of technology, with two options: Digital technology and Precision agriculture. The third group is the continent.

Selection process and extraction

The selection process was performed based on the criteria, two independent author reviews, and discussions with a third author reviewer in case of discordance between the two independent reviewers. The selection process started with an initial screening of the title and the abstract of the study papers collected from the database engine using the above keywords. Afterward, we removed the unsuitable papers, and in case there was uncertainty, the pair of reviewers went through the main text to see whether the article met the criteria [36]. The full-text papers were uploaded to a reference manager, which helped remove the duplicate articles using the DOI. We also used Microsoft Excel to report each selection phase and organized the selected papers and the data collected. We collected and extracted data from the selected papers for the meta-analysis. We extracted two types of data:

- *General data*: title, authors, study area, and publication year.

- *Specific data*: sample size, number of adopters, type of DAT, adoption rate, and coefficient and standard error of socioeconomic variables: age, gender, education, farming size, and income. Note the variable gender is set to 1 for males and 0 for females.

The data extracted were reviewed to identify missing data or incomplete data. We removed the papers that did not record at least a proper adoption rate', even if the determinant variable did exist.

Overview of adoption studies of agricultural technologies

Developing and adopting new agricultural technologies came as a solution for 475 million farmers worldwide, mostly in low- and middle-income countries [37]. This justifies the high number of adoption studies registered in recent decades and the interest of development partners in financing adoption studies. The subject is more pertinent since it mainly involves agricultural decision-makers, especially the end-users and individual households' beneficiaries of the technologies. Adoption is a determinant of economic growth. The most common indicator is the average adoption rate, estimated as follows:

$$Adoption\, rate\ (\%) = \frac{x_i}{X} * \ 100 \qquad (1)$$

where x_i represents the number of farmers who accepted or used technology *i,* and X is the total number of farmers aware of the technology.

Assuming that farmers are rational and aim to maximize an unobserved utility function, adoption is the realized value of an unobserved latent utility estimated through a linear function [38]:

$$U = y\beta + \varepsilon \tag{2}$$

where β is the vector of estimated parameters, ε is the random error term, and y represents the external factors, financial, agricultural management, environmental, behavioral, and socioeconomic elements. The i[it] farmer adopts if the expected utility of the introduced technology is > 0.

$$x_i = \begin{cases} 1, if\ U_i \geq 0 \\ 0, otherwise \end{cases} \tag{3}$$

where x_i is the observed adoption by farmer i.

Several other adoption models are used in the literature [38]. However, the studies selected are based on quantitative data collected using structured questionnaires to assess farmer adoption or absence of technology. The notion of adoption is generally perceived as using the technology for a defined period or not. Although all selected studies did not define what they meant by adoption, the mathematical estimation was still the same across studies. In this study, we consider adoption and the rate as described and estimated in the selected studies.

Meta-analysis

The main task is to analyze the effect size and estimate its determining factors. We used the random-effects model based on the assumption that all selected studies are unlikely to be similar, and the goal is to put together the true effect sizes using the weight [39]. Therefore, the weighted average effect size computed by the random effect estimates the weighted mean of a distribution of true effect sizes. The weight of the i^{th} effect size is determined as follows:

$$W_i = \frac{1}{(\tau^2 + S_i^2)} \quad (4)$$

where S_i^2 represents the within-study variance of study i, while τ^2 is the between-study variance.

We used Der Simonian–Laird, maximum likelihood (ML), and restricted maximum likelihood (REML) models to estimate the variance τ^2 [40].

In addition to the estimation of the effect size based on the adoption rate, we also estimated the partial correlation coefficient (PCC) (and its standard error (SE)) of the socioeconomic characteristics (age, gender, education, farm size, and income) as a measure of the effect size [41]. The PCC and SE were estimated as follows:

$$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}} \quad (5)$$

where t_i represents the t value estimated from the variable coefficient and its standard error and df_i is the degree of freedom of the estimate.

The standard error (SE) of the PCC is estimated as:

$$SE - PCC_i = \sqrt{\frac{1 - PCC_i^2}{df_i}} \quad (6)$$

Different authors have suggested evaluating the effect size based on the PCC. Cohen [42] suggested small, medium, and large effect sizes with a PCC of 0.1, 0.3, and 0.5, respectively, while Doucouliagos [43] proposed a guideline of 0.07, 0.17, and 0.33 for small, medium, and large effect, respectively. We followed Ogundari and Bolarinwa [44] for a consistent analysis and used both guidelines for this study. We used the absolute value of the PCC to appreciate the effect size of the socioeconomic characteristics identified.

Heterogeneity and meta-regression

Because papers were selected based on a common criterion, variability between the studies chosen is required for the results to be consistent [39,45]. It is expected that studies were different to justify the robustness of the results. It is essential to assess the presence of heterogeneity among the selected studies. This study checked for heterogeneity by using a *Chi²* test and P value. These two parameters provided evidence of heterogeneity, and we also used I^2 to quantify the heterogeneity. I^2 is the percentage of the total variability due to the true heterogeneity and is estimated as follows:

$$I^2 = \left(\frac{S-(n-1)}{S}\right) * 100 \tag{7}$$

where *S* is the weighted sum of squares of overall studies, and *n* is the number of studies. Based on the percentage (I^2), the level of heterogeneity was classified as low (I^2<25%), moderate (25% < I^2< 75%), and high (I^2> 75%) [32]. If the studies revealed low heterogeneity, further analysis was not needed. In the opposite case, we conducted a subgroup analysis to investigate the heterogeneity and minimize the random variations between the point estimate and primary studies. We used the subgroup as described in Section 2.3.

To evaluate the correlation between the overall adoption rate, socioeconomic factors, and publication year, we relied on two methods – fixed effects and random effects, as Stanley and Doucouliagos [43] suggested. The fixed-effects model assumes that all studies have a constant effect size and does not consider that studies differ in terms of sample, model, and specification. In contrast, the random-effects model assumes the effect size distribution across the studies and aims to estimate the mean effect size [46,47]. The true correlation varies across studies and study characteristics [47].

We considered the socioeconomic characteristics of the participants for the studies that make them available. Therefore, we included the Age of the participants, Education, Gender, Income, and Farm size. We included these variables only if they were recorded in the study. In addition, we investigated the correlation between the adoption rate and continents and the trend of the adoption rate to see the interest in publication in relation to the adoption rate of DAT over time. Using the study year would have been interesting, but this information was unavailable for most studies. The significance of the regression coefficient explained how the adoption rate changed with a unit increase in the independent variable. We also regressed the PCC of Age, Gender, Education, Farm size, and Income on the study's characteristics to identify the correlation.

Publication bias

Publication bias is a substantial part of systematic reviews and meta-analyses since it can affect the validity of the study and its generalization [48,49]. That is why it is crucial first to identify the presence of publication bias and then quantify it. The literature used two approaches: the selection model using the weight function to adjust the effect size and the funnel plot approach, which offers a graphical overview, and regression to quantify the bias [48]. In this study, we used the funnel plot approach as it provides a graphical estimation of the bias, offers a formal test of the funnel plot asymmetry with Egger's regression, and fills trim analysis, providing an unbiased effect size estimate. This was the most commonly used approach in several meta-analyses [47,50].

1.3. Results

1.3.1. Characteristics of the included studies and geographic distribution

Table 1.3 presents the studies that fit the inclusion criteria and their characteristics. The results showed two types of technologies: DAT and precision agriculture. Approximately 75% of the studies focused on DAT, and 25% focused on precision agriculture. The data also revealed that the technologies were developed for several reasons, including two fields (91% crop production and 9% livestock).

Table 1.3. Includes studies and characteristics.

N`	Authors (Publication year)	Type of Technology	The domain of the Technology	Field	Categories of Access[3]	Use of technology[3]	Subuse Technology[3]	Country
1	Abdullahi et al. (2021)	Precision Tech	Production	Crop production	Access to services	Digital advisory	Smart advisory	Somalia
2	Adrian et al. (2005)	Digital Farming	Extension	Crop production	Access to assets	Smart farming	Equipment monitoring	USA
3	Alam et al. (2018)	Digital Farming	Soil georeferenced sampling	Crop production	Access to services	Digital advisory	Weather information	Bangladesh
4	Ali (2012)	Digital Farming	Information	Crop production	Access to services	Digital advisory	Smart advisory	India
5	Barnes et al. (2019)	Digital Farming	Market information service	Livestock	Access to assets	Smart farming	Equipment monitoring	EU[1]
6	Bolfe et al. (2020)	Digital Farming	Production	Crop production	Access to services	Digital advisory	Smart advisory	Brazil
7	Boyer et al. (2016)	Digital Farming	Web-based	Crop production	Access to assets	Smart farming	Smart shared assets	USA
8	Carillo and Abeni (2020)	Precision Tech	Machine guidance	Crop production	Access to assets	Smart farming	Equipment monitoring	Italy
9	Çetin et al. (2016)	Digital Farming	Crop protection	Crop production	Access to markets	Agri-e-commerce	Inputs and outputs	Turkey

N`	Authors (Publication year)	Type of Technology	The domain of the Technology	Field	Categories of Access[3]	Use of technology[3]	Subuse Technology[3]	Country
10	Chikuni and Kilima (2019)	Digital Farming	Production	Crop production	Access to markets	Agri-e-commerce	Inputs and outputs	Malawi
11	D'Antoni et al. (2012)	Digital Farming	-	Livestock	Access to assets	Smart farming	Equipment monitoring	USA
12	Daum et al. (2021)	Digital Farming	Input information	Crop production	Access to assets	Smart farming	Smart shared assets	Nigeria
13	Dissanayeke and Wanigasundera (2014)	Digital Farming	Extension	Crop production	Access to services	Digital advisory	Smart advisory	Sri Lankan
14	Drewry et al. (2019)	Digital Farming	Production	Crop production	Access to services	Agri digital financial services	Accountability tool	USA
15	Groher et al. (2020)	Digital Farming	Management	Crop production	Access to assets	Smart farming	Livestock and fishery management	Swiss
16	Hartmann et al. (2020)	Precision Tech	Precision fertilizer, precision tillage, weed management, precision	Crop production	-	-	-	Kenya

N`	Authors (Publication year)	Type of Technology	The domain of the Technology	Field	Categories of Access[3]	Use of technology[3]	Subuse Technology[3]	Country
			sowing, and sensors					
17	Hay and Pearce (2014)	Digital Farming	Extension	Crop production	Access to assets	Smart farming	Smart shared assets	Australia
18	Hoang (2020)	Digital Farming	Production	Crop production	Access to markets	Agri-e-commerce	Output	Vietnam
19	Kante et al. (2017)	Digital Farming	Extension	Crop production	Access to markets	Agri-e-commerce	Inputs	Mali
20	Kante et al. (2019)	Digital Farming	Information	Crop production	Access to markets	Agri-e-commerce	Inputs and outputs	Mali
21	Karanja et al. (2020)	Precision Tech	Production	Livestock	Access to services	Digital advisory	Smart advisory	Tanzania
22	Kernecker et al. (2020)	Digital Farming	Production	Crop production	Access to assets	Smart farming	Smart shared assets	EU
23	Khan et al. (2019)	Digital Farming	Production	Crop production	Access to services	Digital advisory	Smart advisory	Pakistan
24	Krell et al. (2021)	Precision Tech	Software application	Crop production	Access to markets	Agri-e-commerce	Inputs and outputs	Kenya
25	Larson et al. (2008)	Precision Tech	Mapping, sampling	Crop production	Access to assets	Smart farming	Equipment monitoring	USA
26	Lencsés et al. (2014)	Precision Tech	Variable rate nitrogen technology	Crop production	Access to assets	Smart farming	Equipment monitoring	Hungarian

N`	Authors (Publication year)	Type of Technology	The domain of the Technology	Field	Categories of Access[3]	Use of technology[3]	Subuse Technology[3]	Country
27	Leng et al. (2020)	Precision Tech	Production	Crop production	Access to services	Digital advisory	Smart advisory	China
28	López-Becerra et al. (2016)	Digital Farming	Production	Crop production	Access to services	Agri digital financial services	-	Spain
29	McCampbell et al. (2021)	Digital Farming	Production	Crop production	Access to services	Digital advisory	Smart advisory	Rwanda
30	Michels et al. (2020)	Digital Farming	Extension	Livestock	Access to services	Digital advisory	Smart advisory	Germany
31	Michels et al. (2020a)	Digital Farming	Input information	Crop production	Access to services	Digital advisory	Pest and disease management	Germany
32	Michels et al. (2020b)	Digital Farming	Production	Crop production	Access to markets	-	-	Germany
33	Mitchell et al. (2018)	Digital Farming	Info crop, financial	Crop production	Access to assets	Smart farming/Precision	Smart shared assets	Canada
34	Mwalupaso et al. (2019)	Digital Farming	Extension	Crop production	Access to services	Digital advisory	Smart advisory	Zambia
35.	Okello et al. (2020)	Digital Farming	Extension	Crop production	Access to markets	Agri-e-commerce	Inputs and outputs	Tanzania
36	Ortiz-Crespo et al. (2020)	Digital Farming	Production	Crop production	Access to services	Digital advisory	Smart advisory	Tanzania

N`	Authors (Publication year)	Type of Technology	The domain of the Technology	Field	Categories of Access[3]	Use of technology[3]	Subuse Technology[3]	Country
37	Owusu et al. (2017)	Digital Farming	Communication, extension	Crop production	Access to services	Digital advisory	Smart advisory	Ghana
38	Paustian and Theuvsen (2017)	Precision Tech	Autosteer GPS guidance system	Crop production	Access to assets	Smart farming	Equipment monitoring	Germany
39	Pede et al. (2018)	Digital Farming	Management	Crop production	Access to markets	Agri-e-commerce	Inputs	India
40	Pivoto et al. (2019)	Precision Tech	Remote sensing	Crop production	Access to assets	Smart farming	Smart shared assets	Brazil
41	Raheem (2020)	Digital Farming	Digital finance	Crop production	Access to services	Digital advisory	Smart advisory	Australia
42	Rajkhowa Id and Qaim Id (2021)	Digital Farming	Decision support	Crop production	Access to services	Digital advisory	Smart advisory	India
43	Schulz et al. (2021)	Digital Farming	Extension	Crop production	Access to services	Digital advisory	Smart advisory	Australia
44	Sheng and Lu (2020)	Digital Farming	Agribusiness	Crop production	Access to markets	Agri-e-commerce	Inputs and outputs	China
45	Tamirat et al. (2017)	Digital Farming	Marketing	Crop production	Access to assets	Smart farming	Smart shared assets	EU[2]
46	Thar et al. (2021)	Digital Farming	Market information service	Crop production	Access to services	Digital advisory	Smart advisory	Myanmar

N`	Authors (Publication year)	Type of Technology	The domain of the Technology	Field	Categories of Access[3]	Use of technology[3]	Subuse Technology[3]	Country
47	Vecchio et al. (2020)	Precision Tech	Precision soil sample tool	Crop production	Access to services	Digital advisory	Product verification	Italia
48	Voss et al. (2021)	Digital Farming	Production	Crop production	Access to services	Digital advisory	Smart advisory	Senegal
59	Walton et al. (2008)	Digital Farming	Market information service	Crop production	Access to markets	Agri-e-commerce	Inputs and outputs	USA
50	Yoon et al. (2020)	Digital Farming	Smart farm	Crop production	Access to services	Digital advisory	Smart advisory	Korea
51	Yu et al. (2020)	Digital Farming	Extension	Crop production	Access to markets	Agri-e-commerce	Inputs and outputs	China
52	Zheng and Ma (2021)	Digital Farming	Agri info Extension	Crop production	Access to markets	Agri-e-commerce	Inputs and outputs	China

[1] Belgium, Germany, Greece, the Netherlands

[2] Denmark/Germany

[3] Classification by Abbie [35]

Figure 1.2 shows that the study covered six continents, including Africa (14 studies), Europe (14 studies), and Asia (13 studies). However, Asia had the highest number of events/participants (15,166), representing 89% of the total. Figure 1.3 presents an overview of the distribution of the selected studies and the number of regression models on the map. It showed how DAT spread around the world. Technological diversity and worldwide spread explain DAT' importance and usefulness.

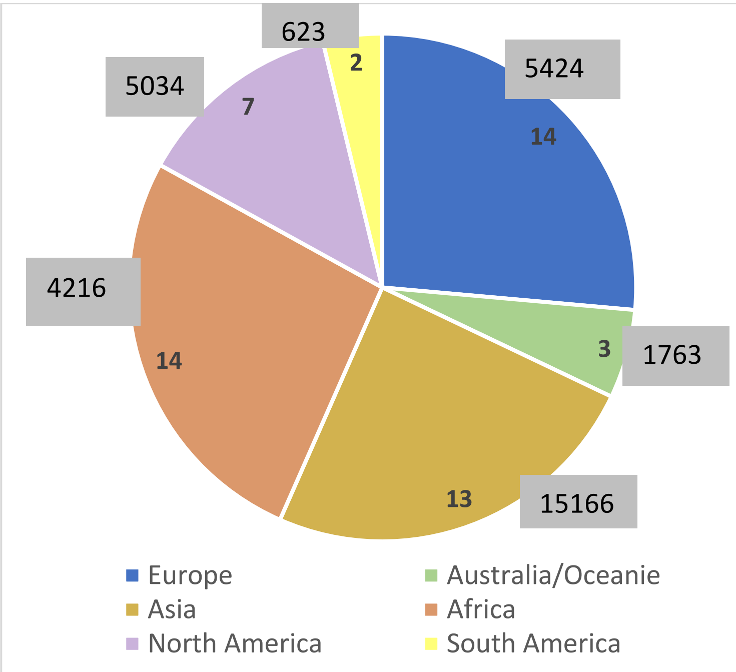

Figure 1.2. Distribution of the studies by continent.

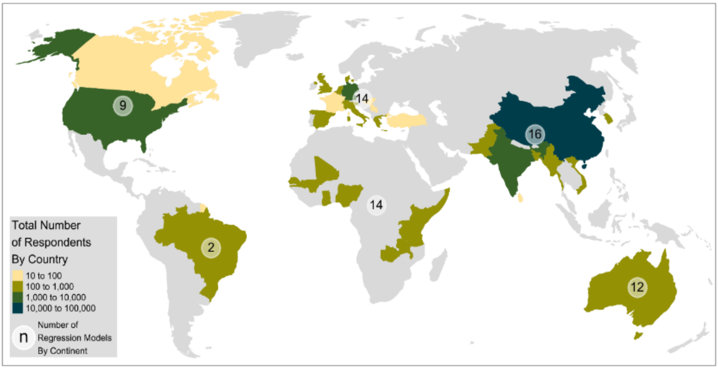

Figure 1.3. Geographic distribution of the number of regression models.

1.3.2. Meta-analysis results

Overall pooled adoption rate and subgroup analysis

Figure 1.4 summarizes the pooled adoption rate of 52 overall studies with 32400 participants worldwide. The results revealed that the pooled digital farming technology adoption rate was 38.95% (CI: 32.74, 45.35). High heterogeneity across the studies was observed (I^2=99.47%, P value ≤ 0.001). This confirms the variability among socioeconomic characteristics, countries, and technologies. We investigated the heterogeneity by conducting a subgroup analysis. The results showed that when comparing the continents, South America had the highest adoption rate, 82.45% (CI: 79.34, 85.36), with 623 participants, followed by Africa, 53.73% (CI: 38.12, 68.98) with 4216 participants. The adoption rate of the technologies developed for the extension was the highest at 46.79% (CI: 34.87, 58.89). Although there was a similar adoption rate for technologies developed related to crop production (ES: 39.11, CI: 32.44, 45.99) and livestock (ES: 37.43, CI: 20.59, 56.00), there was a high number of published papers in agriculture compared to livestock. Regarding the type of technology, digital farming technology had the highest adoption rate: 48.42% (CI: 41.71, 55.18).

Moreover, the results of the subgroup analysis based on the classification by Abbie [35] showed that in the categories of access, service access technologies had the largest adoption rate: 52.20% (CI: 42.76, 61.56), followed by access to market technologies with an adoption rate of 40.55% (CI: 28.72, 52.95). Regarding the category of the use of the technologies, the results revealed that digital advisory technologies had the highest adoption rate: 51.55% (CI: 41.33, 61.70), followed by agri-e-commerce technologies with an adoption rate of 40.90% (CI: 27.66, 54.85).

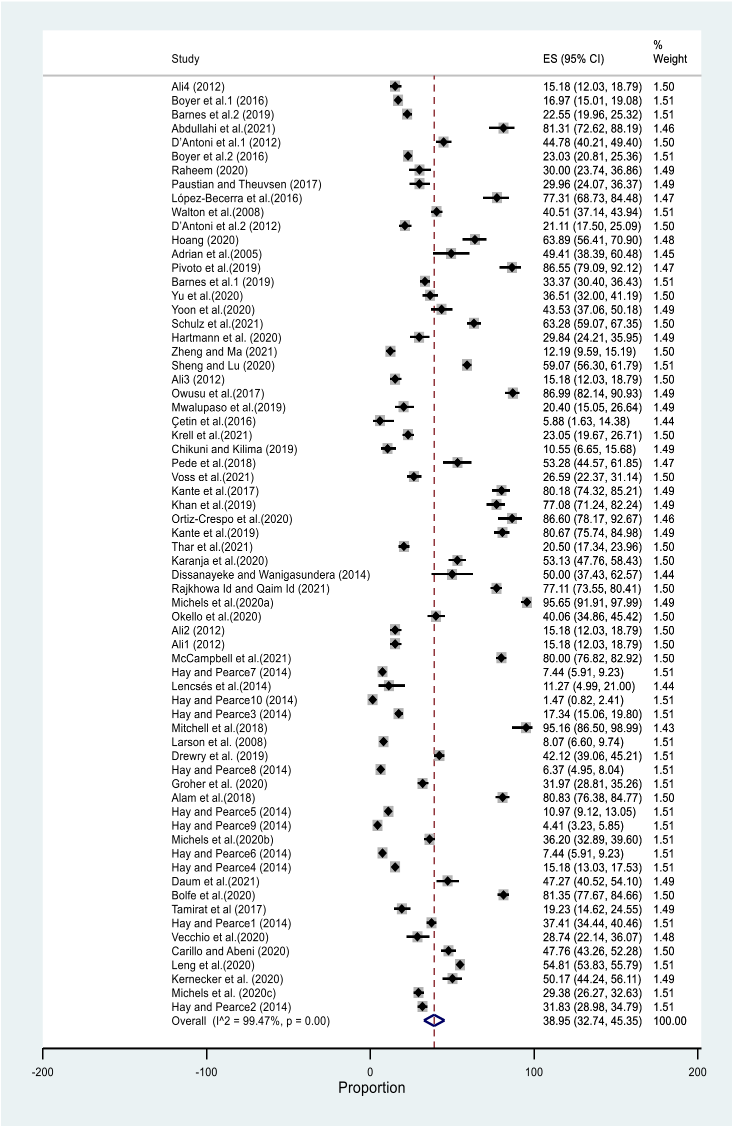

Figure 1.4. Overall pooled effect size (ES) summary.

Meta-regression

The multivariate meta-regression by continent revealed that all six continents were significant. This result shows an overall tendency to adopt digital farming technologies worldwide. The highest mean adoption rate was in South America, at 83.8%. However, it had the smallest number of participants (623) from only two studies, and the adoption rate record could be due to the impact of small sample studies. This justifies why we investigate the effect of the small sample studies on the adoption rate. Africa was the second continent, with a mean adoption rate of 53% (Table 1.4).

Table 1.4. Meta-regression of the continents.

	Coefficient	Standard Error
Africa	0.530***	0.064
Asia	0.428***	0.059
Australia	0.193***	0.067
Europe	0.373***	0.064
North America	0.362***	0.079
South America	0.838***	0.171
I^2 (%) = 96.85		
Prob > chi2 = 0.000		
R-squared (%) = 21		
N=67		
Test of residual homogeneity: Q_res = chi2(62) = 1353.63 Prob > Q_res = 0.000		

***1% significant; **5% significant; and *10% significant

Table 1.5 shows the regression analytical results, showing that the variables of Age, Gender, Income, and Publication year were significant. The variable Age had a coefficient of -0.054 and was significant at 1%. This implies that studies that found more positive age effects tended to have lower overall adoption rates. This result could be explained by the interest of young farmers and their accessibility to new technologies. Even if we assume that older farmers have more experience, digital technologies require a minimum knowledge of ICT tools, and young farmers have more chances to acquire those skills. Even though not significant, the variable Farm size was positive, implying that the studies with positive farm size tended to have greater overall adoption rates. This is an expected sign since we can assume that the larger the farm, the more important it is to improve the management of the resources to reduce losses along the production chain and maximize profit. In general, male farmers tend to adopt DAT more than female farmers, according to the significant and positive variable Gender in the adoption of digital technologies. As expected, the variable Income was positive and significant, implying that the purchasing power of farmers plays a determinant role in the adoption of digital farming technologies. Publication year was also positive and significant. Figures 1.5, 1.6, 1.7, and 1.8 illustrate the shape of the adoption rate for these four variables.

Table 1.5. Random effect meta-regression analysis.

	Coefficient (Standard Error)	Constant	Prob > chi2
Age (N=25)	-0.054***(0.016)	0.400	0.000
Farm size (N=16)	0.028(0.063)	0.313	0.657
Education level (N=19)	-0.543(0.389)	0.453	0.163
Gender (N=12)	0.081**(0.039)	0.484	0.039
Income (N=6)	0.253**(0.112)	0.220	0.023
Publication year (N=67)	0.018**(0.008)	-37.607	0.024

***1% significant; **5% significant; and *10% significant

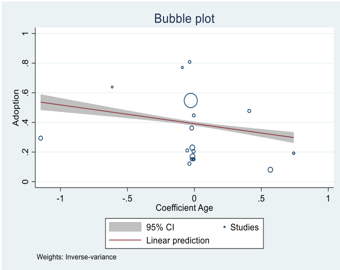

Figure 1.5. Shape of correlation Age coefficient-Adoption.

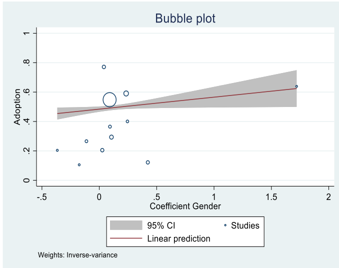

Figure 1.7. Shape of correlation Gender coefficient-Adoption.

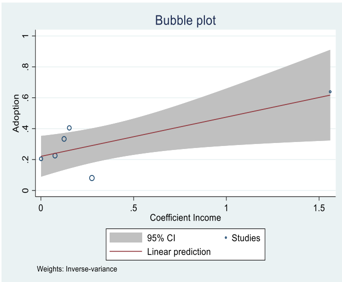

Figure 1.6. Shape of correlation Income coefficient-Adoption.

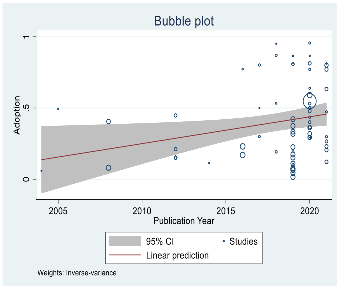

Figure 1.8. Shape of correlation Publication year -Adoption.

Effect of small sample studies on the overall adoption rate

The graphical assessment of the funnel plot suggested a likely presence of publication bias due to the small sample studies (Figure 1.9). The red horizontal line indicates the weighted average effect size across studies. The asymmetry funnel plot confirms the presence of publication bias, which could also be due to the high heterogeneity among studies and small sample studies. To investigate this hypothesis, the funnel plot by group (Continents, Type of technology, Field, and Technology use) showed an asymmetric funnel plot for the different groups. This confirmed that the funnel plot asymmetry is likely not due to the heterogeneity between studies but to the publication bias of small sample studies. The Egger's test confirmed this result and revealed a statistically significant publication bias (p<0.001). The trim and fill analysis (Figure 1.10) showed 26 studies (pulled on the left side of the graph; this does not mean that the adoption of those missing studies was negative), potentially missing studies from the meta-analysis due to publication bias. Using the observed and imputed studies, the computed overall adoption rate was 21.9% (CI: 14.1, 29.5) if the missing studies were included.

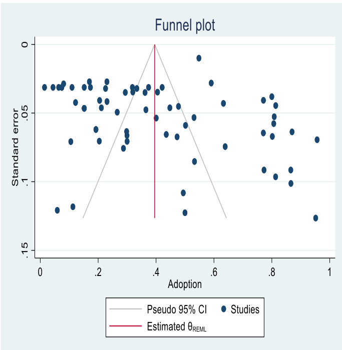

Figure 1.9. Overall funnel plot.

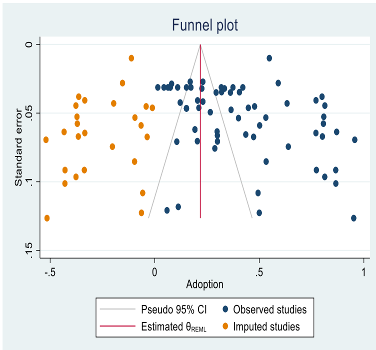

Figure 1.10. Trim and fill funnel plot.

PCC of socioeconomic factors and correlation with technology characteristics

The results of the meta-analysis show that when the studies are taken individually for the variable Age, only one study out of twenty-two had a large effect size (PCC greater than 0.5) according to the Cohen guideline, and the remaining are 0.00 <PCC<0.3. However, considering the Doucouliagos guideline, seven studies out of 22 had a PCC lower than 0.07, and only one had a PCC greater than 0.33. For the variable Gender, two out of 11 studies had a PCC greater than 0.1; therefore, Cohen considered it a small effect size. We counted four studies with PCCs greater than 0.07, considered a small effect size, and two studies with PCCs greater than 0.17, according to Doucouliagos. Regarding the variable Education, we counted six studies with a small effect size and only one study with a medium effect following Cohen. When considering the Doucouliagos guideline, eight studies had a small effect size, and two had a medium effect size. For the farm size variable, four out of twelve studies had a small effect size, one study had a medium effect, and one had a large effect when using the Cohen guideline. These results show only one study with a small effect size, according to Cohen, and a medium effect, according to Doucouliagos.

The estimation of the average PCC (Table 1.6) shows that Age and Income had the largest PCC with 0.103, while farm size had the lowest with 0.001. The distribution of PCC results in Figure 1.11 shows a large amount of variability in the PCC of farm size. When stratifying the PCCs, Table 1.5 shows that according to Cohen's guideline, Age and Income had a small effect size. At the same time, this variable was classified as a medium effect when referring to the Doucouliagos guideline.

The high values of the I^2 statistic identified in all variable meta-analyses showed variability in the results due to study differences. We explored heterogeneity using meta-regression with the study characteristics. Table 1.7 shows no significant correlation between the PCC of the socioeconomic variables and the publication year.

The meta-regression found a negative and significant correlation between the effect size of Age and the technologies related to production, digital farming, crop production, access to service, and digital advisory. This correlation indicates that younger farmers are more likely to adopt the technologies.

We also found that the effect size of gender was positively correlated with adopting DAT related to management, digital farming, crop production, access to the market, and e-commerce. These results indicate that the role of male farmers is an important factor that needs to be considered in the dissemination and adoption process.

A positive correlation was found between the PCC of Education and the technologies related to extension, production, digital farming, crop production, market access, services, e-commerce, and digital advisory. This implies that farmers with higher education levels are more susceptible to adopting digital farming technologies, especially technologies related to extension, production, digital farming, and crop production e-tools, which facilitate access to the market and services and provide digital personalization advisories.

As expected, the results also showed a positive correlation between the effect size of Income and the adoption of digital farming technologies related to production, precision technology, crop production, access to the market, and e-commerce. In any case, the use of digital technology would be free of charge, even if the farmer is a direct user; they will need to have adequate infrastructure and require a minimum investment. However, higher-income farmers are simply more likely to be tech-savvy and, thus, more likely to adopt DAT.

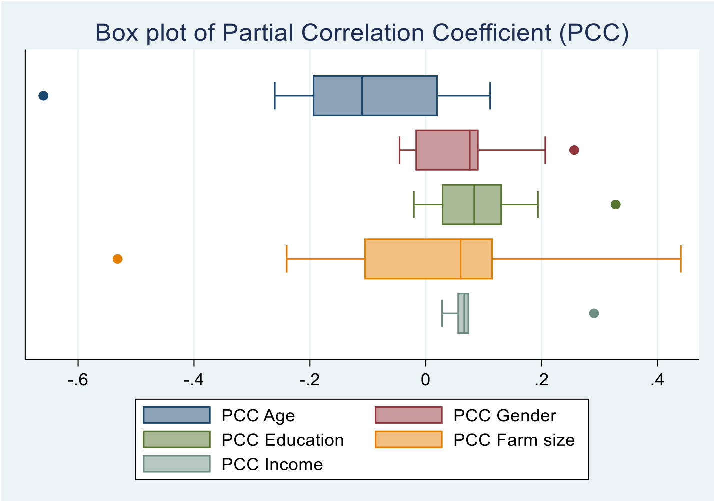

Figure 1.11. Box plot PCCs of socioeconomic variables.

Table 1.6. PCC stratification by Cohen and Doucouliagos.

PCC	Observation	Mean	Standard Deviation	Cohen	Doucouliagos
Age	22	-0.103	0.168	Small	Small
Gender	11	0.072	0.093	-	Small
Education	17	0.094	0.087	-	Small
Farm Size	12	0.001	0.239	-	-
Income	5	0.103	0.106	Small	Small

Table 1.7. Meta-regression of PCCs and study characteristics.

	Age (22*)	Gender (11*)	Education (17*)	Farm size (12*)	Income (5*)
	Coefficient (Standard Error)				
Publication Year	-0.003(0.008)	0.032 (0.043)	0.003(0.005)	-0.010(0.018)	0.009(0.008)
Constant	7.234(16.696)	-64.573 (86.623)	-4.976(0.005)	20.151(36.400)	-19.906(16.139)
Prob > chi2	0.6603	0.4555	0.595	0.5799	0.2151
R-squared (%)	0.00	0.00	0.00	0.00	11.80
Technology Domain					
Extension	-0.085(0.055)	0.057(0.036)	0.073**(0.030)	0.167(0.138)	-
Management	-0.098(0.078)	0.144**(0.068)	0.066(0.042)	-0.017(0.138)	0.121**(0.0563)
Production	-0.130**(0.066)	0.053(0.068)	0.150***(0.038)	-0.073(0.097)	0.028(0.112)
Prob > chi2	0.0499	0.0550	0.000	0.5597	0.0952
R-squared (%)	0.00	0.00	7.03	0.56	0.00
Type of technology					
Digital Farming	-0.142***(0.039)	0.071**(0.027)	0.108***(0.024)	0.025(0.094)	0.290***(0.021)
Precision Technology	0.003(0.064)	-	0.050(0.043)	-0.032(0.111)	0.055***(0.010)
Prob > chi2	0.0014	0.0102	0.000	0.9261	0.000
R-squared (%)	11.64	-	2.16	0.00	96.33
Field					
Crop production	-0.116***(0.037)	0.073**(0.031)	0.101***(0.021)	0.001(0.069)	0.102**(0.047)

Livestock	0.033(0.118)	0.058(0.098)	-0.021(0.085)	-	-
Prob > chi2	0.0072	0.050	0.000	0.9911	0.030
R-squared (%)	2.19	0.00	5.61	-	-
Categories of Access					
Access to assets	0.001(0.070)	-	0.036(0.049)	-0.032(0.117)	0.056(0.057)
Access to markets	-0.063(0.059)	0.111***(0.035)	0.079**(0.035)	0.044(0.151)	0.171**(0.069)
Access to services	-0.182***(0.050)	0.025 (0.038)	0.127***(0.030)	0.010(0.131)	-
Prob > chi2	0.0021	0.005	0.000	0.9827	0.0282
R-squared (%)	13.22	14.68	4.51	0.00	14.37
Use of the technology					
Agri-e-commerce	-0.052(0.065)	0.111***(0.035)	0.078**(0.040)	0.031(0.196)	0.173**(0.07)
Digital advisory	-0.182***(0.050)	0.025 (0.038)	0.127***(0.031)	0.010(0.139)	-
Smart farming	0.001(0.072)	-	0.036(0.051)	-0.032(0.124)	0.056(0.057)
Prob > chi2	0.0065	0.005	0.000	0.9969	0.028
R-squared (%)	9.37	14.68	0.00	0.00	14.37

***1% significant; **5% significant; and *10% significant; [*]We have fewer observations here because not all studies provided the standard error. We then estimated the PCCs for the studies with coefficients and standard errors.

1.4. Discussion

Numerous research and development initiatives have focused on emerging digital technologies and their critical role in agricultural development and economic progress [51–53]. However, several questions still need to be answered to achieve the expected impact. This study followed the PRISMA protocol and proposed a systematic review to obtain an overall view of adopting DAT. The review showed an average adoption rate of 38.95%. However, heterogeneity was found across the studies. The variabilities could be explained by the difference in the socioeconomic characteristics, economic status of the country or continent, the need in terms of technology, or the technology itself. Overall, 38.95% is an accepted adoption rate for the following reasons. First, even though digital technologies are designed for everyone, especially open-source technologies, not all users, particularly farmers in rural areas, can access them. This could negatively affect the overall adoption rate of these technologies. Second, some technologies are well designed but hard to use or useless for farmers, hence leading to low adoption and/or quick dis-adoption. Subgroup analysis showed that South America and Africa, which included most low-income countries, have the highest adoption rates. However, given the few studies recorded in South America (2 studies), we assume that this is not enough to generalize. Sabi et al. [54] used the Technology Acceptance Model (TAM) and found that socioeconomic background is the main factor driving technology adoption in Africa. Other studies estimated the adoption of DAT in African countries [3,55–57]. The interest could be explained by the ability of farmers in developing countries to overtake traditional practices in favor of new technology adoption [12] or by the several agricultural projects and new policies being implemented in these continents for conversion toward modern agriculture. This result confirms the study conducted by Nowak [58] in developed countries, which shows a higher adoption rate of 60 to 80%. However, the use of digital agricultural technology was still relatively low in developing countries compared to high-income countries [59]. This is confirmed by Trendov et al. [12].

Regarding the type of DAT, the review showed that extension technology is the most important. This result should attract the attention of policymakers and investors in the private sector who are interested in digital advisory. For example, in partnership with Precision Agriculture Development (PAD), in 2021, the International Fund for Agricultural Development (IFAD) launched a project to provide personalized agricultural advice to 1.7 million small-scale farmers through mobile phones in Kenya, Nigeria, and Pakistan [60]. Several digital advisory services and applications were developed to provide farmers with quality and more efficient information [61,62]. The digital extension service covered both crop production and livestock. However, there is more interest in crop production, demonstrated by the low number of published papers on livestock. Our findings aligned with Shang et al. [29], who removed livestock papers from the systematic review due to the limited number of articles available.

The acceptance and adoption of DAT could be seen as an opportunity for the younger generation to invest in agriculture. Our findings go in this direction and could be explained by several factors favorable to young people, such as accessibility to new technologies, the use of new technologies, and accessibility to information. Even with a low e-literacy, young farmers were more open to innovation and were more likely to be familiar with digital technology [63]. This finding is in line with that of Czaja et al. [64] and Penard et al. [65], who also found that adults were less likely to adopt new technologies than young adults who are susceptible to being educated and, therefore, more open to ICT use and adoption. However, older people would experience a better quality of life, income, and wellbeing if they used the new technologies [66], including DAT with the appropriate business model [21,67,68]. This is open for discussion since e-literacy, access to information, and knowledge of ICT tools differ from one continent and country to another. According to a 2016 United Nations Education, Scientific, and Cultural Organization report, e-literacy is important for the knowledge economy and information society [69]. The European Commission argued that e-literacy had become an essential life competence, and its inability could become a barrier to social integration and personal development [70]. High-income countries have better access to ICT and better e-literacy. Therefore, this is not a barrier to adopting DAT. Our review also revealed that the size of the farm is a determinant factor and has a positive effect on the decision to adopt digital agricultural technology. This means wealthy farmers have better access to digital tools and better e-literacy. Another issue to consider is that some technologies, especially the precision agricultural technologies in the Global North, require an initial investment or payment of a recurrent from farmers. As a farm grows, it becomes more crucial to utilize its resources effectively to minimize losses and expenses and increase profit. Digital technologies and precision tools could be the appropriate solution to achieve this. This means that larger farms will find it easier to adapt, but small-scale farmers may lag. Blasch et al. [71] also found that farm size and economies of scale are crucial for adoption since larger farms value DAT more than small farms. The authors found that small farms value less fertilizer saving, water quality improvement, and personalized advice than farmers of large farms. This explains why precision tools are more adopted in high-income countries since they have an intensive agricultural production system and value DAT. This result aligns with Shang et al. [29], who found that farm size and education positively affect farmers' decisions to adopt DAT. When assessed from an opposite view, if we consider that small farms are under more pressure as they have fewer or limited resources and manage to use them more efficiently. Smaller farms are exposed to more risk aversion, as any slight change in farming practice may imperil their food security; therefore, they are less likely to be early adopters.

With the impact of adopting different DAT and considering the barriers, the adoption rate has increased over the years. This may result from implementing many projects, service-based business development, infrastructure development (more farmers live in areas with network coverage, more farmers have access to electricity, or more farmers own phones), and farmers' willingness to adopt. However, the adoption rate is still low, notwithstanding the efforts, which is why further strategies, policies, and business models are needed [68] (lack of ICT skills, financial support, lack of infrastructure, etc.) to overcome the barriers to adoption [72]. The meta-regression also showed that although all six continents were significant, there was a difference in the adoption rate tendency. South America has the highest mean adoption rate, implying a positive adoption tendency of DAT. Note that we registered only two papers in South America, which may be too small to generalize. However, this result provided an overview of farmers' ability to adopt DAT. The finding also reveals that low- and middle-income continents (Africa, Asia, and South America) have an adoption rate higher than high-income continents (Australia, North America, and Europe) and are currently the most open to adopting the technologies. This could be explained by the fact that the adoption of DAT is not a great challenge for high-income continents as it is in low and middle continents, as seen through the number of papers registered in these continents, which is relatively lower compared to low and middle continents. Furthermore, this could be explained by the number of ongoing projects and technology developments supporting DAT and their dissemination in Africa. Both research and development partners are working through technology development, start-up funding, technical support, and policymakers for technology dissemination. It is worth noting that the high-income continents are where we registered the lowest adoption rate tendency compared to the low and middle-income continents. This information is relevant, especially for private investors searching for agribusiness opportunities or technology developers searching for an appropriate environment to introduce new technology. In addition, the overall 39% adoption rate is a ballpark figure that can help investors in private digital farming initiatives estimate the return on investment. It is also crucial for policymakers to develop policies and strategies to support the development and introduction of new technologies favoring farmers.

The results of the socioeconomic variable PCCs meta-analysis allow us to appreciate how large or small the effect size is. Gender plays a determinant role in the adoption process. Even though the study shows that male farmers have more access and are more likely to adopt DAT, the role of females is still essential, and they should also be involved in the adoption process. Female involvement is suggested to be from technology development to dissemination using their voices and channels to reduce the gender gap in adopting DAT [56] or by applying systematic gender-inclusive participatory design methodologies [73]. These findings align with those of Kinkingninhoun Medagbe et al. [74], who also established gender inequality where men have more access to technology and are more likely to adopt technology information and knowledge in West Africa. The effect sizes of the level of education and income were also positively correlated with adopting DAT. Education is seen as an essential factor in facilitating e-literacy and the adoption of DAT. Suggesting that many DAT and services are not yet fully inclusive to farmers with low levels of education. More could be done to support adoption by these farmers, for example, by avoiding the need for literacy or including a literacy program in the dissemination plan. In some cases, extension services appear to substitute for formal education in promoting adoption [38], indicating that farmers with less education need more support and training to learn the importance of using DAT. On the other hand, farmers willingness to use technology and their level of education or e-literacy and purchasing power are critical factors to adaptation since the direct use of DAT requires a minimum infrastructure (devices, network, electricity, etc.), which needs to be acquired by the end user.

1.5. Conclusion and implications

Global development, particularly agriculture, requires modern solutions to meet economic development expectations' challenges and ensure long-term development. This research contributes by shedding light on the key development tools that have increased in the last decade. It provides a global perspective on adopting DAT, including evidence of each continent's global adoption rate and determinants. It also includes information on adopters' behavior and the factors influencing the adoption of various DAT. We believe that developing and disseminating DAT must be accompanied by a business model that considers end-users socioeconomic characteristics and potential.

The question of adoption, which comes after technology development and dissemination, is one that research, development, and decision-makers are paying close attention to. There is a need to answer the question: How is the global uptake of digital agriculture technology going? What variations in adoption are there when socioeconomic characteristics are considered? What factors can technology developers base their designs on to make them more suitable in the future? and What effects do socioeconomic factors have on the uptake of various technologies? By gathering quantitative information on the rate of adoption and determinant factors of technologies adopted by farmers, the study attempted to answer these questions.

DAT could play a significant role in agricultural and sustainable development and contribute to farmers' wealth. However, adoption is still controversial, especially in developing countries with low purchasing power and low e-literacy. Nevertheless, this does not make it impossible to find an appropriate solution that fits each country's socioeconomic reality. This study proposed a worldwide overview of the adoption of agricultural digital technologies and the determinants for the first time. Based on the studies identified, the data collected, and the analysis, the study derived the following main points:

- The study found a clear interest in adopting DAT and its pertinence defined by farmers' willingness to use the technologies through the papers reviewed. We found 39% and 22% adoption rates when considering the potentially missing studies. Africa and South America were the two continents that proved to have the highest adoption rates.
- We also found a negative correlation between the adoption rate and Age, which indicates that younger farmers adopt more. A positive correlation between publication year and the adoption rate shows the interest and increase in adopting agricultural digital technologies research.
- The studies also revealed a positive correlation between gender and income, implying their importance in adoption.
- A significant correlation was found between the effect size of the socioeconomic variables (age, gender, education, and income) and the adoption of DAT related to production, management, digital farming, crop production, access to markets and services, and digital advisory.

The study's findings are relevant and valuable to policymakers, private investors, and the academic community. Using the findings on the most adopted type of technology, policymakers, and private investors could make better decisions on the type of technology to develop and promote. This information is also crucial for the academic community as it provides new and quantitative findings to the existing literature on adopting DAT. Furthermore, the characteristics that drive the adoption are also important factors that policymakers could use to design a better and sustainable adoption approach. Private investors can also use it to design tailor-made technology with a higher probability of adoption. Nevertheless, the role of policymakers and external partners is crucial in supporting innovation and encouraging the use of DAT by end-users and extension agents.

Limitations and future studies

Within this study, we adhered to the PRISMA protocol to provide accuracy and a more realistic result. This paper has some limitations. First, because of the outcomes reported and the nature of the selected studies, we did not assess the certainty of evidence. Second, only the technology created for agricultural purposes was considered digital agricultural technology. Therefore, this excludes digital technologies or devices not intended for agricultural use but are nonetheless used for that purpose, such as cellphones, smartphones, tablets, software, computers used for agriculture, precision tools, television, and radio. Therefore, a study that includes all those layers could have different results. Third, the papers included in the study were found using only Scopus and Web of Science and were based on pre-defined keywords. Different keyword searches and other search tools, like "Google Scholar," may yield different input studies, leading to different results. Therefore, any research paper on the adoption and determinants not included in these databases may have gone unnoticed. However, the challenge here was to find papers that assess both the adoption and the determinants, which was not the case for most papers initially found. This may be a reason as to why the literature reviewing the adoption is mostly qualitative and does not include the determinants. Lastly, some residual heterogeneity could not be quantitatively explained despite our use of meta-regression, subgroup analysis, and partial coefficient correlation to examine the heterogeneity of the included studies. This heterogeneity was most likely caused by variations in the adoption rates of different technologies between the various countries and when surveys were conducted. However, this does not affect the accuracy of our findings because we explored heterogeneity using suitable methodologies.

Future research may examine digital technologies that aren't intended for agriculture but are nonetheless utilized for agricultural purposes. Additionally, another research search engine, like Google Scholar, might be added to the search database to increase the probability of finding appropriate published papers.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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2. An extended Canvas business model: A tool for sustainable technology transfer and adoption

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Abstract

The rise of new agricultural technologies represents an opportunity for agricultural development, especially to achieve the 2030 Sustainable Development Goal. However, farmers in developing countries struggle with adopting new agricultural technologies due to several socio-economic factors. This study proposes a service-based business for transfer and sustainable scaling of new technologies to increase household resilience. Two segments, (i) cost-benefit and (ii) sensitivity analysis was added to the original Canvas business model. We used two innovative technologies: a personalized extension application and a rice threshing machine to apply the business model. Quantitative data from 700 randomly selected rice farmers in

Kano State, and qualitative data collected using the Delphi method were used. The adapted Canvas business model is profitable when both technologies are used separately, with an Internal Rate of Return (IRR) of 23 and 28% for the threshing machine and the application, respectively. However, higher profitability is observed when both technologies are combined in one business model. In this case, the business has an IRR of 33%. Moreover, the study shows that the combined business model is vulnerable to the service price. Therefore, we recommend re-evaluating the business model to determine a fair price and payment method for both the service recipient and the provider.

Keywords: Adapted business model, Service-based, developing countries, Extension App, Threshing machine

2.1. Introduction

Besides the invention of new technologies, the scaling and sustainable adoption of the innovation is a challenge that requires attention to ensure the successful and sustainable transfer of the technology. Generally, technological change is defined in terms of the invention (development of a new idea), innovation (development of the new concept through technology), and diffusion (scaling of the technology in a potential market) [1]. The contribution of the new technology to economic growth can only occur through its widespread diffusion and successful adoption [2]. However, the diffusion and adoption process include two main questions: (*i*) by what means should the technology be presented to a potential user? and (*ii*) what factors determine sustained technology adoption? Stoneman and Battisti [3] defined technological diffusion as a process in which a new production process accompanies the change in the market. These authors mention that adopting the new technology results from analyzing the interaction between supply and demand, which brings us to the need for an upstream study to define how the technology should be presented to users. We believe that a service-based business model is the best way to introduce new technology, analyze the market and the interaction between supply and demand.

This study presents the case of two technologies developed by Africa Rice Center (AfricaRice) and its partners. *(i)* a modern threshing machine named ASI thresher from the initial of the institutions involved in the conception (AfricaRice; Senegal River Valley National Development Agency and the Senegalese Institute of Agricultural Research) and (*ii*) a digitized extension application (RiceAdvice). The ASI thresher was first introduced in Senegal, increasing technical and economic efficiency by improving productivity and saving time [4]. The switch to mechanical operations would eliminate the problems connected with traditional methods based on a high share of manual labour input needed for the growing cycle and causing grain damage and a high yield loss [5]. The digitized extension application called "RiceAdvice" is a science-based crop management decision support tool that explicitly helps rice farmers get personalized farm management advice. RiceAdvice generates recommendations tailored to the characteristics of the field and the farmer. A study analyzing the impact of RiceAdvice in Kano State (Nigeria) showed the positive impact of adopting this technology on rice yield and household income [6]. Furthermore, the study conducted to analyze the applicability of the advice and requirements to scale up the technology found that, apart from improving access to finance and involving female service providers, RiceAdvice requires the design and testing of a business model [7]. Both technologies were introduced and widely disseminated among farmers and local authorities through several studies in Nigeria.

Despite its enormous oil wealth, Nigeria's economy is still largely dependent on the agricultural sector [8]. Rice production in Nigeria is among the most important crops in the agricultural sector. It plays an essential role in ensuring the food security of the most populated country on the continent [9]. As the population grows, the demand and consumption of rice have been increasing every year, which leads to massive rice imports [10,11]. On the other hand, Nigeria has the full potential of natural and economic resources to be self-sufficient in rice production [12]. The primary constraints in rice production include the lack of financial resources, high input cost, lack of equipment for production and post-harvest, lack of information, and climate change [13]. New technologies came as a solution to tackle these problems and contribute to the eradication of rural poverty [14]. However, the adoption remains an issue because of two reasons: first, the high costs of the threshing machine (a single smallholder farmer cannot afford it), and second, the use of the RiceAdvice technology requires minimum knowledge of how to use a smartphone and access to the internet to download the application. This study proposes a service-based business model approach to provide service to farmers using these technologies. The business model could also be helpful for young people/farmers interested in agribusiness, especially in the private extension sector, and for policymakers to have information to support the private extension sector. But still, the business model needs to be profitable for sustainability. Thus, the main objective of this study is to design the business model framework and evaluate its financial profitability. The following research questions (RQ) were raised to reach these goals. RQ1: since RiceAdvice is a new technology that is not widely used on the market, how much are rice farmers willing to pay to receive a personalized extension service? RQ2: will a service-based business model using a threshing machine and RiceAdvice be profitable? If yes, to what extent? RQ3: What are the weaknesses of the business model? The answer to these questions may lie in transferring the technologies to government agents. However, the literature shows the government extension service's limits and inefficiency (known in the literature as the traditional or conventionnel technology transfer approach), leading to the increase of the private extension service [15,16]. In this study, we use the most recent and appropriate business models widely used in academic research, which is based on the definition proposed by Osterwalder and Pigneur [17]: "A business model describes the rationale of how an organization creates, delivers, and captures value". The proposed business model dubbed "Canvas" is based on nine interrelated components that provide an analytical overview of the content of the business model. The Canvas model is widely used due to its holistic approach and flexibility [18]. To our knowledge, this study is one of the few that proposes a service-based business model approach for adopting agricultural technologies and assessing the business's profitability.

Description of the technologies

This study has investigated two technologies (ASI thresher and the RiceAdvice) of interest. The ASI thresher machine (Figure 2.1) is a throw-in type machine originally from the Philippines, which AfricaRice redesigned to fit African rice varieties [19]. The machine was redesigned to increase efficiency by reducing labour quantity and processing time during the threshing and winnowing. It also helps reduce the manual method high post-harvest losses of 47.63% [20]. The machine can perform three different post-harvest activities: threshing, winnowing, and densimetric separation [4], which are essential steps to guarantee the quality of rice. However, the disadvantage could be the cost of the machine, which is high for a single farmer.

Figure 2.1. ASI Thresher machine.

The second investigated technology is an IT application developed to provide tailor-made advice to rice farmers. The RiceAdvice, a free Android application, is a decision support tool that farmers, extension agents, or private service providers can use to generate personalized advice for rice production management. The recommendation provides a nutrient management plan, the appropriate production plan, and a calendar [6]. Figure 2.2 presents the personalized advice generated based on the data entered.

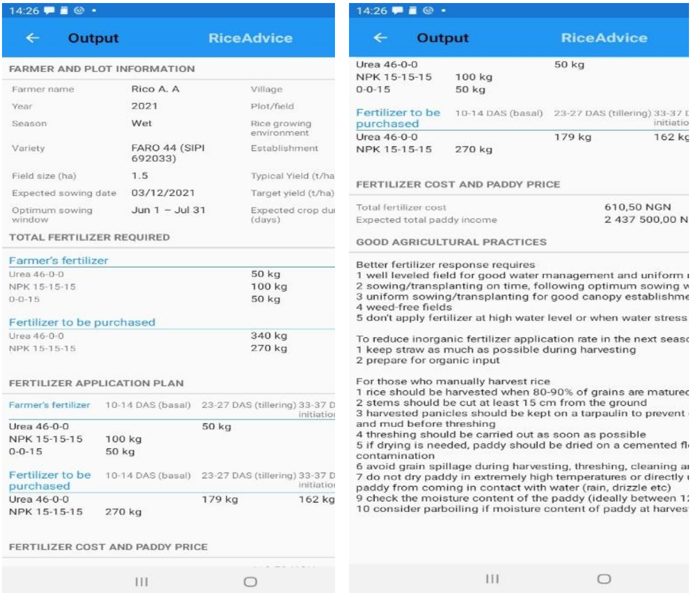

Figure 2.2. RiceAdvice interface of outputs.

2.2. Methodology

Nigeria's extension service and Study area

Nigeria's national agriculture extension service is resumed to disseminate information, build farmers' capacity, and transfer technology [21]. It also serves to establish the interconnection between farmers, researchers, and other value chain actors by promoting new and improved crops, varieties, and new technologies [22]. However, this practice has limitations related to inefficiency, the quality of the service provided, and the government backing up investing in the sector. Therefore, AfricaRice, in collaboration with the national extension service, has introduced the RiceAdvice and ASI thresher through an innovative platform in Kano State. The promotion of the technologies was carried out through the training of fifty youth extension agents on business development and the use and maintenance of the ASI thresher. Also, the donation of six ASI threshers to twenty-eight youth in five Local Government Areas and the training of sixty-eight youth on the use of efficient fertilizer management tool which is RiceAdvice.

The Kano state (Figure 2.3), which comprises an estimated population of 13.4 million, is one of the thirty-six Nigerian states located in the northern part of Nigeria [23]. The state represents around 7% of Nigeria's total landmass, with agriculture as the main activity. The Kano state is located near the Nasarawa, Niger, and Zamfara States. It is characterized by an average rainfall of 980 mm per year [7] and two seasons (rainy and dry). Rice is the favorite crop, which is why the National research institute and partners have chosen the state as the priority area for rice research intervention. Moreover, the study focuses on only one country which is Nigeria, for three main reasons. First, both ASI Thresher and RiceAdvice Application were available in Nigeria. Second, the government of Nigeria, through its "Agricultural Promotion Policy 2016-2020" put a particular emphasis on business model development in agricultural sector, and third, Nigeria is one of the biggest countries in Africa in terms of population, economy, and agricultural development.

Therefore, the ASI thresher was introduced, built, and sold to big farmers or entrepreneurs. However, its adoption rate is still low because of the size and the high acquisition cost. Regarding RiceAdvice, a test was conducted by AfricaRice in Kano State, where a free personalized extension was provided to rice farmers. As a result, the beneficiaries were willing to pay for the service provided using the RiceAdvice Application.

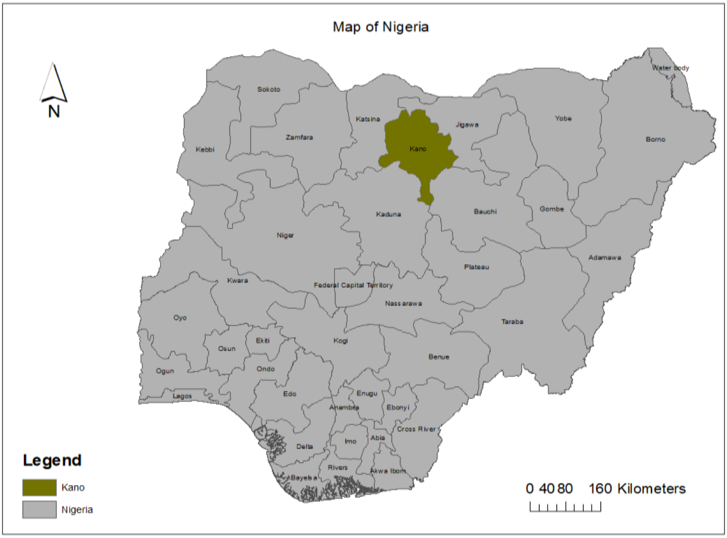

Figure 2.3. The study area of Kano state, northern Nigeria.

2.2.1. Data collection

AfricaRice collected quantitative data to assess the impact of RiceAdvice using a Randomized Control Trial approach among 700 households from 35 villages selected using a clustered randomization in 2016. The rice farmers were randomly assigned to the treatment and control groups as follow:

Treatment A represents a group of farmers (n_1 = 100 farmers) informed by an extension service on the quantity of fertilizer required for proper rice management based on RiceAdvice and received a financial grant to purchase the needed fertilizer.

Treatment B represents a group of farmers ($n_2 = 260$ farmers) advised by an extension service on the quantity of fertilizer required based on RiceAdvice. However, they did not benefit from any grant to purchase it.

Control C is a group of control farmers ($n_3 = 340$ farmers) who neither received advice from extension service based on RiceAdvice nor a grant to cover inputs.

Qualitative data were also collected using the Delphi method in 2019 and aimed to gather information on the technologies from different experts to reach an overall consensus. This method is known for flexibility and ability in research [24]. According to scientific and practical experience, this study identified five experts around the technologies (RiceAdvice and the ASI threshing machine) in terms of published papers and field interventions. These experts were program leaders, research assistants, doctoral candidates, researchers, and field agents who work with the technologies. First, a structured questionnaire for each technology was designed and sent to the experts online via emails/Google Forms. Then, initial responses were collected, summarized, and sent back to the experts to reach a consensus on technical and financial aspects. After that, the final answers were collected, summarized, and analyzed.

2.2.2. Data used

This section (Tables 2.1 and 2.2) contains the essential data required for financial analysis. Except for the secondary data collected from different sources, all data presented here are based on assumptions. The assumptions in tables 2.1 and 2.2 are based on data collected from rice actors (rice farmers, millers, etc.), secondary data from manufacturers (cost of equipment), the willingness of farmers (RiceAdvice cost), and the data collected to assess the impact of RiceAdvice [6].

In the first year of entering the market, we assume that the business will begin to retain customers, threshing (350 tons) of rice per year at US$0.0216/kg, advising on 550 hectares of rice at US$12/ha. According to Deloitte [25], the tax rate on farm income in Nigeria is 30%, while the minimum wage is around US$80/month, according to the ILO [26]. For both the ASI Thresher and RiceAdvice markets, we assume an expected price growth of 2% per year, growth in variable costs of 1%, and a growth in fixed costs of 1%.

Table 2.1. Input data on the economics of ASI thresher.

		Value	Assumptions		
Car cost		US$5,000.00		The market value of the car at a salvage	US$ 200
Equipment cost	ASI big size	US$2,400		The market value of the equipment at salvage	US$ 100
First-year sales (in number of kgs threshed)		350,000		The tax rate on operating income	30% [25]
The growth rate in unit threshed		10%		Growth in sale price	3%
Threshing price unit (per Kg)		US$0.0216 [27]	500-700 Naira per 75kg we assume the mean 600 Naira per 75kg or US$1.64/75kg or US$0.022/kg	Growth in Variable cost	1%
Net operating working capital		10%		Growth in fixed cost	1%
Variable cost per unit	Fuel/Gasoil	US$0.0004	1 l for 2,500 kg and 0.0004 l for 1 kg; 1 l of gasoil at US$ 1.00		

	Oil for engine	US$0.00012	0.017 l for 1hectare; or 0.017 l for 2500kg; and US$17.68 per 1 of Oil
Total Variable cost (US$/kg)		US$0.00052	
Fixed cost	Net Salary	US$996.00	average salary is around US$83.00. 2 people employed for 6 months (2 seasons, 3 months each season)
	Rent	US$300	US$ 50 monthly rate assumed, 3 months of threshing activities, and 2 seasons per year
	Engine maintenance	US$0.00071	US$1.77 expected costs for engine maintenance repair and cleaning over one hectare or 2,500 kg
	Car insurance (US$/year)	US$13.50	
	Radio Advertisement	US$58.97	
	Communication	US$4,000	
Total fixed operational cost	-	US$5,368.47	

Table 2.2. RiceAdvice input data.

	Value	Assumptions		
Motorbike cost	US$1,500		The market value of the car at a salvage	US$150
RiceAdvice cost	0		The market value of Tablets at salvage	US$10
Tablets	US$800		The tax rate on operating income	30%
First-year sales (in number of a hectare)	550		Growth in price	3%
The growth rate in the number of hectares threshed	10%		Growth in Variable cost	1%
Advice unit price (per hectare)	US$12	Based on the willingness to pay analysis, we assume a price between US$12 to US$20 per hectare	Growth in fixed cost	1%
Net operating Working Capital /sales	10%			

Variable cost per year	Fuel for Motorbike (US$)	US$720	Assuming US$2 of fuel per day per Motorbike for 6 months (20days per month) or 180 days in a year
	Oil for engine	US$48	Assuming US$4 of oil per month per Motorbike for 8 months
	Engine maintenance	US$24	Assuming US$2 per month per Motorbike for 8 months
Total Variable cost (US$/year)		US$792	
Fixed cost			
	Net Salary	US$996	According to World Bank 2002, the Average salary

			is around US$83; we employed 2 people for 12 months
	Rent	US$300	Assuming a monthly rent of US$50
	RiceAdvice License	US$200	Assuming US$200 for one year License
	Internet	US$84	US$14 data per month for 6 months
	Radio Advertisement	US$58.97	
	Communication	US$4,000	
Total fixed operating cost		US$5,638.97	

Depreciation plan

We assume a business unit useful life of five years for the car and ASI threshing equipment and three years for the motorcycle. Based on this, the annual depreciation expense has been evaluated using the following formula:

$$\text{Depreciation (US\$)} = \frac{\text{Cost of goods} - \text{Value at salvage}}{\text{Life span in years}} \quad (1)$$

2.2.3. Data analysis

Data analysis was conducted in three steps accordingly to answer the research questions: (i) Willingness to pay analysis of RiceAdvice, (ii) Business model formulation and cost-benefit analysis, and (iii) Business model simulation for the sensitivity analysis.

Willingness to pay analysis

This study first attempts to determine farmers' willingness to pay for RiceAdvice. Since the threshing machine is already introduced and is used in the market, we used the market price to calculate the cost and profit. Therefore, we do not estimate the willingness to pay for the ASI thresher.
During the survey conducted in 2016 by AfricaRice, rice farmers were asked to express their willingness to pay for the RiceAdvice per quarter of a hectare. We then used a t-test analysis to compare the mean for the three groups/treatments (A × B, A × C, and B × C). Based on the qualitative interview, the open discussion with rice farmers during the data collection, the following hypothesis was posed:

Hypothesis 1: Average amount that farmers in group A are willing to pay is higher than the average amount that farmers in group B are willing to pay.

Hypothesis 2: Average amount that farmers in group A are willing to pay is higher than the average amount that farmers in group C are willing to pay.

Hypothesis 3: Average amount that farmers in group B are willing to pay is higher than the average amount that farmers in group C are willing to pay.

The goal here is to find an interval of the price we will use to design and simulate the business model.

Including cost-benefit analysis to Business Model Canvas and simulations

As a basis, we used the Business Model Canvas (BMC) developed by Osterwalder and Pigneur [17]. However, the sustainable adoption of technology is only possible if the business is profitable for the service provider at an affordable price. For this reason, we added two new segments to the original Canvas framework to assess financial profitability using key metrics. These segments were Net Present Value (NPV) (equation 2), Internal Rate of Return (IRR) (equation 3), and Profitability Index (PI) (equation 4), and sensitivity analysis to identify potential weaknesses of the business model and to develop strategies how to reduce them (see figure 2.4).

<table>
<tr><td rowspan="2">Key partners</td><td>Key activities</td><td rowspan="2">Value proposition</td><td>Customer relationship</td><td rowspan="2">Customers</td></tr>
<tr><td>Key resources</td><td>Channels</td></tr>
<tr><td colspan="3">Cost structure</td><td colspan="2">Revenue streams</td></tr>
<tr><td colspan="5">Cost-benefit analysis and Sensitivity Analysis</td></tr>
</table>

Source: Based on Osterwalder and Pigneur [17]

Figure 2.4. Original Canvas framework with added cost-benefit and sensitivity analysis.

$$NPV = \frac{R^t}{(1+i)^t} \quad (2)$$

Where, R_t is the net cash flow at time t, i the discount rate, and t the time of the cash flows.

$$IRR = \frac{(Cash\ flows)}{(1+r)^i} - Initial\ Investment \quad (3)$$

$$PI = \frac{Present\ value\ of\ cash\ flows}{Initial\ Investment} \quad (4)$$

In this case, since two technologies are involved, we assume it will be more realistic and profitable for a business unit to have both technologies (implying more activities and income) than just one because the threshing machine is used only after harvest and the RiceAdvice during production. If a business unit is using only the technology RiceAdvice or a threshing machine, it means the unit will only work during the pre-harvest phase (using RiceAdvice) with no follow-up activities (no revenue) in the post-harvest period or the opposite. Thus, we first designed a Canvas model for each technology and then found the relationship between the two business models and combined them to create only one model for the above reasons.

The cost structure and revenue in the Canvas business model describe all costs necessary to operate the business model and the cash generated by the unit. However, in this business model and the context of the study, a cost-benefit analysis has been carried out based on the assumption that the business model's profitability can or cannot be predicted. The sensitivity of the business model is assessed to show the best way to enter into this business [28,29]. The business model was simulated, considering expected costs, revenues, and capital costs. Profitability was assessed using the depreciation method, net present value, and internal rate of return. Simulations were carried out using linear programming in Microsoft Excel. The analysis of the business model was divided into five parts: (1) input data, (2) depreciation schedule, (3) residual values, (4) expected/projected net cash flows, and (5) Net Present Value and Internal Rate of Return and three scenarios:

i. business model, where the profitability of both technologies is analyzed separately as two independent or mutually exclusive businesses,
ii. business model, where two technologies are analyzed as a single business, combining cash outflows and inflows to forecast the profitability of the business model,
iii. sensitivity analysis was carried out based on a 10% reduction and increase of the financial analysis factors to determine which factor influences mostly the business.

In the study, we use the "One-at-a-time" sensitivity approach [30,31] and run two scenarios at a 10% margin on factors such as the service price, the projected sales, the variable costs, and the fixed costs (for both the ASI Thresher and RiceAdvice technology). The following two scenarios have been used:

i. the pessimistic scenario (10% decrease): meaning in the disadvantage of the business and then a reduction of 10% of the service prices forecast sales and an increase of 10% in variable and fixed costs,
ii. the optimistic scenario was based on the opposite situation.

Subsequently, we checked the effect of each scenario on the NPV was tested. The analysis was conducted using linear programming with Microsoft Excel.

2.3. Results and discussion

2.3.1. Willingness to pay for RiceAdvice service

Willingness to pay using the average amount

The results showed that out of 700 producers, 305 producers are willing to pay US$2.7 per quarter of hectare for RiceAdvice, i.e., an average amount of US$6.63 with a standard deviation of US$4.57. Moreover, 36 producers are willing to pay less than US$0.56 (Table 2.3).

Table 2.3. Willingness to pay for RiceAdvice in US$ per ¼ of a hectare (n=700).

(US$)	>2.70	2.70	2.20	1.60	1.10	0.56	<0.56
Number of farmers willing to pay	91	305	35	53	103	77	36
Average amount	2.78 (0)	6.63 (4.57)	2.40 (0.13)	1.86 (0.14)	1.32 (0.12)	0.70 (0.11)	0.08 (2.37)

Note: Numbers in parenthesis/brackets refer to standard deviation.

Willingness to pay with a comparison of means

Here we compared the average willingness to pay for RiceAdvice between groups in the Randomized Control Trial. We assume that group "A", which uses the technology and has received input support, should have a higher willingness to pay than groups B and C. We also assume that the producers in group "A" are aware- of the advantages and disadvantages of RiceAdvice and then would indicate a genuine willingness to pay. We developed three hypotheses. The first hypothesis compares groups "A" and "B" (hypothesis 1). The second hypothesis compares groups "A" and "C" (hypothesis 2), and the last hypothesis compares groups "B" and "C" (hypothesis 3). The results presented in table 2.4 show that hypotheses 1 and 2 are significant at 1%, as *t* equals 4.05 and 4.35, respectively. Hypothesis 3 is not significant.

Hypothesis 1: the p-value is smaller than $\alpha = 0.05$ (p-value = 0.000), we reject H_0 and conclude that the willingness to pay of producers who used RiceAdvice and received input grants is greater than that of producers who received only advice from

RiceAdvice and no input grant. This means that producers in group "A" are willing to pay a higher price of US$5.3 per quarter of hectare for RiceAdvice than those in group "B" (US$3.60 per quarter hectare).

Hypothesis 2: The purpose here is to see the impact of exposure to RiceAdvice and receiving input grants on the willingness to pay for the advice received from RiceAdvice. The p-value is smaller than $\alpha = 0.05$ (p-value = 0.000), we reject the null hypothesis H_0 and conclude that the producers in group "A" are willing to pay a higher price than the producers in group "C". The difference of US$2.10 between the two groups could be seen as the effect of using RiceAdvice and receiving input grants.

Hypothesis 3: In this model, we can see the effect of using only RiceAdvice. This model compares the mean value between the group "B" (those exposed only to RiceAdvice and without the subsidy) and the control population "C". The result shows that for the two-way test, we do not reject H_0 and we conclude that there is no significant difference between the willingness to pay for these two populations.

Table 2.4. Comparison of willingness to pay according to stated hypotheses.

Hypothesis 1: A × B					
Group	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Treated A (n=100)	5.32	0.49	4.92	4.34	6.31
Treated B (n=260)	3.60	0.18	3.06	3.23	3.96
Combined (n=360)	4.05	0.19	3.71	3.67	4.42
diff	1.72	0.42		0.89	2.56
Hypothesis 1: A × C					
Group	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Treated A (n=100)	5.32	0.49	4.92	4.34	6.31
Control C (n=340)	3.22	0.22	3.96	2.78	3.65
Combined (n=440)	3.71	0.20	4.30	3.30	4.12
diff	2.10	0.48		1.15	3.05
Hypothesis 1: B × C					
Group	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Treated B (n=260)	3.60	0.18	3.06	3.23	3.96
Control C (n=340)	3.22	0.22	3.96	2.78	3.65
Combined (n=600)	3.39	0.14	3.57	3.11	3.68
diff	0.37	0.29		-0.19	0.95

the service price is a key factor in the business financial analysis, the willingness-to-pay results show that rice farmers are willing to pay between US$3-5 per quarter of hectare to receive personalized advice. This result is in line with the findings of Zossou et al. [7], who also concluded that rice farmers are willing to pay for the services offered with

RiceAdvice. The difference is that the authors did not estimate how much rice producers are willing to pay, which we did here.

2.3.2. Empirical extended business model Canvas

New business model pathway for technology transfer

In response to farmers' challenges and difficulties, technologies are developed to support and increase their performances. It implies transferring information, new agricultural practices, physical technologies, and IT tools from research and development through extension agents to farmers [32,33]. However, this circle of technology transfer did not succeed for the reasons sub-cited. The studies also show that users (in our case, farmers) pay more attention and use more wisely what they pay for. Therefore, we propose a new circle (figure 2.5) for the transfer involving the user in the process at a payable fee. The positive correlation between innovative entrepreneurship through the private extension service and the research and development [33] needs to be supported by the government, which still has the most significant network with farmers [34]. Promoting the agricultural technology transfer through the private extension will discharge the government in financial resources and create employment for youth or entrepreneurs interested in investing in agribusiness.

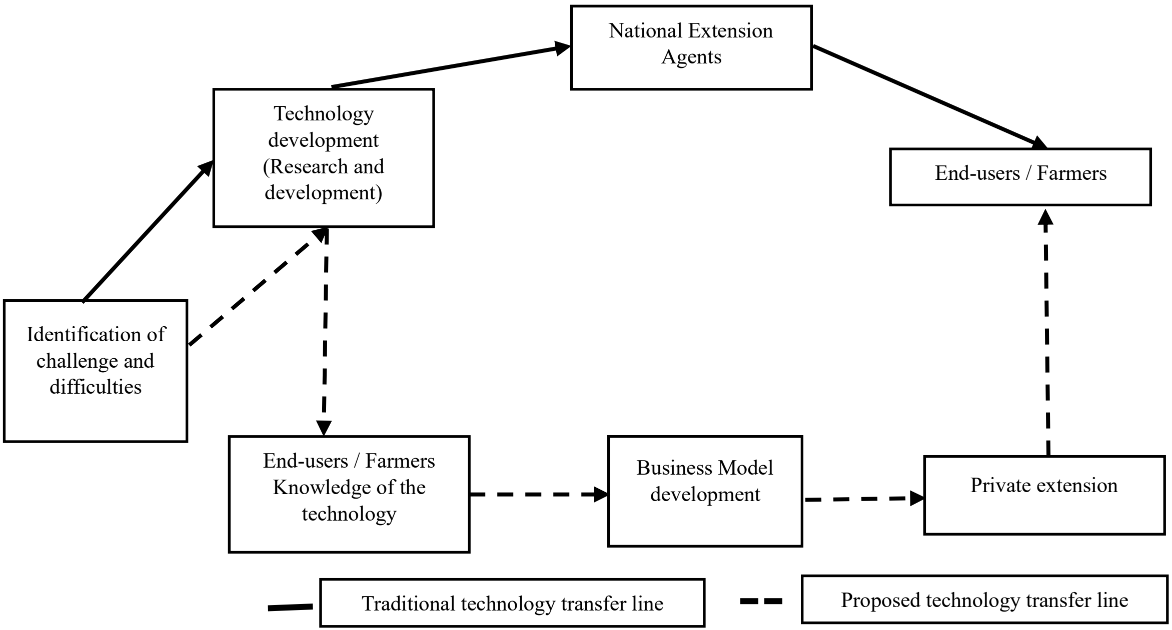

Figure 2.5. New transfer line of technologies.

Before the business model design, an upstream analysis proposes a flexible business conception and evaluation pathway. To ensure a successful business model implementation and sustainable adoption of the technology. We propose an oriented concept based on the most current theoretical and empirical work. The pathway of the extended version of the original Canvas business model (figure 2.6) provides steps for the sustainable adoption of new technology. Starting with a PESTEL (Political, Economic, Social, technological, Environmental, and Legal) analysis to assess the environment in which the business will be implemented. It also provides details on the benefits and likely impacts of these factors on the business model. Then the Poter's Five Force evaluates the competitiveness of the business. The case study result of this upstream analysis is not presented here in the paper.

The second part of the pathway is a downstream analysis using the original Canvas framework by adding two new lines to assess the business's profitability and identify the weaknesses. Furthermore, it is essential not to stop at the business model design for a more reliable and efficient approach but to perform an ex-ante and ex-post assessment. These two analyses, even though expensive, will provide all the information needed to guarantee a successful implementation of the business model, an efficient transfer of the technology to primary users (business unit or government), and sustainable adoption of the technology by the end-users. However, with an increasing interest in the business model innovation and sustainability [35,36] throughout the proposed service-based business approach, the oriented approach of the business model is still not widely used. The most oriented approach used and developed is sustainability-oriented, which still needs to be diffused and scaled up [37]. In addition, there is still confusion on the terminology of *sustainability-oriented business model* and *Business model for sustainability*. There is no consensus on the Sustainability-oriented business model and how it can be designed. Ludeke-Freund et al. [38] propose an oriented version of the business model. The authors proposed a sustainability-oriented business model assessment based on five secondary logic of the business model: the marketing logic, financial logic, capabilities, and resources logic, production logic, and contextual logic. The authors also highlight the limitations of this study, especially when using the five logics, which do not provide an extensive description of the business model. Since it is designed for the sustainability-oriented business model, this assessment approach could be used for the triple-layer bottom business model [39]. A study was also conducted by Keerativutisest [40] where the author also highlights the gap in the financial aspect of the business model Canvas. The author proposed an extended version of the original Canvas in six steps analysis to assess the financial feasibility for entrepreneurial finance.

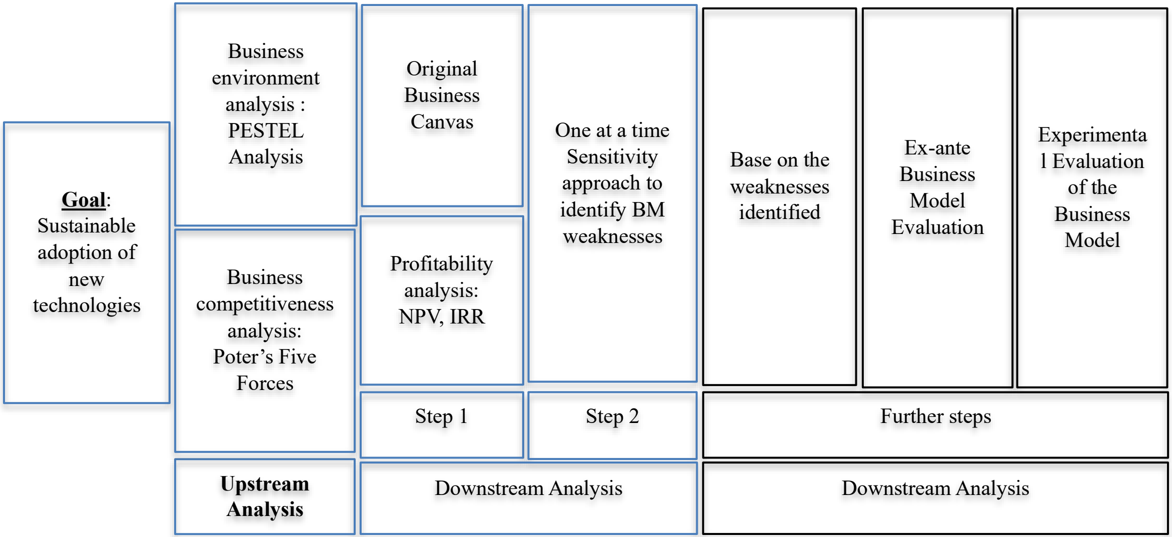

Figure 2.6. Pathway of the extended business model Canvas design by the authors.

Extended Canvas business model of RiceAdvice and ASI thresher

Here we present the extended version of the original Canvas with the additional lines.

Table 2.5. Extended version Canvas business model combining both technologies RiceAdvice and ASI thresher.

Key partners	**Key activities**	**Value proposition**	**Customer relationship**	**Customers**
Technology suppliers (AfricaRice; ASI thresher manufacturers), Rice farmers association; agricultural extension agents.	- Market shares analysis, advertisement using radio, - Mouth-to-mouth communication, - Meeting with the Rice Farmers Association to explain the importance of the technologies. - Services (consulting rice farmers with RiceAdvice, and rice threshing with ASI Thresher). - Building up staff capacity.	Personalized advice on rice field management with RiceAdvice and threshing with ASI threshers. This service package is associated with customer support and capacity building on a specific and valuable topic such as financial management and profitability analysis of rice cultivation, contract	High quality of services provided; full availability and support of rice farmers to ensure high and competitive customer service, leading to customer retention.	Rice farmers; large producers or rice farmers' associations put together their threshing production. But RiceAdvice will address all rice farmers who want advice and are willing to pay for the service. We

	Key resources Physical resources: we need the ASI thresher machine; transport (car); field accessories (glove, trunk...); tablets; computer and office for the business center.	farming; field planning and timetable; preliminary market analysis.	**Channels** - Mouth-to-mouth communication, - Awareness-raising through local radio,	could also offer some free services or bonuses to encourage farmers to create customer

	Human resources: Within this business and especially for the technologies we will use, we need to recruit young people who know mechanization for ASI thresher. Financial Resources: This part of the business model is described in blocks eight and nine of the business model through financial analysis.		- Collaborate with the rice farmers association, - Using the social network by creating a WhatsApp group for customers to share helpful information and invite new rice farmers to join the group and perhaps be persuaded to use our services or start rice production if they were not producers.	loyalty or any other specific case requiring our services
Cost structure*			**Revenue streams***	
Cost-benefit analysis and Sensitivity Analysis*				

Cost-benefit analysis and financial indicators

Table 2.6 shows the financial indicators that help assess the profitability and compare the two technologies. Table 2.7 presents the cost of capital over five years of business activities. The result shows that both technologies are profitable and will create wealth for the investor. However, together both technologies are more profitable, with a net present value of US$17,381.84 and an IRR of 33%, which is higher than the interest rate (12%) in Nigeria according to the Ministry of Budget and National Planning, which means that investment in any of these three businesses is more profitable than leaving the money in the bank saving. In addition, this result shows that it is worthwhile to combine the two technologies, RiceAdvice and ASI thresher because they share a production factor that can be used for both technologies.

Table 2.6. Summary of financial indicators.

Indicator	ASI Thresher	RiceAdvice	ASI Thresher and RiceAdvice
Net Present Value (US$)	2,403.0	1,515.73	17,381.84
Internal Rate of Return (%)	23	28	33
Payback Period (Years)	3.56	3.91	3.12
Profitability Index (US$)	1.29	1.59	1.67

Table 2.7. NPV and IRR values for ASI Thresher and RiceAdvice.

Years	ASI Thresher		RiceAdvice	
	Cash Flows (US$)	NPV (US$)	Cash Flows (US$)	NPV (US$)
0	$(8,156.00)	$(8,156.00)	$(2,560.00)	$(2,560.00)
1	$1,650.44	$1,447.75	$326.07	$286.03
2	$2,105.41	$1,620.04	$883.44	$679.78
3	$2,825.29	$1,906.99	$(579.47)	$(391.12)
4	$3,645.80	$2,158.61	$2,113.00	$1,251.06
5	$6,595.71	$3,425.61	$4,332.15	$2,249.98

2.3.3. Financial analysis for decision making on ASI Thresher and RiceAdvice

Here we want to see the crossing point of the two business models and what business model should be selected, whether we have an independent business (meaning we can choose both businesses) or a mutually exclusive business (we can only choose one business). This part of the study helps analyze and clarify whether RiceAdvice and ASI Thresher are "independent" or "mutually exclusive". Figure 2.7 shows that the NPV for RiceAdvice and ASI thresher technologies equals US$887.27 if the discount rate "k" (required rate of return) is 20%.

- Independent business shows that results in both business models have a positive NPV. In addition, they will both generate wealth for the shareholder; thus, either business model could be chosen.
- Mutually exclusive business: If the two business models of the technologies ASI thresher and RiceAdvice are mutually exclusive, only one technology can be chosen. We aim to choose the best business model based on the NPV and the discount rate. In this case, the ASI technology

is chosen instead of RiceAdvice because at k < 20%, NPV for ASI rice thresher > NPV for RiceAdvice with low discount rate. However, at k > 20% NPV for ASI thresher < NPV for RiceAdvice. In this case, the RiceAdvice technology is chosen because it has the highest NPV and IRR compared to the ASI thresher business (figure 2.5).

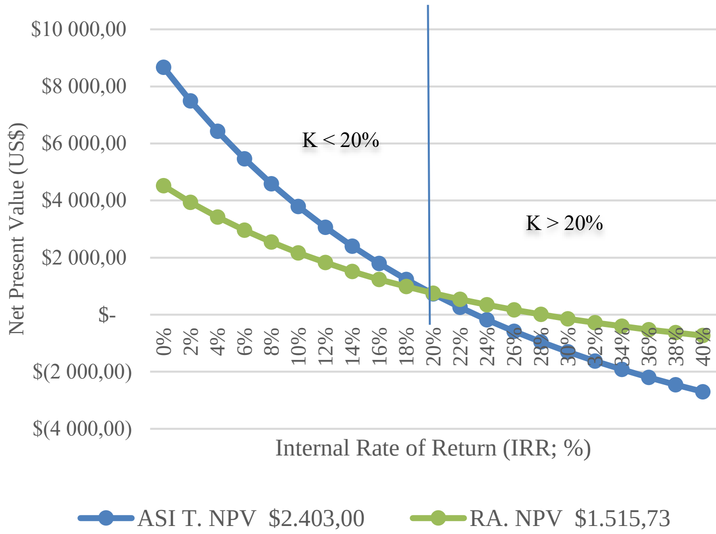

Figure 2.7. NPV and IRR profiles for RiceAdvice and ASI Thresher.

Nowadays, the adoption of new technologies is fundamental for the development of the agricultural sector and is the center of most policy interest in developing countries [41]. ICT-based is an effective and cost-efficient way to provide services in the presence or distance, and the current pandemic should serve as a motivation [42]. The case study shows a profitable service-based business model and the need to analyze further the service price and the suitable payment method for beneficiaries and service providers. In the literature, little research focused on assessing the impact of adopting new agricultural technologies or the farmers' level of profitability. Copley et al. [43] went in our direction. The authors stated that for the successful dissemination of agricultural technologies, entrepreneurs must develop strategies to transfer the technology to the market and introduce a suitable business model for adopters. They continue to argue that several technologies were developed and continue to be developed, especially in rice production and IT. Still, many IT projects have failed to reach the user or did not sustain [44]. Especially nowadays, with the rise of digital farming technologies, an appropriate approach is needed to get the social and economic impact of the technology. Commercialization would be the ideal way to disseminate and sustain technology adoption. In the same line, a cost-benefit analysis of the Integrated Pest Management (IPM) tool developed for potatoes production is revealed profitable with a net present value of US$5.2 million and benefit-cost ratio of 1.63 when the adoption rate is 46% [45].

Regarding the change proposed on the Canvas model, Koko [46] used the Canvas business model to design a business model for 17SunsAgri. This agricultural business innovation proposed a solution to take advantage of the business environment and favorable conditions such as land reform, lack of investment, and inefficiency of producers in South Africa. On the other hand, Pek et al. [47] also designed an extended business model, Canvas, called "EBMC", for the small forest owners. The difference is that the authors add three additional lines (customer needs, business solutions, and competitors) to the original Canvas of Osterwalder and Pigneur [17], which is an upstream study that needs to be done before designing the model. Considering that we need a simple, fluid, flexible, and sustainable business model in contrast to the above-mentioned one.

Another comprehensive approach of the original Canvas was developed by Joyce and Paquin [39]. The authors added two parallel layers to the original economically oriented Canvas layers to investigate the business model's environmental and social value creation. The environmental layer aims to evaluate the ecological benefits and impacts of the business model, while the social layer evaluates the social impacts and benefits of the business [48]. Unlike what was presented in this study, this model includes the environmental and social factors in the downstream layer and does not consider the other factors (political, technological, and legal), which are very important when building a sustainable business model. Therefore, this model is more suitable for businesses that use technology directly impacting the environment. This business model fits better to a development project or a non-profitable activity. This is because sustainability refers to the environment rather than the business model. Due to its flexibility, the Canvas approach has been used in several areas. Moreover, another derivative of the Canvas framework was developed by Hamwi et al. [49] using the demand response approach, which is focused on electrical science. In addition, Daou et al. [50] recently developed the EcoCanvas, which is similar to the triple-layer and includes three forces: economic and legal, environmental, and social.

2.3.4. Business model simulation and sensitivity analysis

The sensitivity analysis is a scenario analysis that helps identify the business model's weaknesses. We used the "one at a time" approach to estimate the change in outcome when a factor is increased or decreased. For this purpose, selected input factors were increased (optimistic assumption) and decreased (pessimistic assumption) to see how much 10% (increase and decrease) of these factors will affect the net present value. Figure 2.8 shows that the business model is more sensitive to ASI Thresher. It shows that a 10% increase in the forecast amount of rice to be threshed will increase the net present value by 19% and otherwise decrease it. A 10% increase in the thresher price also increases the net present value by 19.4% and otherwise decreases it. The results also show that the model is less sensitive to the variable costs per unit for the RiceAdvice and ASI threshing technologies. Therefore, it is crucial for an investor to allocate as many resources as possible to find customers, especially for ASI Thresher, and to have time to develop a strategy for increasing the price of services.

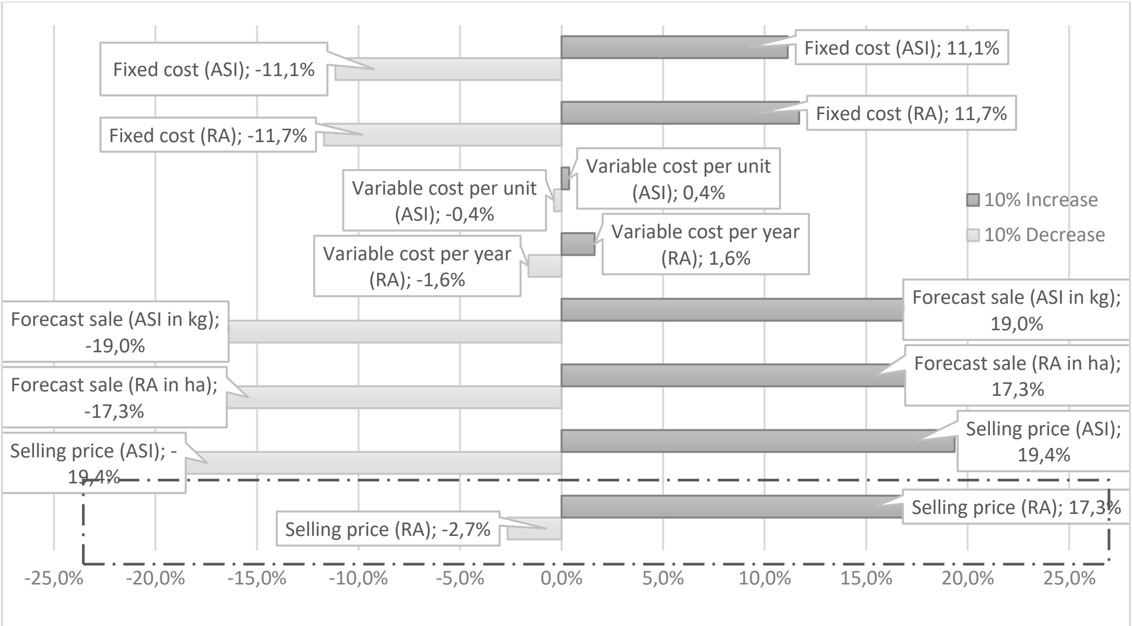

Figure 2.8. Sensitivity analysis of the business model

2.4. Conclusion and policy implications

The service-based business model represents an ideal framework for transferring and upscaling new technology to potential end-users. Our study provides a new line for technology transfer, a new approach to business model literature for users who aim to introduce and achieve a sustainable adoption of new technology. The Canvas approach is a straightforward tool adaptable to any new technology, especially agriculture. However, we suggest an upstream analysis to assess the market, the environment, and the possible effect of environmental factors on the business model. The results show that producers who have tried RiceAdvice technology were willing to pay US$12-20 per hectare to receive personalized (private) advice using RiceAdvice. This indicates that rice producers have realized how valuable the technology is and how it can improve their efficiency and productivity. In addition, few producers and investors have purchased and have been using ASI thresher to provide services to other producers, but this is far enough to meet demand. The extended business model shows the business profitability for ASI thresher NPV of US$2,403, IRR of 23%, and PI of US$1.29, meaning that US$1 spent in the ASI thresher business brings in US$1.29. The RiceAdvice business does have a lower NPV compared to the ASI thresher business. However, it does have an IRR and profitability index higher than the ASI thresher business. Results show that both technologies are profitable and have their weaknesses and strengths. However, the combination of both businesses shows the highest NPV of US$17,381.84, an IRR of 33%, and a profitability index of US$1.67, indicating that the best and most efficient way to run this business is to combine both technologies into a single business unit. An essential and innovative aspect of the approach we proposed is the weaknesses of the business model that need to be further analyzed. The study describes a sustainable way for technology transfer and adoption in agriculture. Based on our results, the rice farmers have adopted the threshing machine and are willing to pay for the personalized advice provided by RiceAdvice. This study leads us to three main conclusions:

- farmers are willing to use and pay for new technologies. It is crucial to identify the need and propose a strategy and appropriate business model to ensure that users are satisfied with the service;
- it is possible to establish a profitable service-based business using new technology where business promotor and user/customer (farmers) are satisfied;
- the business model design and profitability assessment are not enough. It is essential to search for the business weaknesses and develop a strategic plan for the business development.

The study recommends future research conducting an ex-ante evaluation of the model based on the constraints to develop strategies to reduce them. Further research needs to be performed on the price of the service and the appropriate payment method for the service recipient and provider. We also strongly recommend testing the business model before implementation.

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Data availability and material

The data used for the analysis are available with the correspondent author on request.

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3. Analysis of the factors influencing the adoption of digital extension services: Evidence from the RiceAdvice application in Nigeria

Adapted from: Amoussouhoui, R., Arouna, A., Bavorova, M., Verner, V., Yergo, W., Banout, J., Analysis of the factors influencing the adoption of digital extension services: evidence from the RiceAdvice application in Nigeria. 2023. The Journal of Agricultural Education and Extension 30, (3): 387–416. https://doi.org/10.1080/1389224X.2023.2222109 .

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Abstract

We propose an indirect adoption approach to address direct adoption challenges such as limited access to technological devices, a lack of technological infrastructure, and application knowledge. The research questions addressed were: what socioeconomic factors influence rice farmers' decision to prefer one business profile over another? Given the characteristics of the proposed extension services, which business profile is most preferred and likely to be adopted by rice farmers? What are the attributes and socioeconomic characteristics required to create the best business profile? The study proposes ten hypothetical business profiles tested with a sample size of 1440 farmers. Using the RiceAdvice application as a case study, we used a choice experiment and the alternative-specific mixed logit model to determine the most preferred business profile and analyse its determinants. The preferred business profile for adopting digital extension services was predicted by gender, age, education level, rice production experience, technology knowledge, contact with extension agents, rice farm size, and household income. The first popular adoption approach accounted for 49.4% of the farmers, selecting cash payment after harvest at 9.70 US$/hectare for more than two seasons-contract. Cash payment after harvest at 14.50 US$/hectare for one season-contract was chosen by 44.7% of farmers as the second popular option. Our results highlight the ideal business profile, which should consider all levels of education, with 14.50 US$/hectare/season as the optimum price for a cash payment after harvest and no access to credit. The study expands the applicability of a new adoption approach combined with an econometric approach in the context of digital extension service adoption. With the rise of digital extension technologies and the challenges associated with smallholder farmers' adoption, this study evaluates an indirect approach to the long-term adoption of digital extension technologies.

Key words: Agricultural extension, Sustainable development, Extension application, Business profile, Nigeria

3.1. Introduction

Overview of digital extension technologies

Agricultural extension services play an essential role in guiding farmers to improve the efficiency and effectiveness of their production by transferring new technologies through training, visits, or farm school (Van Campenhout, Spielman, and Lecoutere 2021). An effective agricultural extension service improves farmers' technical habits, such as fertilizer use, and leads to more efficient decision-making and better outcomes for farmers (profit, income, food security, etc.). However, the traditional approach of government extension services (Sylla et al. 2019; Wuepper, Roleff, and Finger 2021) and external support provided by development partners such as NGOs and other international institutions, on the other hand, have proven their limits and must be updated to address today’s challenges. This is especially true in Sub-Saharan Africa, where public agricultural extension frequently fails to adequately serve farmers due to financial insecurity and a high reliance on government or donor funding, which is unreliable and leads to the discontinuation of many promising solutions. The traditional agricultural extension approach was criticized for its limited action based on systemic advice delivery, including the role of intermediation (Leeuwis and Aarts 2011; Munthali et al. 2022). Furthermore, the traditional approach's insufficient performance in collaborating with value chain actors in problem-solving situations and providing effective market and credit information was highlighted (Klerkx and Rose 2020; Karpouzoglou et al. 2016).

The rise of digital extension technologies presents an opportunity to boost agricultural output, strengthen the value chain and contribute to food security (Rodríguez et al. 2021; Gow et al. 2020). Digital extension technology is a tool to better provide agricultural recommendations to farmers through digital applications. Any digital tool or technology used in the management of decision-making processes in agriculture or along the value chain are referred to as digital extension technologies (Gow et al. 2020; Klerkx, Jakku, and Labarthe 2022; McCampbell et al. 2021). It is arguably the best solution to climate variability, providing relevant information and advice for effective decision-making (Coggins et al. 2022). Extension digitalization is expected to improve farmers' technical skills, address socio-economic challenges, improve food traceability, and reduce environmental impact (Dawkins 2016; Balafoutis et al. 2017; Klerkx, Jakku, and Labarthe 2022). Digital extension technologies aim to reduce inefficiencies coming from grossly simplified recommendations from traditional extension, thereby raising the productivity and profitability from adopting improved inputs (Aminou Arouna et al. 2020). Digital extension technologies may also help to reach large number of beneficiaries. The literature on digital extension focused on technology development and technical performance, with less emphasis on policy and innovative adoption approaches to ensure the technology's long-term adoption (Wolfert et al. 2017). Although the literature has demonstrated the potential impact of digital extension services, farmers must also see how the technology adds value to their activities and fits their needs before we can expect a long-term adoption (Amoussouhoui et al. 2022). The digital extension service (refers to the use of Information and Technology (IT) systems such as mobile applications or devices to provide extension service to farmers) can help farmers overcome the abovementioned limitations and improve their performance. The significance of digital extension technologies is reflected in the numerous investments and projects made in the last decade (Oliveira et al. 2020). However, the direct adoption of digital extension technologies by farmers, especially smallholder farmers, is still a challenge when considering the barriers to the adoption of digital technologies. According to Ayim et al. (2022) and Barakabitze et al. (2015), the main challenges to smallholder farmers' adoption of digital extension technologies are poor infrastructure, a lack of ICT knowledge, financial capability, ineffective ICT policies, and inefficiencies in agricultural institutions. The authors argued that most African countries' infrastructure development is still deficient, with poor agricultural development policies. Ferrari et al. (2022) classified digital agricultural technology adoption barriers as socio-cultural, technical, economic, environmental, and regulatory-institutional. As a result of these barriers, smallholder farmers adopt digital extension technologies at a low rate (Coggins et al. 2022). Given the requirements for the direct use of digital technologies and the barriers mentioned above, a new mechanism for adoption and dissemination must be developed in collaboration with smallholder farmers (Shang et al. 2021). Such an approach will aid in addressing various factors influencing the proposed technology's adoption.

Case study of digital extension application: RiceAdvice

The Consultative Group for International Agricultural Research (CGIAR) center AfricaRice developed a digital extension technology called RiceAdvice to improve the performance of rice farmers. RiceAdvice is a free Android application, a digital advisory application for science-based crop management, and a decision support tool that provides rice farmers with personalized farm management advice. RiceAdvice generates recommendations based on field characteristics to increase farmer efficiency. RiceAdvice's recommendations include a nutrient management plan, an appropriate production plan, and a production calendar. The application is free and available to AfricaRice's twenty-seven member countries. Studies conducted by Arouna et al. (2020), Zossou et al. (2020), and Cotter et al. (2020) revealed: *1)* many rice farmers agreed to use the application, *2)* to adopt the application or pay for services provided using the application, and *3)* adoption of the application has a positive impact on rice yield and food security.

Nonetheless, due to several barriers, direct adoption of the application by smallholder farmers remains a topic of debate. As evidence, the Competitive African Rice Initiative (CARI) has taken over the application in 2015 and established a semi-commercial initiative in collaboration with rice miller companies since its development. Using the application, trained extension agents (working for the rice millers' private company) were to provide personalized extension service to rice farmers. CARI and the Rice millers then covered the service fee. However, because it is a project, the initiative ended in 2020. Through this initiative and other scaling, over 100,000 recommendations from RiceAdvice had been generated for use by farmers by the end of 2020. The main barriers to direct adoption of digital technologies by smallholder farmers in African countries, especially in Sub-Sahara-Africa, are a lack of or insufficient internet access, a lack of financial resources and proper equipment or infrastructure (mobile phone, internet, and smartphone) (Oliveira et al. 2020; Smidt 2021; Kieti et al. 2022; Porciello et al. 2022) and a lack of knowledge on how to use the technology (Owusu, Yankson, and Frimpong 2017). Given the aforementioned adoption barriers, new approaches are required to facilitate and ensure the long-term adoption of digital extension technologies.

Given these obstacles, this study proposes an indirect adoption approach based on a paid extension service provision via the application. This approach considers local conditions to overcome the barriers and increase farmer adoption (Birner, Daum, and Pray 2021; Zossou et al. 2020). The indirect adoption approach entails a business framework (Amoussouhoui et al. 2022) that proposes and provides farmers with quality extension services in exchange for a fee. Therefore, the approach is expected to result in broader and more sustainable adoption since it will remove two major constraints: farmers' limited knowledge of direct digital technology use and limited access to adequate infrastructure or devices. It should be noted that this adoption approach could also provide them with a solution to their financial problem. In this approach, farmers are not expected to adopt digital extension technology directly but rather to adopt a business profile or a proposed service. However, given that smallholder farmers are already experiencing liquidity issues along the supply chain and have limited access to financial institutions, the challenge will be to find the best service fee for both farmers and service providers, which is why an ex-ante evaluation of the approach is required.

As a result, an ex-ante evaluation of the proposed businesses is required to select the most appropriate business profile, make necessary corrections before implementation, and thus achieve a higher adoption rate. In this study, a business profile refers to a set of services, also known as attributes, offered to farmers as a package. It includes the service price, payment method, type of contract, and other services that may be useful to the farmer. It is referred to as a "Business profile" because it is a pay-for-service approach that can be used by both private investors looking to invest in agribusiness and institutions looking to design new extension policies. This study proposed ten theoretical business profiles for rice farmers based on preliminary information from farmers and actors. The research questions addressed by this study are as follows:

- What socioeconomic factors influence rice farmers' decision to pursue one business profile over another?
- Given the characteristics of the proposed extension services, which business profile is most preferred and likely to be adopted by rice farmers?
- What are the attributes and socioeconomic characteristics required to create the best business profile?

The ex-ante assessment of the theoretical business profiles was conducted using a choice experiment approach in this study. Information was provided to identify the appropriate and promising business profile for the application's long-term adoption. The study proposes a business approach with applicability to overcome the constraints and barriers (e.g., limited access to technology infrastructures such as smartphones, internet, knowledge of the use of new technologies, and lower education level) of smallholder farmers' direct adoption of the application.

3.2. Methodology

3.2.1. Study area, sampling method, and data collection

The research was carried out in Nigeria's Jigawa State. It is located in the country's northwest and encompasses 27 Local Government Areas (LGA). The agricultural sector served as the state's economic backbone in the previous decade, with rice as the primary crop. Therefore, this state was chosen because it is a major rice hub in Nigeria. Furthermore, the CARI initiative was completed in this state, allowing us to train extension agents for the experiment. As a result, we have extension agents in this state who are familiar with the RiceAdvice application and rice partners (e.g., millers and intermediaries) who already do business with rice farmers.

The data for this study were collected as part of the first phase of a Randomized Control Trial experiment on the RiceAdvice application. Data on rice production, food security, and sociodemographic and economic characteristics were collected using a questionnaire. The questionnaire was created with the CSPro software and then transferred to Android tablets for data collection. The data was collected in June 2021. The LGAs, villages, and households to be surveyed were chosen using a multi-stage stratified sampling method. Nine LGAs were chosen on purpose based on the number of rice farmers and the LGA where the rice millers work. In addition, the security issue of terrorist threats in northern Nigeria was also considered. The security issues were discussed with the extension agents, and high-risk areas were excluded. The sample size was determined using power calculation. Based on the financial means, 20 rice farmers per village in 72 villages were surveyed, giving a sample size of 1440 rice farmers. The number of villages surveyed was determined proportionally and based on the number of villages in each LGA. The villages and farmers in each LGA were then chosen at random.

3.2.2 Experimental design of the business profiles

Choice experiment approach

The choice experiment is a widely used method to determine users' preferences (Ellison et al. 2016; Krah et al. 2019; Martey et al. 2021; Waldman et al. 2017). It is based on Lancaster's theory (Lancaster 1966), which assumes that individual choice is based on utility derived from the attributes of the proposed product. Following this theory, the attributes in this study represent the characteristics that define each proposed business profile. The choice experiment is the most straightforward and robust approach and is also called the Discrete Choice Experiment (DCE) (Weber 2019). Unlike conjoint analysis (CA), which is based on conjoint measurement (which is not a behavioural theory), DCE is based on the theory of choice behaviour proposed by Thurstone (Thurstone 1927), called random utility theory (RUT). The RUT states that each choice characteristic cannot observe a latent factor "utility". Therefore, for each individual i who chooses a business profile j, the indirect utility function U_{ij} is decomposed into a deterministic factor (V) and a stochastic factor (ε) that represents the unobservable of the individual's choice. The utility U_{ij} of a rice farmer i when choosing a business profile j is expressed as follows:

$$U_{ij} = V_{ij}(X_{ij}) + \varepsilon_{ij} \quad (1)$$

Where U_{ij} represents the latent unobservable utility that an individual i associates with the choice of a business profile j, V_{ij} is the deterministic or observable component representing the vector of characteristics associated with the business profile j; X_{ij} is the vector of the characteristic of a business profile j for an individual i, and ε_{ij} is the non-observable stochastic part of the utility that considers the uncertainty.

Based on the assumption that the stochastic factor is independently and identically distributed, the probability of a business profile *j* is chosen as the most preferred is stated in a logistic distribution. The multinomial logit (MNL) model is commonly used in discrete choice models (Crastes dit Sourd, 2023), but it has two limitations. The first is related to the Gumbel hypothesis of identically distributed independence (IDI) of the error terms between the alternatives and the individuals, which assumes homogeneity of preferences, which is impossible because farmers' preferences are heterogeneous. The second limitation is the hypothesis of independence of irrelevant alternatives (IIA). To overcome the limits, the mixed logit model (MXL) is the most used and most appropriate because it helps to identify the unobserved heterogeneity in preference choice (Faustin et al. 2010). Compared to the original MNL, the MXL provides an additional β parameter representing the coefficient of the mean attributes; and the parameter ω for the presence of heterogeneity (A. Arouna et al.

2017). When significant, it indicates the heterogeneity of preference in the data (A. Arouna et al. 2017). However, the mixed logit implies the decision between a set of alternatives, sometimes resulting in numerous alternatives between which the decision-maker must choose. Since each alternative has different attributes, this choice is sometimes difficult for respondents. For this reason, we use the alternative-specific mixed logit in this study, which is more flexible than the simple mixed logit model (Streletskaya et al. 2023). The alternative-specific mixed logit model estimates the parameters of the mixed logit model using the maximum simulated likelihood (MSL) and relaxes the assumption of the independence of irrelevant alternatives (IIA).

In this study, we proposed ten hypothetical business profiles to be tested with farmers for the choice experiment. However, for the same reasons stated above, we randomly divided both the farmer sample and the ten business profiles into two groups (five business profiles for each group). This allows farmers to select from five business profiles rather than ten, ensuring the most realistic choice. The dependent variable is the chosen business profile (BP1....BP10), which has the value "1" if the farmer chose the business profile and "0" otherwise. We also included in the model case-specific variables that vary across farmers, such as sociodemographic and economic characteristics. The alternative-specific mixed logit analysis aims to examine rice farmers' decisions. The analysis allows us to predict which independent variables significantly predict whether or not a farmer will select a business profile. We assume no business profile is the default result (status quo). Based on the alternative-specific variables (attributes/characteristics of the proposed business profile), we expected rice farmers in each group to select one of the business profiles, one through five and six through ten.

We ran two models, each with five business profiles and the status quo (see Table 3.1). Stata/SE 16 was used for the analysis. A sample of the dataset for two rice farmers is shown in appendix 3.1.

We also use Cronbach's alpha test to measure the internal consistency (Grunert et al. 2018) of farmer's choice and Pairwise correlation to assess the validity (Appendix 3.2 and 3.3). The test shows a calculated Cronbach's alpha of ''Good'' (scale reliability coefficient: 0.87) for Group 1, meaning good reliability, and acceptable reliability (scale reliability coefficient:0.76) for Group 2.

Attribute choice and level of attributes

The choice experiment approach comprises six key stages: attribute selection, attribute level assignment, experimental design selection, choice set construction, preference measurement, and estimation procedure (Weber 2019). The attributes represent a critical feature of the offered product or service that can influence individual preference. We determined the preferences of rice farmers based on a literature review and a workshop organized on May 28th, 2021, with the stakeholders involved (rice farmers, millers, traders, extension agents, and the external partner CARI) as the experiment in this study is based on a statistical design and a hypothetical profile. The workshop consisted of a discussion and interactive session between rice farmers and service providers to define the various components of a business profile and their options. As moderators and facilitators, AfricaRice and CARI were present. As a result, we set the attributes and their level based on both sides discussion and agreement.

We first considered (i) rice farmers' preferences based on Lancaster's utility maximization theory and (ii) service providers' interests in reducing prices and maximizing profit. Then, eight attributes and their levels were chosen based on these two factors and discussions (Table 3.1).

Table 3.1. Attributes and levels of the business profiles.

	Attributes	Levels	
		Group 1	**Group 2**
1	RiceAdvice Payment method	0=No personalized advice; 1=Cash payment at delivery 2= Cash payment after harvest	0=No personalized advice; 1=Cash payment after harvest. 2= Cash payment after harvest incorporated into the rice price
2	Price of service (US$/ hectare)	0; 9.70; 14.50; 19.40	0; 9.70; 14.50
3	Length of partnership	0=Not interested; 1=1 season; 2=More than two seasons	
4	Contract farming (Trading contract)	0=No; 1=Yes	
5	Credit	0=No; 1=Yes	
6	Additional paid services (threshing, etc.)	0=No; 1=Yes	
7	Agreement on the Quantity	0=No; 1=Yes	
8	Agreement on the Quality	0=No; 1=Yes	

Logics behind the selection of attributes and the related levels are as follows

Payment method - one of the most significant constraints in agriculture and rice cultivation, particularly during the cropping season, is a financial constraint (Nonvide et al. 2018; Soullier et al. 2020). Because the technology is new, asking rice farmers to pay for an unusual new service is a significant challenge. As a result, three payment methods were proposed based on the literature and farmers' contract farming experience. The business profile is a collection of activities and services provided to rice farmers, but the most crucial factor is the payment method. We hope to make payment to rice farmers (end users) easier so that it does not become a barrier to adoption. The first payment method is postharvest cash payment, meaning that the rice farmer will benefit from personalized advice and pay after harvest. We assume this will give the farmers enough time to find a buyer to cover their expenses. The second payment method is also after harvest, but the service fee is included in the rice price. This payment method gives rice farmers more flexibility because it is only based on the quantity sold. When the service provider or miller purchases the rice, the service price is fixed and deducted directly from the rice price. The third payment method is cash on delivery, which requires the farmer to pay immediately after the service is rendered. On the other hand, some farmers would rather not owe anything and be free to make their own decisions after harvest.

Price of service - the challenge is convincing rice farmers to pay for a new service that they are unfamiliar with and are also unfamiliar with paying for extension services. Rice farmers were offered a free personalized extension service in a previous experience where extension agents, CARI, and millers/rice traders collaborated to disseminate RiceAdvice, but the approach could not last long. This approach failed due to CARI's limited financial support and the lack of a business framework to assist rice millers in taking over. According to recent research, adopting new technology in agriculture is influenced by performance expectations, the effort required (Beza et al. 2018; Ogwuike, Arouna, and Ogwuike 2021), and the cost of use (Beza et al. 2018). These two factors could be evaluated by testing the technology and polling users on their willingness to use and pay for it. As a result, the optimal price must be determined for both technology users (rice farmers) and service providers. During the workshop, various business profiles were presented and explained to the audience. We collected rice farmers' willingness to use and pay for the advice provided to them using the RiceAdvice application. The information gathered enabled us to propose prices, attributes, and levels for the business profiles presented in this study (Table 3.1).

Length of partnership - the length of a partnership reflects the acceptance of technology by rice farmers. A long-term partnership benefits both partners (rice farmers and service providers) by ensuring farmer efficiency and a sustainable business for service providers, increasing the stability of the whole chain. On the other hand, farmers may choose a short-term partnership as a test or may be unwilling to make a long-term commitment. The duration of the partnership is also a means of following up with the farmers and providing them with up-to-date information to ensure their efficiency throughout the partnership. On a business level, the service provider would prefer a long-term partnership, which the farmers may be unwilling to sign for. As a result, we propose in this study to rice farmers both short-term and long-term partnerships based on the length of a season. We have a partnership based on a single season or more than two seasons and the option of not signing any partnership. This means they can request the service provider's services whenever they need them, with the risk that the price will vary depending on the service provider's availability. When rice farmers decide on their preferred business profile, this is clearly explained to them.

Contract farming - as an additional service, the service provider could offer to buy rice from rice farmers after harvesting, which would be a separate contract. The rice farmers can sell their products to the service provider in addition to the RiceAdvice service. The farmer's payment method could be harvest-related if the farmer accepts a commercial contract. The RiceAdvice service will be paid for after harvest, or the service fee will be included in the rice price. This is a trading contract offered to farmers to guarantee a market and give them a reason to use digital extension services. The terms of this contract must be agreed upon and signed by both parties by the country's formal trading contract regulations. Farmers could use this as a guarantee to request agricultural credit to finance production and post-production activities. It should be noted that the payment method and the price of the rice purchased by the service provider are separate contract terms that must be specified in the trading contract. This business option provides rice farmers with two guarantees that can be used to improve their access to credit. The first guarantee is that they will be provided with accurate advice, increasing their efficiency and reducing the risks that financial institutions are afraid of. The second is when farmers sign up for a trading contract with a service provider, which could also be used as leverage to gain access to a financial institution.

Credit - rice farmers face significant financial constraints (Soullier et al. 2020), and few have access to financial institutions (Ojo et al. 2021). However, some rice farmers may benefit from a cash or in-kind loans from partners such as millers or traders. Due to their limited access to financial institutions and the need to finance production and post-production activities, rice farmers may occasionally apply for in-kind or cash credit through an unofficial structure. These deals are not always beneficial to farmers, but they appear to be the most accessible option for rice farmers. In rural areas, this practice is very common and well developed. That is why we offer rice farmers the option of applying for credit or not. Both parties should discuss and agree on the nature of the credit (cash or in-kind).

Additional paid service - because this is a collaboration and rice farmers are used to paying for other agricultural services, it will be interesting to see if they are open to additional paid services. It is viewed as an opportunity for other services that farmers may be interested in or require. It could also be viewed as an incentive approach for farmers to respond to their needs individually during the production process. Rice farmers and service providers could discuss the potential additional service and decide whether or not to sign up for it.

Agreement on the quantity and the quality – these features are consistent with the trading contract. Depending on the partnership agreement, they may or may not be included in the trading contract. These features are required for the service provider to ensure the quantity and quality of the product. On the other hand, rice farmers may see this as a constraint. The options here are then agreement or not on the rice's quantity and quality.

Experimental design of the choice set and implementation

The success of the experimental design depends on the attributes and their level. With a total of eight attributes (Table 3.2), two of which have three levels and six with two levels, we could have a total of 2^3 x $6^2 = 288$ combinations and possible theoretical business profiles. However, it is unrealistic for rice farmers to choose between 288 business profiles. Therefore, the orthogonal fractional factorial approach in SPSS version 16 software was used to reduce the number of business profiles. This approach reduces the number of profiles without affecting the experiment's validity. We obtained sixteen business profiles, which we consider much more realistic than the 288 profiles. As explained by Teece (2018), two important conditions can ensure the sustainable adoption of the application and the business: (i) the viability of the business and (ii) the feasibility of the business. In addition to the external factors that may positively or negatively affect the business, we must consider these two factors when selecting the potential business profile. Out of the sixteen theoretical business profiles, we retain ten business profiles that we believe meet the two conditions. The reasons for deleting six business profiles are explained in appendix 3.4.

Tables 3.2 and 3.3 show the groups of business profiles (BP) presented to the rice farmers. At this point, we explained (providing the details and the content of each business profile) the five business profiles to each farmer in each group, and then the farmer stated their preferred business profile.

Table 3.2. Experimental design group 1.

Attributes	BP1	BP2	BP3	BP4	BP5	No BP	
Payment Method	Cash at delivery	Cash at delivery	Cash payment after harvest	Cash payment after harvest	Cash payment after harvest	No personalized advice	Do not like either option (Option-out)
Cost of service per hectare (US$)	14.50	19.40	9.70	14.50	19.40	0	
Length of partnership	1 season	1 season	More than 2 seasons	More than 2 seasons	More than 2 seasons	Not interested	
Credit	No	Yes	No	Yes	No	No	
Additional paid services (land preparation, threshing, etc.)	Yes	No	Yes	No	Yes	No	
Contract farming	Yes	Yes	Yes	Yes	Yes	No	
Agreement on quantity	No	Yes	Yes	Yes	No	No	
Agreement on quality	Yes	No	Yes	Yes	No	No	

Table 3.3. Experimental design group 2.

Attributes	BP6	BP7	BP8	BP9	BP10	No BP	
Payment Method	Cash payment after harvest	Cash payment after harvest	Cash payment after harvest	Payment cash after harvest incorporate into the rice price	Payment cash after harvest incorporate into the rice price	No personalized advice	Do not like either option (Option-out)
Cost of service per hectare (US$)	14.50	9.70	9.70	9.70	9.70	0	
Length of partnership	1 season	More than 2 seasons	1 season	1 season	1 season	Not interested	
Credit	Yes	Yes	No	No	Yes	No	
Additional paid services (land preparation, threshing, etc.)	Yes	No	No	Yes	No	No	
Contract farming	No	Yes	No	Yes	Yes	No	
Agreement on quantity	No	No	No	Yes	No	No	
Agreement on quality	No	No	No	No	Yes	No	

Overview of the variables included in the models

Table 3.4 presents the definition and details of the variables included in the models and the expected sign of the socioeconomic characteristics. The dependent variable is binary (1=Yes; 0=No), indicating each rice farmer’s choice of a business profile. The alternative variable represents the ten business profiles divided into two groups of five business profiles, each plus the status quo. The choice of the independent variables was based on the existing literature on the adoption of digital farming technologies and the adoption of business profiles (Khan et al. 2019; Leng et al. 2020; López-Becerra, Arcas-Lario, and Alcon 2016; Hoang 2020).

Greater education, we believe, could contribute and help rice farmers better understand the proposed value and assist them in their decision. Since the proposed business profile implies rice farmers paying for a service, purchasing power is an essential factor influencing rice farmers’ decisions. Another important parameter is the knowledge of RiceAdvice, which is the core of the proposed business profile. A previous study shows that rice farmers appreciate the technology, use it, and would be willing to use it again and pay for it [16]. We know that the reality might be different and challenging as rice farmers face financial constraints every season. According to Miranda et al. (2016), Amoussouhoui et al. (2022) and Arouna et al. (2020), one of the key steps to the adoption of a new technology is knowledge of the technology.

Table 3.4. Definition of variables used in the models.

Variable	Definition	Measurement	Mean () Standard Deviation	Expected sign (+/–)
Dependent variable				
BP Choice	Choice of the Business Profile	1=Yes; 0=No	0.17(0.37)	
Alternative Variable				
BP	Represents the five business profiles + status quo in each block	See table 2 and 3 for details	3.5(1.71)	
Independent variables (Socioeconomic variable)				
Gender	Gender of the respondent	1=Male; 0=Female	0.16(0.36)	+
Age	Age of the respondent	Years	42.84(10.68)	–
Level of education	Formal education level of the respondent	1=Yes; 0=No	0.87(1.04)	+
Experience in rice production	Number of years of experience in Rice production	Years	16.87(9.27)	+
Knowledge of RiceAdvice	Respondent's knowledge of RiceAdvice	1=Yes; 0=No	0.84(0.37)	+
Contact with an extension agent	If the respondent has been in contact with the extension agent	1=Yes; 0=No	0.50(0.50)	+
Member of association	If the respondent is a member of an agriculture association	1=Yes; 0=No	1.46(0.84)	+
Farm size	Rice farm size	In hectare	1.47 (1.23)	+
Household income	Overall household income per year	In US$/Year	6,569.10 (5,181.40)	+

3.2.3. Identification of the most preferred business profiles

The most preferred business profile was identified using a post-estimation command from the alternative-specific mixed logit model. It generates a prediction probability that a farmer j chooses a business profile or alternative i. The predicted probability of farmer j choosing alternative or business profile i is calculated as in equation 2.

$$\widehat{P}_{ia} = (1/M)\sum_{m=1}^{M} P_{ia}(\beta^m) \qquad (2)$$

Where M is the number of random draws and $P_{ia}(\beta^m)$ are the logistic probabilities.

3.2.4. Building the optimum business profile

Even if the predicted probability of choosing a business profile will provide the most preferred business profile, it does not inform about the attributes and socioeconomic characteristics essential to propose an optimum business profile. Therefore, we use the Chi-square automatic interaction detection algorithm (CHAID) analysis to identify the essential attributes of a successful business profile. The CHAID analysis implies algorithms that determine the close interaction between the independent variables (the attributes of business profiles and the socioeconomic characteristics) and the dependent variable (the most preferred business profiles) using the chi-square test and the likelihood ratio method (Dollman, Gunn, and Hull 2021; Vial et al. 2021). This methodology presents four main advantages: (i) it allows the use of both quantitative and qualitative data; (ii) the result generates a decision tree straightforward to interpret; (iii) it facilitates the identification of the interaction between independent and dependent variables and, (iv) does not require the assumption of homoscedasticity, multicollinearity, and independence (Rodríguez-Sabiote et al. 2021). Therefore, this study considers the first three most preferred business profiles (based on the predicted probability) as the dependent variables and their attributes and socio-economic characteristics as the independent variables.

3.3. Results

This section discusses the findings in detail by responding to the research questions. The long-term adoption approach of the digital extension service is based on the determinant factors and primary attributes for successful service provision. Before looking deeper into the analysis details, Figure 3.1 summarizes the findings.

Figure 3.1. Infographic of the findings.

3.3.1. Determining factors of the chosen business profile

Tables 3.5 and 3.6 present the results of the determinant analysis for the two groups. Results showed that based on the Wald chi-square test [Waldχ2(45) = 256.59, $p < 0.001$] and [Waldχ2(45) = 246.02, $p < 0.001$] for the overall models for groups 1 and 2, respectively, containing the complete set of predictors are significant. This implies that at least one of the regression coefficients is not equal to zero.

Overall, socioeconomic and institutional characteristics affect the choice of farmers. Among the nine variables included in the models, six were statistically significant for group 1, and eight were found statistically significant for group 2. Specifically, the variable gender is significant for group 2, and the log-odds of female rice farmers adopting business profiles 6, 8, 9, and 10 were 1.718, 1.107, 1.120, and 1.867. This means that females are more likely to adopt these business profiles. The variable age is significant in both blocks 1 and 2. In group 1, age is significant at 5% for business profile 1 and 1% for business profiles 2, 3, and 4. In group 2, age is significant at 10% for business profile 8, 5% for business profiles 6 and 7, and 1% for business profile 9. The positive slope indicates that the older the farmer, the more likely he is to choose a business profile.

The education level, considered an essential parameter, is significant in both models. The variable is significant at 1% for business profiles 1, 2, 3, 4, 6, 7, and 8; at 5% for business profile 5, and 10% for business profile 9. This result implies that more educated rice farmers with formal education are more likely to choose a business profile.

The variable experience in rice production is significant and surprisingly negative for business profiles 3 and 4 in group 1 and all the business profiles for group 2. This is an unexpected sign as we assumed that rice farmers with more rice production experience would better understand the necessity of the opportunity in the proposed business profiles and, therefore, could be more open to adoption. However, rice farmers choose a business profile based on their experience individually.

Knowledge of the RiceAdvice, as expected, is positive and significant for business profiles 1, 3, and 6 at 1% and surprisingly negative and significant for business profile 9. The positive slope confirms the importance of first sharing the information and informing the rice farmers about the technology and the business profiles. However, note that the significance and positive slope were found on three business profiles over ten, which is not enough to generalize overall models.

The variable contact with the extension agent is significant and positive for business profile 1 and negative for business profile 7. This result confirms the uncertainty regarding the knowledge of the technology. Furthermore, if the agents do not have the information or do not transfer the information efficiently, this could have a negative effect, as recorded on the business profile 7. Otherwise, the extension agents could play a role in disseminating the information and proposing the service to the farmers.

Along the same line, the association, also known as a channel of learning and sharing information, is significant and positive at 1% for business profiles 1, 6, and 9; and 5% for business profile 10. This means that farmers of an agricultural association are more likely to choose these business profiles.

The size of the rice production is significant and positive at 1% for business profiles 2, 3, 6, and 8; at 10% for business profile 10. This is an expected sign since we assume that the bigger the farm size, the more interested rice farmers will be in using the technology and choosing a business profile.

The household income is significant and positive for business profiles 1, 3, 4, 5, and 9 but is negative for business profiles 6 and 7. The positive sign implies that the higher the household income, the more likely rice farmers will adopt the technology and therefore be open to choosing the business profiles. However, the negative sign could be due to the payment method, which is the common attribute of business profiles 6 and 7.

Table 3.5. Alternative-specific mixed logit of group 1.

	Coefficients (Standard Errors)				
	Business Profile 1	Business Profile 2	Business Profile 3	Business Profile 4	Business Profile 5
Gender	0.150(0.411)	0.777(0.662)	-0.024(0.457)	0.098(0.650)	0.213(1.030)
Age	0.043**(0.019)	0.089***(0.027)	0.090***(0.020)	0.085***(0.029)	0.046(0.050)
Education level	0.660***(0.185)	1.302***(0.223)	1.081***(0.188)	0.833***(0.237)	0.822**(0.371)
Experience in rice production	-0.022(0.019)	-0.043(0.029)	-0.084***(0.021)	-0.088***(0.033)	-0.086(0.063)
RiceAdvice knowledge	1.621***(0.348)	0.397(0.489)	1.340***(0.371)	-0.056(0.486)	1.028(0.909)
Contact with an extension agent	1.878***(0.347)	0.743(0.524)	0.352(0.347)	-0.020(0.508)	0.153(0.844)
Member of association	1.103***(0.204)	0.447(0.332)	-0.230(0.233)	0.057(0.327)	-0.178(0.605)
Rice farm size	0.178(0.228)	0.771***(0.259)	0.609***(0.231)	0.160(0.352)	0.056(0.626)
Household income	1.125***(0.219)	0.217(0.316)	1.014***(0.237)	1.575***(0.401)	1.957***(0.715)
Constant	-20.796(3.168)	-10.485(4.620)	-18.764(3.423)	-26.936(5.787)	-32.789(10.280)
Number of observations	4,320				
Number of cases	720				
Alternatives per case	6				
Wald chi2 (45)	256.59				
Log likelihood	-765.67				

Table 3.6. Alternative-specific mixed logit of group 2.

	Coefficients (Standard Errors)				
	Business Profile 6	Business Profile 7	Business Profile 8	Business Profile 9	Business Profile 10
Gender	1.718***(0.432)	0.152(0.568)	1.107**(0.509)	1.120*(0.630)	2.260**(0.990)
Age	0.033**(0.015)	0.036**(0.018)	0.031*(0.018)	0.074***(0.022)	0.036(0.046)
Education Level	0.446***(0.154)	0.791***(0.163)	0.498***(0.173)	0.419*(0.228)	0.510(0.367)
Experience in rice production	-0.054***(0.017)	-0.059***(0.020)	-0.061***(0.020)	-0.142***(0.030)	-0.097*(0.058)
RiceAdvice Knowledge	0.831***(0.330)	0.448(0.387)	0.102(0.370)	-1.193***(0.462)	-0.092(0.839)
Contact with an Extension agent	0.276(0.265)	-0.910***(0.309)	-0.364(0.319)	-0.217(0.465)	-0.449(0.839)
Member of association	1.581***(0.275)	0.644(0.299)	0.489(0.329)	1.232***(0.348)	1.174**(0.546)
Rice farm size	0.487***(0.166)	0.687(0.175)	0.852***(0.173)	0.055(0.350)	0.660*(0.370)
Household Income	-0.815****(0.188)	-0.579***(0.218)	-0.272(0.226)	0.633*(0.387)	0.810(0.660)
Constant	8.262(2.582)	5.643(3.043)	1.324(3.162)	-12.729(5.506)	-17.678(9.700)
Number of observations	4320				
Number of cases	720				

Alternatives per case	6
Wald chi2 (45)	246.02
Log likelihood	-876.385

3.3.2. Identification of the most preferred business profiles

Table 3.7 displays the predicted likelihood of the selected business profiles by group. According to the findings, business profile 3 has the highest probability in group 1 and thus is the most likely business profile to be adopted by 49.4% of the farmers in group 1. Business profile 6 (44.7%) in group 2 is the second most preferred, and business profile 1 (26.8%) in group 1 is the third most preferred. Intuitively, we will keep/promote the business profile with a 25% chance of being chosen. At this point, we can keep the first three business profiles that rice farmers are likely to select: business profiles 1, 3, and 6.

Table 3.7. Summary statistics of the predicted probability.

Business Profiles Group 1			Business Profiles Group 2		
BP	Predicted probability (%)	Standard Deviation	BP	Predicted probability (%)	Standard Deviation
1	26.8	0.131	6	44.7	0.144
2	5.1	0.046	7	16.9	0.082
3	49.4	0.143	8	14.0	0.052
4	4.4	0.046	9	5.3	0.078
5	1.1	0.009	10	1.3	0.019

3.3.3. Identifying the attributes and socio-economics characteristics for the optimum business profile

The first three business profiles are made up of attributes that do not help determine which business profile is most likely to be suitable. Figure 3.2 depicts the selected variable by the algorithm as the essential attributes among the variables (length of partnership; payment methods; price of service; access to credit; additional pay services; contract farming; agreement on quantity; quality agreement; household income; gender; knowledge of RiceAdvice; education level; farm size; experience in rice production; member of agricultural association and contact with extension agent) included in the model.

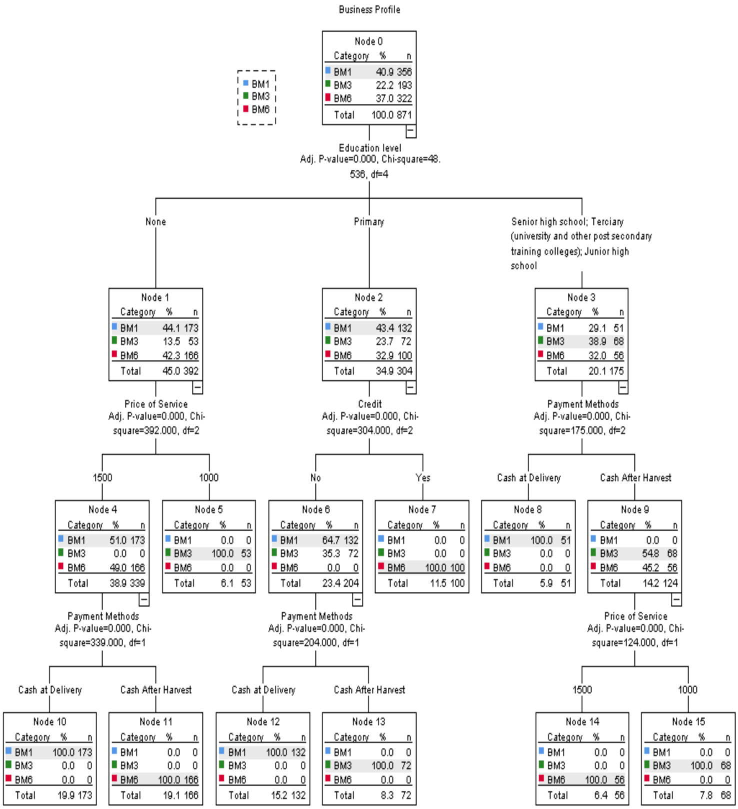

Figure 3.2. CHAID Diagram tree of the most preferred Business profiles.

The algorithm identified education level as the first predictor, followed by service price, credit availability, and payment method. According to the farmer's education level, the model recommends three optimal business profiles. For farmers with no education, the model recommends a price of 14.50 US$/hectare (6000 Naira/hectare). However, when it comes to payment methods, we have two suggestions. The first has the highest percentage (35.4%), indicating that the payment method is "cash at delivery." The second option is to leave the payment method open and allow rice farmers to select a suitable payment method. The model suggests not providing credit to farmers with a primary education level. Cash after harvest at 9.70 US$/hectare (4000 Naira/hectare) would be the most appropriate payment method for senior or tertiary-level farmers.

3.4. Discussion

Digital agricultural extension technologies provide an opportunity to improve farmer efficiency and public extension quality. However, adoption remains a topic of interest that requires attention. In response to farmers' constraints and barriers to direct adoption of digital extension technologies faced by developing countries, the study proposed an indirect adoption approach based on a personalized service business model. An ex-ante evaluation of the proposed business could increase its chances of success. Our research employs a digital extension application designed to provide rice farmers with personalized advice. Using a choice experiment approach, the study determines the factors that may lead farmers to select a business profile offering a remunerated service through the application. In addition, we were interested in the socioeconomic characteristics to extrapolate our findings.

The findings revealed several significant parameters that determine the choice of rice farmers. The gender parameter is a crucial factor for adopting a business profile, as Zossou et al. (2020) highlighted. Results revealed that women are more likely to adopt four over ten business profiles. The role of women in the adoption process is widely covered in the literature (Chatterjee, Dutta Gupta, and Upadhyay 2020; Orser, Riding, and Li 2019). A study conducted by Hay and Pearce (2014) revealed that women used rural technology three times more than men. Similarly, Gichuki and Mulu-Mutuku (2018) showed the importance of women in adopting mobile money technologies. However, the authors also mention that women are less likely to adopt mobile banking technologies viewed as prestigious services with hidden fees out of their social class. Therefore, mobile banking technology may not fit the needs of women. Along the same line, Chatterjee et al. (2020) and Orser et al. (2019) developed the role of technology in women's empowerment and its importance for gender-inclusive entrepreneurship. Other research found that women are less likely to adopt agricultural technology than men (Aryal et al. 2020). Although both men and women have access to new technologies, as long as they are in the same environment, women are less likely to adopt digital technology. Voss et al. (2021) explained this by referring to the social-cultural reality in rural area in which IT devices such as Cellphones, radios, and televisions are primarily controlled by men, implying that men are the primary owners and have authority over the device in the household. Involving women in developing and adopting digital extension technologies would significantly reduce the gap and increase the adoption rate (Voss et al. 2021). It should be noted that most of the abovementioned studies focus on women using the technology by themselves, which is different from the approach of our study since we propose a service using the technology based on indirect adoption of the technology, which can be considered as an advantage.

The parameter Age is positive and significant for the overall business profiles. This implies that older rice farmers would be more likely to choose a business profile and therefore adopt the technology. This could be explained by the fact that older farmers (hypothetically based on their experiences) are more aware of IT advantages than young rice farmers. However, they do not know how to use it or access the required infrastructure, which makes this an opportunity to take advantage of and guarantee more successful production. Furthermore, it makes farming more manageable since farmers will execute the activities according to the advice. Also, since older farmers have more experience in farming, they could be in a better position to evaluate more accurately the necessity of adopting digital extension technologies through the business profile. However, the opposite effect could be seen (Berkowsky, Sharit, and Czaja 2017), showing the unlikely probability of older farmers adopting new technology. This result is opposite to that of Paudel et al. (2021), who found that older farmers are less likely to adopt precision agriculture technologies, while Roberts et al. (2004) stated that older farmers do not adopt technology compared to younger farmers. This is understandable as we cannot objectively expect older farmers (usually with no/or limited access or knowledge of digital technology) to adopt digital farming technology directly. However, the adoption rate could increase if the adoption is indirect, as proposed in the case of this study.

The education level, perceived as an open-minded factor, could play a determining role in rice farmers' decision-making and effectively contribute to a better understanding of the concept. Therefore, the positive coefficient of the parameter is expected. It should guide the business design by involving educated rice farmers and providing basic educational knowledge as a supplementary service to those who are not educated. This could help to improve their decision-making capacity and make them feel more comfortable and open to new technologies and opportunities. Carrer et al. (2017) reported the same positive effect of education on the likelihood of adopting computers. The authors argued that highly educated farmers express an interest and the need for accurate information and could appreciate and evaluate the advantages of using IT as a tool for decision-making. On the other hand, the experience in rice production is significant and negative for seven of the ten business profiles. This is unexpected since we hypothesized that farmers with more experience would be more open to choosing a business profile. Nevertheless, the negative sign advises that this variable should be looked at during the dissemination process to understand and determine how to turn this parameter in favor of a better adoption. The result could also be justified by the fact that farmers with more experience in rice production were aware of the importance of the proposed service, especially in terms of using digital extension applications for advice. Still, they cannot see the impact on their activities without mentioning the financial constraints that lead most rice farmers to informal loans. In addition, the variable experience could be a double-sided blade where their experience provided valuable insight. It can also hinder their willingness to use or adopt the service as they might consider themselves too knowledgeable.

Knowledge about the technology as a driver in the adoption process is necessary and, if well done, should provide farmers required information on the technology and therefore ensure that potential adopter is aware of the value proposition and that their decision is entirely based on their utility function and that the non-adoption is not due to a lack of information. This finding is in line with Ferrari et al. (2022) and Coggins et al. (2022), who argue that educational support should be used to facilitate digital knowledge by training farmers, followed by the creation of innovative digital centers. In the same line as Voss et al. (2021), farmers' knowledge about the new technology influences their decision to adopt it, along with the availability of the technology and how farmers perceive the impact of the adoption on their activities. Smallholder farmers are very cautious when adding additional costs to their production line, especially when considering financial constraints and the high-risk environment, unless they have the appropriate knowledge and information, particularly in terms of outcome (Vercillo, Weis, and Luginaah 2020; Voss et al. 2021). Along the same line, we believe that the role of the extension agent is crucial for sharing information and educating farmers on the potential and opportunities related to the adoption of digital technologies (Amoussouhoui et al., 2022; Fabregas et al., 2022). Since there is direct contact with the user, the extension agents would explain better. Even if the variable is significant and positive in business profile 1, it is negative in business profile 7. It could be due to the quality of the information or the lack of information. This result is in line with Walisinghe et al. (2017) and Suvedi et al. (2017), who found that extension services positively affect farmers' decisions to adopt new technologies.

Farmers could also receive information about technology adoption or service proposition through agricultural associations. Farmers of an agricultural association are likelier to choose business profiles 1, 6, 9, or 10, including all the different payment methods. This shows the diversity in the choice, especially if we assume that the choice is mainly based on the payment method. Therefore, involving farmers in agricultural associations would be beneficial to disseminate the information better. This result is in line with Suvedi et al. (2017), who also found a positive effect of membership, extension service, and age on technology adoption.

The choice of a business profile could also depend on whether the rice farmer has a small or big rice farm when it needs more human and financial resources. As hypothesized, the farmers with big rice farms would be more interested in choosing a business profile. In the study, five of the ten business profiles were chosen with diversity in the payment method and other attributes of the business profiles. The business profile implies rice farmers paying for a service that we know could be a barrier to adoption. It is also well known that farmers face many financial difficulties along the production chain. Therefore, adding a new expense would be very challenging, even if the service is beneficial and impactful. That is why we proposed different payment methods. However, we hypothesized that if the household income were more open, this household could choose a business profile. This hypothesis is verified with five (1, 3, 4, 5, and 9) of the ten business profiles. This result is consistent with the findings of Paudel et al. (2021), who reported that higher-income households could easily access the technology since they have cash, which is not the case for lower-income households. The same effect is also reported by Isgin et al. (2008), with a positive effect of income on the adoption of precision farming technologies. However, two business profiles (6 and 7) negatively affected household income. This result could be due to the payment method (Cash payment after harvest), which is the common attribute of the two business profiles that users can see as a constraint.

Besides analyzing determinants, we also generate the predicted probability of the chosen business profiles, which show the most preferred business profile. Intuitively we consider business profiles that have a minimum of 25% probability. Based on that, figure 3.3 depicts the shape of the business profiles and shows the three business profiles (1, 3, and 6 see Appendix 3.5) that fit the criteria and are considered the most preferred.

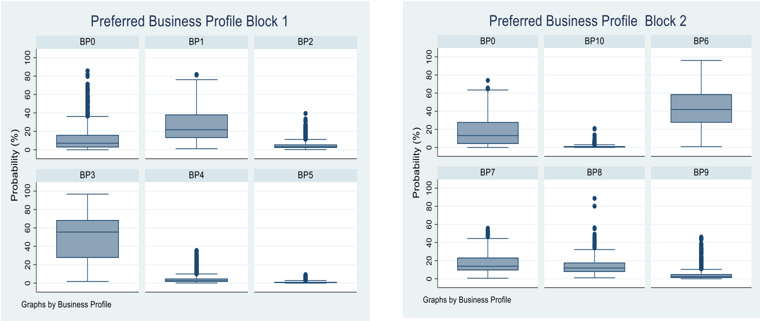

Figure 3.3. Boxplot of the predicted probability of adoption groups 1 and 2.

Business profile 3 has the highest predicted probability of being adopted at 49.4%, with a cash payment after harvest for the service provided at 9.70 US$/hectare (4000 Naira/hectare) for more than two seasons contract, followed by business profile 6 with a predicted probability of 44.7%, with cash payment after harvest for the service provided at 14.50 US$/hectare (6000 Naira/hectare) for 1 season contract, and the business profile 1 with predicted of 26.8% with a cash payment at delivery for 14.50 US$/hectare (6000 Naira/hectare) for the one-season contract. Most farmers in the two blocks choose business profiles 3 and 6. The result confirms that farmers would have difficulty paying cash, but this is an affordable option after harvest. It is also to the advantage of the service provider to have an overview of his customers (farmers) from the beginning of the season and, therefore, put in place a financial and structural plan for the intervention. Further analysis was also conducted to identify the crucial attributes and socioeconomic factors. This could help to compute the optimum business profile. Results reveal that for an optimum business profile, the attributes of the price of service, access to credit, and payment method are the most important ones that need to be considered. The education level was the most important factor among all the variables included in the model and the foundation for an optimum business profile. Therefore, the algorithm proposes three possibilities according to the education level. Overall, the optimum business profile would include all education levels, 14.50 US$/hectare (6000 Naira/hectare) as an optimum price for a cash payment after harvest with no access to credit. However, access to credit (cash or input) could be an attractive option to convince farmers.

Limits of the study

This is the first study in the literature to propose a new adoption approach for digital extension services, and an evaluation for long-term adoption. However, we would like to highlight some limitations of the study.

- We did not use the traditional choice experiment, which involves submitting a group of attributes to farmers to make a choice uncomplicated and more efficient for them. We believe that explaining this to farmers would have been more complex, and we see this study as a first step.
- Some of the business profile attributes could be combined (Agreement on quality, Agreement on quality, trading contract) to reduce the number of alternatives and thus make the choice easier for farmers.
- We proposed a hypothetical model for adoption, and it would be beneficial to conduct a follow-up study in collaboration with rice value chain actors such as extension agents, private advisors, farmers, and rice traders. On the

other hand, in a future study, we recommend reducing the number of business profiles as well as the attributes and conducting a randomized control trial study to see if farmers would indeed adopt and pay for digital extension services, as well as evaluating the impact of their adoption on key factors such as production, wellbeing, and food security.

3.5. Conclusion and policy implications

The traditional extension service provided by government extension agents has shown its limits. Therefore, new approaches and policies are required to provide farmers with more efficient and impactful advice. With the rise of new digital extension technologies, the study provided an operational solution to support adopting the digital extension approach. The case of the present study is a digital extension technology designed to provide tailored advice for rice farmers in Sub-Sahara Africa. As a solution to facilitate and guarantee a sustainable adoption of digital extension technology, the study proposes a business approach based on service providing as an indirect adoption approach. This approach can be used by the private sector interested in investing in agribusiness and external agricultural partners (NGO and International Organizations) to support the digitalization of extension and also for policymakers to adopt policies and make government extension agents more efficient. The study also provides a solution to decreasing public support for agriculture, especially regarding extension in developing countries. The outcome provided by the experimental choice approach offers much more information that we believe is useful to build a more appropriate business profile with a higher adoption rate of digital extension technologies. The results of this study lead to three main conclusions:

- Age, education level, rice production experience, knowledge of RiceAdvice, contact with extension agent, association membership, rice production size, and household income are socioeconomic and institutional parameters that influence rice farmers' choice of a business profile,
- Cash payment after harvest at 9.70 US$/hectare for more than two seasons contract, cash payment after harvest at 14.50 US$/hectare for one season contract, and cash payment at delivery at 14.50 US$/hectare for a one-season contract are the most preferred profiles and thus more likely to adoption by rice farmers,
- The best business profile should prioritize education level as the first and most important predictor, followed by service price, credit access, and payment options that are appealing to rice farmers.

However, as a technology design, this study is a step forward toward a long-term approach for ensuring the adoption of digital extension technologies despite existing barriers. Government and extensionists must support, promote, and disseminate the idea of a business approach using digital extension technologies to support smallholder farmers. This adoption approach represents a business opportunity for private investors and an opening for developing new policies and strategies to assess farmers' needs and develop appropriate technologies to support them. With this approach, all farmers willing to pay for the proposed service can receive advice from digital extension technologies even if they do not know how to use them.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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4. Analyzing farmers' behavior in the adoption of paid digital extension service: Experimental evidence of RiceAdvice in Nigeria

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Credit author statement: Rico Amoussouhoui: Data curation, Formal analysis, Original draft, Writing - review & editing, Methodology. **Aminou Arouna**: Conceptualization, Investigation, Funding acquisition, Writing - review & editing. **Marija Cerjak**: Conceptualization, Methodology, Writing - review & editing. **Wilfried Yergo**: Data collection, Data curation, Conceptualization, Review-editing. **Jan Banout**: Conceptualization, Supervision; Writing - review & editing; Validation.

Abstract

Adopting digital extension technologies by smallholder farmers in developing countries, particularly in Africa, is challenging due to various barriers, such as lack of infrastructure, farmers' low e-literary, and limited access to technology. The purpose of the study was to find out farmers' attitudes toward the use of new technological adoption approaches to bypass these barriers. The study investigated how farmers perceive the paid extension approach, and the usefulness of the services proposed. The study employed an experimental design conducted in Jigawa and Kano states in

Nigeria with a total sample size of 1560 rice farmers selected through a multistage stratified sampling approach. Three distinct paid extension services were randomly assigned to farmers grouped separately as a treatment and a control group. The study first subjected the data to reliability, validity, and consistency tests using Cronbach's Alpha method to test the reliability and then applied the Partial-least Square Structural Equation Modeling method to analyze the data. Depending on the service, there are notable differences in the impact of "perceived usefulness" and "perceived ease of use" on "attitude," "adoption," and "actual use" on farmers' decisions. However, we found that a solid and favorable perception of farmers using paid digital extension services exists. Furthermore, our evidence suggests that price options and payment methods positively influence farmers' decisions to accept the assigned extension service. The study contributes foremost to the empirical literature on farmers' behavior in adopting paid extension services and how much farmers might pay for the proposed service.

Keywords: Digital extension technology; Adoption; Developing Countries; Paid extension services, Experimental approach.

4.1. Introduction

Digital extension technologies are playing a more important role in agricultural development by providing adequate solutions to multiple challenges, such as climate change, farmers' inefficiency, and market information. Digital extension innovations have proved to be one of the most reliable solutions for numerous agricultural challenges, and the impact of their adoption has been proven worldwide (Khanna 2021; Klerkx *et al.* 2019; Rotz *et al.* 2019; Wolfert *et al.* 2017). This innovation provides information support, optimizes agricultural resource use, reduces ecological challenges, and converts traditional agricultural practices into more efficient agriculture (Jiang *et al.* 2022; Khanna 2021). However, connecting farmers to technological innovations is key for agricultural development, making their sustainable adoption a crucial subject of interest. Sustainable adoption not only helps to build farmers' capacity but also helps to change the traditional farming approach, reduce production cost, improve management skills, reduce poverty, improve access to market opportunities, and result in economic growth (Asfaw *et al.* 2012; Wossen *et al.* 2019, 2017; ZHENG *et al.* 2022). However, adoption is still controversial, especially in developing countries, where there are several barriers to adopting digital agriculture innovations. Among them are the lack of adequate infrastructure, lack of Information Technology (IT) skills, financial support, inaccessibility to technology, and knowledge of digital agricultural technologies (Amoussouhoui *et al.* 2022; Benyam *et al.* 2021; Tinarwo and Uwizeyimana 2021). Even if the innovation is reliable, impactful, and solves a particular problem, it is important that the technology reaches the end user and that a strategy is designed to ensure sustainable adoption. This can be achieved through better knowledge of the socio-economic characteristics of the potential end-users and their willingness to use and adopt the technology. This study considers the case of a digital decision support tool developed by AfricaRice to provide personalized extension advice to rice farmers in Africa. After technology development, several studies were conducted to evaluate rice farmers' willingness to use the technology, their adoption, and the impact of the adoption of the technology (e.g., Amoussouhoui et al. (2022), Amoussouhoui et al. (2023), Arouna et al. (2020), Cotter et al. (2020), and Zossou et al. (2020)). These studies revealed that rice farmers appreciate technology, are ready to adopt it, and even pay for the technology's service. However, no theoretical and empirical framework supports farmers' adoption behavior in the context of an indirect adoption approach, which this study aims to establish through an experimental design. Future policies and initiatives aiming at adopting digital agricultural technologies in developing countries may use the findings of this study as a guide. In this context, this study aims to analyze rice farmers' behaviors in adopting the paid service for digital extension advice, evaluate their level of acceptability, and compare the results between farmers who experienced the service and those who did not. In this study, the proposed digital extension services named ''Business profile'' imply a set of services, including the price of the service, the payment method, the duration of the partnership, and the sale contract. Based on the socio-economic condition of developing countries affecting the adoption of digital extension technologies, two hypotheses were made: (i) the treated farmers have a significant and positive perception of the adoption of digital extension services compared to control farmers, therefore, would be more willing to continue the adoption; (ii) there is a significant difference in the effect of ''perceived ease of use'', ''perceived usefulness'', ''perceived payment method'' and ''perceived price'' on ''adoption'' and ''attitude'' between treatments and control.

The novelty of this study can be outlined in three points. First, this study proposes an extended Technology Acceptance Model (TAM) approach by adding two new constructs related to the perception of the price and the payment method of the service proposed. This provides a more specific and detailed analysis of farmers' behavior and their acceptance of the new adoption approach through the proposed business profiles. The TAM model is widely used in agricultural studies and especially in the extension literature (e.g., Almaiah et al. (2016), Verma & Sinha (2018), Strong et al. (2014), and Caffaro et al. (2020)). Second, this study experimented with using ''service provision'' as an indirect adoption approach of digital extension technologies, which implies providing paid services to farmers. In the context of agricultural extension in general and this study in particular, the term "service provision" suggests using digital extension technology by an outside actor with IT know-how to offer farmers customized extension advice in exchange for payment. By using the suggested services, farmers will subsequently adopt the extension technology indirectly. This approach not only removes farmers' barriers to the adoption of digital extension technologies, but it also represents a business opportunity for agri-business entrepreneurs. This provides the first experimental evidence of the use of the TAM approach. Third, this study proposes an analysis of a multi-group comparison between three treatments (three digital extension services) and one control group in an experimental study for the adoption of digital extension technologies.

In the following lines of this paper, we first provide details on the experimental design, the sampling and data collection, and the materials and methods in section 2. Results and discussion are presented in sections 3 and 4, respectively. In the final section, we concluded and provided related recommendations and policy implications.

4.2. Experimental design, sampling, and data

This study is an integrated Randomized Control Trial study being conducted to assess rice farmers' adoption of the digital extension technology through a business profiles adoption approach. The experiment consisted of two groups, the first being the treatment group with three treatments (three digital extension services differentiated by their characteristics) and the second being the control group. The treatment group consisted of three groups of farmers to whom we randomly assigned one of the three business profiles described (Table 4.1), while the control group consisted of farmers who did not receive any business proposition.

We used a multistage stratified sampling approach to identify the Local Government Areas (LGA), villages, and rice farmers for the field experiment. First, we chose the LGAs based on the following criteria: rice production, accessibility, farm distance, and security. Second, we used the same criteria to randomly select villages within the LGA. The villages were randomly assigned to one of the two groups: treatment or control. Finally, we randomly chose 20 rice farmers in each village that had at least 30% women. We have in total 400 rice farmers for treatment 1 (BP1), 400 each for treatments 2 (BP2) and 3 (BP3), and 360 for the control, giving us a total sample size of 1560 rice farmers (Figure 4.1). The data was collected in Jigawa and Kano states, in sixteen LGA and seventy-eight villages.

The data collection was done using a face-to-face survey with an Android tablet. We collected data on rice farmers' personal, socio-economic, demographic, and production information, as well as information on rice farmers' adoption and the TAM study from the three treated and one control groups. On a 5-point Likert scale (1–5) ("strongly disagree" to "strongly agree"), the respondents were asked to rate each statement for each construct for the treated and control group (See statements in Appendix 4.1).

Table 4.1. Proposed business profiles.

Attributes	**BP1**	**BP 2**	**BP3**	**No BP**
Payment method	Cash payment after harvest	Payment cash after harvest and incorporated into the rice price	Cash at delivery	No choice
Price $/hectare	US$13/hectare	US$0.66/200 kg	US$8.8/hectare	
Length of partnership	2 seasons	More than 2 seasons	1 season	
Contract farming	Yes	Yes	Yes	

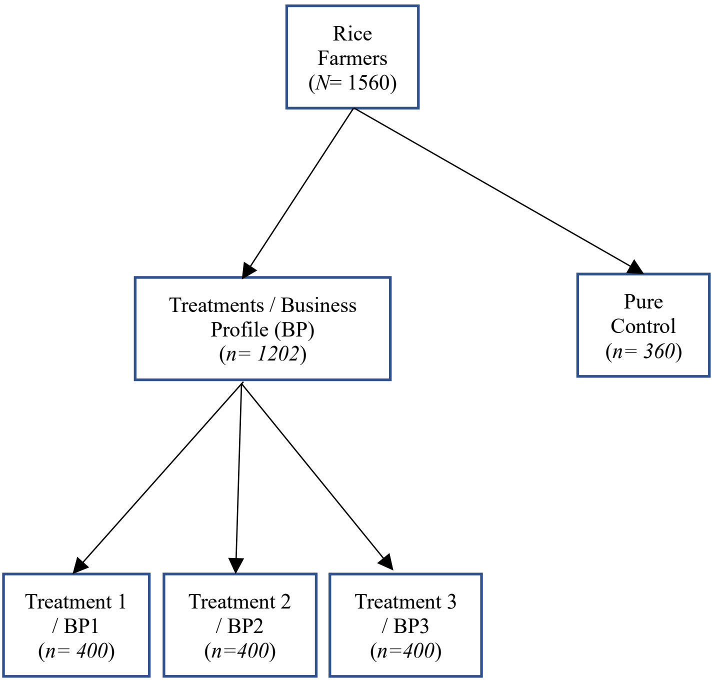

Figure 4.1. Experimental design.

4.3. Materials and methods

The extended TAM

The technology Acceptance Model is an approach from the theory of reasoned action (TRA) proposed by Davis et al. (1989). The model analyses the external factors that may affect the potential attitude, behavior, and thoughts. TAM was first used to evaluate the acceptance of Information Technology

(IT). However, due to the quick advancement of technology, it is now widely used to study the spread of emerging technologies, including IT and non-IT technologies (Vu and Lim 2022).

The first version developed was based on the Perceived Ease of Use (PEU) and the Perceived Usefulness (PU), which focus on users' ability to easily use the technology and the degree to which the use of the technology increases their productivity. The TAM model highlighted that the ease of use could also predict the usefulness and are related to the technology features (Natasia *et al.* 2022; Oyman *et al.* 2022). Later, two more versions of the model were introduced. The first, TAM-2 was developed, including experience and voluntariness as moderators and a new determinant for Perceived usefulness. The second, TAM-3 considers a set of determinants as external factors that may affect users' perception and behavior (Venkatesh and Bala 2008; Venkatesh and Davis 2000). According to the meta-analysis conducted by William and June (2006), TAM was the appropriate method with good results (Natasia et al. 2022). The basic TAM is based on five interrelated constructs as described as follows.

Perceived ease of use (PEU) is how the user understands the skills needed to use the technology (Davis 1989). In the case of this study, the perceived ease of use refers to how the rice farmers understand the business profile or service proposed to them and how easy the requirements are. Since it is not about farmers using the technology directly, their perception of the proposed business profile is what we search for.

Perceived usefulness (PU) aims to analyze how farmers perceived that the proposed business profile would likely improve their productivity and efficiency (Davis 1989). The idea here is to analyze how useful farmers perceived the adoption of the proposed extension services using the digital tool.

Attitude (ATT) represents the user's positive or negative behavior towards the technology (Jain and Goyal 2016). It describes the degree to which a farmer is persuaded to use the technology after weighing its benefits and drawbacks.

Intention to Adopt (ITA) is defined as the user's intention to adopt the technology (Davis 1989). The acceptance of a particular technology is determined by its perceived usefulness and ease of use, leading to the user deciding to adopt it (Davis 1989; Katebi *et al.* 2022). The intention to adopt measures the user's willingness to change and how much they are ready to do so (Ajzen and Driver 1991). In the context of the present study, we analyzed rice farmers' behavior in adopting the business model assigned to them for the treated farmers and the control group's intention to adopt the business model approach if proposed to them.

Actual Use (AU) refers to when a user has used the technology or considers the technology easy to use (Tangke 2004). This construct aims to analyze the perception of farmers who adopted and used the proposed business profile.

Image (IM) aims to analyze the importance of the external point of view in the use of digital extension services. It describes the extent to which one's status within their social system is perceived to improve using digital extension services (Landmann *et al.* 2021).

In the case of this study, we used the TAM for treated rice farmers who participated in the experiment and, therefore, were submitted to the use of the application through the adoption of the extension service assigned to them and a second TAM for the control group who have no access to the technology. The idea is to analyze the behavior in adopting the type of service assigned to treated farmers and, second, to analyze the control group's intention to adopt this new adoption approach. Both results were then compared to analyze rice farmers' behavior in this business profile. For this reason, we used an extended TAM by adding two more constructs to the original TAM constructs:

Perceived usefulness of the payment method (PUPM) refers to how useful the payment method is in adopting the digital extension service.

Perceived price (Pr) is considered as an important adoption factor. It is also important to analyze how useful farmers see the definition of price in adopting the service. For the control, the idea is to analyze their behavioral intention of paying for such a service. The cost of the technology referred to in this study as the price of the service provided is seen as an important predictor in the intention to adopt a technology or related service (Chen *et al.* 2017). Based on the TAM approach, we formulated the statements (loading factors) (Appendix 4.1) and hypotheses (Tables 4.2 and 4.3) for each construct.

Table 4.2. Hypotheses and pathway for the treated farmers.

H1. Perceived usefulness (PU) of using the business profile positively influences the adoption (ADP)	PU → ADP
H2. Perceived ease of use (PEU) of the business profile positively influences the adoption (ADP)	PEU → ADP
H3. Farmer’s attitude (ATT) towards IT positively influences the adoption (ADP)	ATT → ADP
H4. Perceived usefulness (PU) of using a business profile positively influences farmer’s attitude (ATT)	PU → ATT
H5. Perceived ease of use (PEU) of business profile positively influences farmers’ attitude (ATT)	PEU → ATT
H6. Adoption (ADP) positively influences Actual use (AU)	ADP → AU
H7. Image (IM) positively affects the adoption (ADP)	IM → ADP
H8. Image (IM) positively affects the Actual use (AU)	IM → AU
H9. Perceived usefulness of the payment method (PUPM) positively affects the adoption (ADP)	PUPM → ADP
H10. Perceived usefulness of the payment method (PUPM) positively affects the Actual use (AU)	PUPM → AU
H11. Perceived price (Pr) positively affects the adoption (ADP)	Pr → ADP
H12. Perceived price (Pr) positively affects the Actual use (AU)	Pr → AU

We have reviewed the hypothesis for the control group and adapted it to rice farmers’ knowledge. Since they did not receive any business proposition, we collected their Intention to Adopt (IAD). We removed the construct ‘’actual use’’ specific to the treated farmers. The initial hypothetical extended TAM is presented in Figure 4.2. The figure shows the constructs, their related loading factor, and the hypothetical interaction between the constructs.

Table 4.3. Hypotheses and Path for the Control Group.

H1. Perceived usefulness (PU) of using the business profile positively influences the Intention to adopt (IAD)	PU → IAD
H2. Perceived ease of use (PEU) of the business profile positively influences the Intention to adopt (IAD)	PEU → AID
H3. Farmer's attitude (ATT) towards IT positively influences the Intention to adopt (IAD)	ATT → IAD
H4. Perceived usefulness (PU) of using a business profile positively influences farmer's attitude (ATT)	PU → ATT
H5. Perceived ease of use (PEU) of business profile positively influences farmers' attitude (ATT)	PEU → ATT
H6. Perceived ease of use (PEU) of business profile positively influences perceived usefulness (PU)	PEU → PU
H7. Image (IM) positively affects the Intention to adopt (IAD)	IM → IAD
H8. Perceived usefulness of the payment method (PUPM) positively affects the Intention to adopt (IAD)	PUPM → IAD
H9. Perceived price (Pr) positively affects the Intention to adopt (IAD)	Pr → IAD

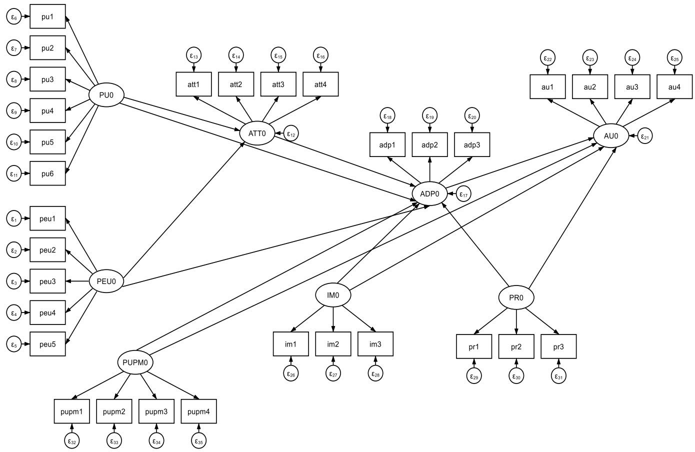

Figure 4.2. Initial hypothetical model of extended TAM.

4.4. Data analysis

We used the Partial-least Square Structural Equation Modelling (PLS-SEM) approach to analyze the data collected. PLS-SEM is a well-known and widely used approach to estimate the dependence and minimize the residual variable (Hair *et al.* 2017). It is used for extrapolating and merging the characteristics of principal component analysis and multiple regression (Latan 2018). Initiatively, SEM was used to identify the relationship between dependent and independent variables in a multivariate environment because there were multiple measurement items against constructs. PLS-SEM method has recently gained popularity among researchers (Ban *et al.* 2023; Katebi *et al.* 2022; Ly and Ly 2022) because it enables them to estimate complex models with multiple constructs, indicator variables, and structural paths without imposing distributional assumptions on the data. Compared to other prediction approaches, such as covariance-based testing, PLS-SEM is more accurate (Henseler 2018; Ly and Ly 2022) and allows this study first to analyze the relationship between the constructs for treated and control group, analyze farmers' behavior in adopting, the intention to adopt and a multi-group analysis between treatments.

Before the model estimation, the validity and reliability of the model were checked by examining the latent variables' similarities and internal and external consistency. We tested the statements' reliability and internal consistency using Cronbach's Alpha and Dillon-Goldstein's statistics (Fornell and Larcker 1981; Rodgers and Nicewander 1988). Although Hair et al. (2017) recommend that the values of Cronbach's alpha and Dillo-Goldtein's be higher than 0.7 in order to be considered "satisfactory good", values higher than 0.6 can be considered as "acceptable" in order to determine the reliability of the variable. After that, we evaluate the convergent validity using the Average Variance Extracted (AVE). The discriminant validity was also assessed using the Heterotrait-Monotrait (HTMT), which is advised to be lower than 0.90, indicating no discriminate validity issues (Hair *et al.* 2017). The data analysis was done using Stata 16.1.

4.5. Results

4.5.1. Reliability and consistency of the model

The finding shows that only 50% of the constructs have a Cronbach's alpha value greater than 0.6 for the first run. This is because the observed value derived from the constructs statement is very low. We decided to keep the loading factors for each construct while eliminating those with values less than 0.6. This led to seven over height constructs higher than 0.6 for Cronbach's alpha and seven over height constructs higher than 0.7 for Dillon-Goldstein's Rho in the second run. It should be noted that only the constructs "perceived usefulness" and "perceived price" have a value higher than 0.7 for Cronbach's alpha, meaning "satisfactory good" while the construct "adoption" failed to have values up to 0.6 for Cronbach's alpha. The treated model shows good internal and external consistency, except for one factor and estimated values for Cronbach's alpha and Dillon-Goldstein's Rho (Appendix 4.2.1). The control model (Appendix 4.2.2) is shown to be more internally and externally consistent than the treated model. The values of Cronbach's alpha and Dillon-Goldstein's Rho are all higher than 0.7 for all constructs and loading factors.

The results show a value of HTMT less than 0.90 for both the treated and control models. The constructs' pseudo-R^2 and average variance extracted (AVE) were estimated to evaluate the structural model's quality. The pseudo-R^2 for the height constructs in the treated model ranges from 0.311 to 0.668 (Appendix 4.3.1), indicating a reasonable fit. Except for "perceived price", other constructs have a value greater than

0.5, according to the convergent validity calculated using the AVE. The constructs in the control model have higher pseudo-R^2 values than those in the treated model (Appendix 4.3.2). Even though the constructs "attitude" (0.764) and "image" (0.760) are slightly higher than 0.75, the value is still in the range of 0.7135 and 0.760, indicating a reasonable fit. Like the treated model, all of the constructs showed convergent validity with AVE values greater than 0.50.

4.5.2. Path modeling results

Table 4.4 shows PLS-SEM findings, which reveal a generally favorable correlation between the variables. Results show that farmers' attitudes towards adopting digital extension services are directly and positively influenced by their perceptions and understanding of the technical skills required to use the extension service assigned to them. In this study, the skills or means required to use the proposed service, the level of understanding of the proposed service, the behavior of the farmers towards the proposed service, and how farmers assess the significance of an outside perspective on their decision to adopt or use the proposed service are all strongly correlated with adoption. However, farmers' perceptions of the price and the payment method appear to have both a direct and an indirect impact on the use of the service. Even though these factors are to be determinants in the adoption of a paid extension service, the correlation identified here is not as high as expected from farmers already exposed to the technology. However, this could be interpreted as a more realistic effect compared to those who were not in the situation of paying for the extension service or using a specific payment method. We can assume in that case that adopters' behavior will not be the same as non-adopters'. Furthermore, and as expected, the actual use of the proposed service is strongly correlated with the adoption, the image, and the payment method, while a lower correlation is found with the price.

All nine hypotheses show a positive correlation according to the PLS-SEM result for the control group (Table 4.5). As expected, the perceived usefulness of the proposed service is correlated with the perceived ease of use. The degree to which they understand the service affects their skills or means needed to use or execute the provided service. On the other hand, the attitude of farmers reflected by their positive or negative behavior towards the proposed service is affected by how farmers understand the proposed service, the impact of its adoption, and the skills or means required to use the service. The result also reveals a relatively strong and expected correlation between farmers' intention to adopt the paid digital extension service and their understanding of the proposed service, its utility, and the external view of the individual. In contrast to treated farmers who already used the service, the payment method and the price option ideas strongly affect control farmers' intention to adopt the proposed service.

Table 4.4. PLS-SEM result for treated farmers.

	Hypotheses	Direct effects	Indirect effect	Overall effect
H1	Adoption-> Perceived Usefulness	0.330	0.238	0.567
H2	Adoption -> Perceived of Ease Use	0.375	0.213	0.588
H3	Adoption -> Attitude	0.673		0.673
H4	Attitude -> Perceived Usefulness	0.353		0.353
H5	Attitude-> Perceived Ease of Use	0.316		0.316
H6	Actual Use -> Adoption	0.668		0.668
H7	Adoption -> Image	0.515		0.515
H8	Actual Use -> Image	0.272	0.344	0.616
H9	Adoption -> Perceived Payment Method	0.376		0.376
H10	Actual Use->Perceived Payment Method	0.379	0.251	0.631
H11	Adoption -> Perceived Price	0.251		0.251
H12	Actual Use -> Perceived Price	0.253	0.167	0.421

Table 4.5. PLS-SEM result for control farmers.

	Hypotheses	Direct effects	Indirect effect	Overall effect
H1	Intention to Adopt -> Perceived Usefulness	0.503	0.387	0.890
H2	Intention to Adopt -> Perceived Ease of Use	0.304	0.554	0.859
H3	Intention to Adopt -> Attitude	0.811		0.811
H4	Attitude -> Perceived Usefulness	0.477		0.477
H5	Attitude -> Perceived Ease of Use	0.220	0.201	0.421
H6	Perceived Usefulness -> Perceived Ease of Use	0.422		0.422
H7	Intention to Adopt -> Image	0.863		0.863
H8	Intention to Adopt -> Perceived Payment Method	0.888		0.888
H9	Intention to Adopt -> Perceived Price	0.864		0.864

4.5.3. Multi-group comparison among treated

Table 4.6 compares the loading factors between the business profiles, and Table 4.7 compares the path coefficients for the overall model and between the business profiles (Appendix 4.4). The results show that the loading factors ''PEU1'' (The collaboration during my RiceAdvice partnership went very well), ''ATT2'' (All things considered, I think that adopting this partnership by rice farmers is not a good idea.), ''ADP1'' (I will likely continue to adopt RiceAdvice through the partnership proposition), ''AU1'' (I have used and adopted the partnership assigned to me), ''IM1'' (Using the recommendation provided by the RiceAdvice application make me feel confident), ''PUPM1'' (I found appropriate and useful the proposed payment method), '' PUPM2'' (The payment method was respected accordingly to the partnership), '' PUPM3'' (I think the payment method should be reviewed to offer more options to farmers), ''PR1'' (I found the price of the service too high for me compared to the service offered), and ''PR2'' (I think the price should be reviewed and put down) are significantly different between the business profile 2 and 1 at 10%, 5%, and 1%. A significant difference is also found between business profiles 3 and 1. The loading factors ''PEU3'' (I feel comfortable and confident using the advice from the application), '' PUPM4'' (I think farmers should be free to choose any payment method without affecting the price), and price are significant at 1% while ''PU2'' (The adoption of partnership increases my productivity.) is significant at 5% and ''ADP1'' (I will likely continue to adopt RiceAdvice through the partnership proposition). ''IM2'' (Using the partnership has created a good image for my farm) and ''pupm1'' (I found appropriate and useful the proposed payment method) are significant at 10%.

Table 4.6. Multi-group comparison (treat) – Measurement effect.

Measurement effect	Global	BP1	BP2	BP3	AD_2vs1	AD_3vs1
Perceived Ease of Use -> PEU1	0.731	0.690	0.778	0.707	0.088*	0.018
Perceived Ease of Use -> PEU2	0.708	0.684	0.752	0.694	0.068	0.010
Perceived Ease of Use -> PEU3	0.656	0.694	0.697	0.551	0.003	0.144***
Perceived Ease of Use -> PEU4	0.727	0.732	0.727	0.729	0.004	0.003
Perceived Ease of Use -> PEU5	0.342	0.296	0.313	0.397	0.017	0.101
Perceived Usefulness -> PU1	0.682	0.680	0.674	0.689	0.007	0.009
Perceived Usefulness -> PU2	0.663	0.683	0.723	0.589	0.040	0.094*
Perceived Usefulness -> PU3	0.699	0.681	0.682	0.723	0.002	0.043
Perceived Usefulness -> PU4	0.604	0.578	0.630	0.595	0.052	0.017
Perceived Usefulness -> PU5	0.709	0.716	0.715	0.682	0.000	0.034
Perceived Usefulness -> PU6	0.041	0.008	0.104	0.013	0.096	0.005
Attitude -> ATT1	0.794	0.764	0.802	0.803	0.038	0.039
Attitude -> ATT2	0.034	-0.023	0.157	-0.008	0.180**	0.015
Attitude -> ATT3	0.733	0.707	0.726	0.744	0.020	0.037
Attitude -> ATT4	0.687	0.697	0.663	0.716	0.034	0.019
Adoption -> ADP1	0.745	0.649	0.791	0.763	0.141***	0.114**
Adoption -> ADP2	0.709	0.741	0.671	0.727	0.070	0.014
Adoption -> ADP3	0.723	0.700	0.738	0.726	0.039	0.026
Actual Use -> AU1	0.713	0.678	0.764	0.668	0.087*	0.009
Actual Use -> AU2	0.698	0.709	0.688	0.699	0.021	0.009
Actual Use -> AU3	0.636	0.615	0.674	0.614	0.059	0.001

Actual Use -> AU4	0.721	0.696	0.724	0.745	0.027	0.049
Image -> IM1	0.812	0.740	0.842	0.841	0.102**	0.101**
Image -> IM2	0.672	0.688	0.658	0.672	0.030	0.016
Image -> IM3	0.735	0.717	0.751	0.734	0.034	0.016
Perceived Payment Method -> PUPM1	0.683	0.575	0.755	0.693	0.180***	0.118**
Perceived Payment Method -> PUPM12	0.758	0.805	0.709	0.779	0.096**	0.026
Perceived Payment Method -> PUPM13	0.479	0.373	0.575	0.453	0.202***	0.080
Perceived Payment Method -> PUPM14	0.768	0.810	0.795	0.691	0.015	0.120***
Perceived Price -> PR1	0.139	-0.180	0.410	0.016	0.590***	0.196***
Perceived Price -> PR2	0.031	-0.347	0.259	0.032	0.606***	0.379***
Perceived Price -> PR3	0.997	0.952	0.949	0.997	0.003	0.045***

Note: **10%; * 5%, *** 1%; AD: Absolute Difference; VS: Versus

The path coefficient compared between business profiles in Table 4.7 led to the conclusion that the effect of the ‘’perceived ease of use’’ on ‘’attitude’’ is higher in business profile 2 than in business profiles 1 and 3. This difference is significant at 1% between business profiles 2 and 1; and 10% between business profiles 3 and 1. Business profile 2 has the highest effect (0.457). The effect of ‘’perceived usefulness’’ on the ‘’attitude’’ is higher in business profile 3 than the business profiles 2 and 1. The difference is significant at 10% and 1%, respectively, between business profiles 2 and 1 and 3 and 1. There is a stronger impact of "perceived usefulness" on "adoption" in business profile 1. We also found a significant difference of 10% between business profiles 3 and 1 for the effect of ‘’Perceived payment method’’ on ‘’Actual Use’’ and between business profiles 2 and 1 for the effect of ‘’Perceived Price’’ on ‘’Adoption’’.

Table 4.7. Multi-group comparison (treat) – Structural effect.

Structural effect	Global	BP1	BP2	BP3	AD_2vs1	AD_3vs1
Attitude -> Perceived Ease of Use	0.370	0.259	0.457	0.408	0.198***	0.149**
Adoption -> Perceived Ease of Use	0.376	0.428	0.321	0.359	0.107	0.070
Attitude -> Perceived Usefulness	0.433	0.328	0.467	0.508	0.139**	0.180***
Adoption -> Perceived Usefulness	0.373	0.468	0.325	0.324	0.143**	0.144**
Adoption -> Attitude	0.673	0.646	0.729	0.636	0.083*	0.010
Actual Use -> Adoption	0.717	0.719	0.740	0.677	0.021	0.041
Adoption -> Image	0.426	0.475	0.404	0.418	0.071	0.056
Actual Use -> Image	0.377	0.330	0.412	0.370	0.082	0.039
Adoption -> Perceived Payment Method	0.284	0.310	0.308	0.245	0.002	0.065
Actual Use -> Perceived Payment Method	0.502	0.412	0.502	0.583	0.090	0.171**
Adoption -> Perceived Price	0.189	0.085	0.293	0.170	0.208**	0.085
Actual Use -> Perceived Price	0.323	0.353	0.292	0.328	0.061	0.025

Note: **10%; * 5%, *** 1%; AD: absolute difference

4.6. Discussion

The direct adoption of digital extension technology is challenging, especially in developing countries (Amoussouhoui et al. 2023; Ayim et al. 2022). This study analyzed an indirect adoption approach through a paid service provided to farmers using digital extension technology. The study determined whether the adoption of the proposed service through three business profiles is well understood and analyzed the factors that affect the adoption and the intention to adopt farmers non-exposed to the proposed service.

For the treated farmers, the findings revealed that farmers' attitude towards the proposed service is affected by the perceived ease of use and the perceived usefulness of the proposed service. Given that this is a novel approach, this relationship is expected, and it is crucial for the beneficiary to fully understand all the conditions surrounding the suggested service. This finding is similar to the results reported by Verma & Sinha (2018), who also concluded that the perceived ease of use and the perceived usefulness positively affect attitude. Similar results were also found by Bakhsh et al. (2017) and Choi et al. (2014). Similarly to the attitude, the study reveals a positive effect of perceived ease of use and perceived usefulness on farmers' adoption. Same as the positive effect of attitude on the adoption.

This study concerned exposed farmers who used the proposed digital extension service and those not exposed to the technology from whom we then analyzed their behavioral intention to adopt the new adoption approach. As proof, the control group's PLS-SEM revealed the positive effect of perceived ease of use, perceived usefulness, and attitude on farmers' behavioral intention to adopt the digital extension service. This finding is similar to Kabir et al. (2022), who also established a positive relationship between the perceived ease of use and the perceived usefulness, the perceived ease of use and farmers' intention to adopt, and the same for the perceived usefulness and the attitude. Similar results were found by other researchers, such as Diop et al. (2019), Verma & Sinha (2018), Gurtner et al. (2014), Zin et al. (2023), and Caffaro et al. (2020). Results also showed that the effect of attitude (0.811) is greater than the effect of perceived ease of use (0.220) and perceived usefulness (0.477). A similar result was observed for the adoption model (McDonald et al. 2015; Obiero et al. 2019).

The finding reveals a direct and indirect relationship between perceived payment method, perceived price, and actual use. Only a direct effect is observed on the adoption. This means that the cost of the service has a significant effect on both adoption and actual use. This finding is in line with a similar study conducted by Kelly et al. (2023), who showed that users are more likely to use the technology if the perceived price offers a good opportunity cost. In the literature, very few studies have been done to establish the relationship between the perceived price and the adoption or actual use.

Note that even if the effect is the same for the control farmers, the effect of the perceived payment method and the perceived price on farmers' intention to adopt is up to 0.888 and 0.864. The difference is that treated farmers have already used the services and the payment method and paid the proposed price, and therefore, we could assume that their effect is likely more realistic, which is why their effect is lower. However, three business profiles were submitted to farmers, and it is important to seek the existence of significant differences between the loading factors and the path models. The result of the multi-group comparison showed significant differences between the three business profiles for several loading factors. This is an expected finding due to the business profile characteristics defined by the payment methods and price options. One finding in this study is the difference in the path's effect between business profiles. The results show that the effect of perceived ease of use on farmers' attitudes significantly differs from one business profile to another, with a higher effect in business profile 2. This means that particular attention needs to be paid to rice farmers' perception of how easy the business profile is. 2. The higher the effect on attitude, the more complex the perception of farmers will likely be, which may lead to an uncomprehensive partnership between service providers and farmers. Similarly, the effect of perceived usefulness on farmers' attitudes and adoption differs from one business profile to another. The effect of perceived usefulness on farmers' attitudes is higher in business profiles 3 and 1 for the effect on the adoption. This finding confirmed that while the perceived ease of use and the perceived usefulness are the two most important constructs in the TAM model (Ghazizadeh *et al.* 2012; Verma and Sinha 2018), it is important to highlight that the attitude and adoption are also very important constructs that contribute to farmers' decision and sustainable usage of the technology (Ge *et al.* 2023; Jami Pour *et al.* 2023). Our finding also reveals that the two new constructs integrated into the TAM model ‘’perceived payment method’’ and ‘’perceived price’’ significantly affect the actual use and adoption from one business profile to another. The payment methods and price options determine how rice farmers actually use and put into practice the advice received from the service provider and will, therefore, define their decision of continuous use. In the sense that a farmer paying cash at service delivery at a lower price and another paying after harvest at a higher price will not have the same behavior of the usage made of the received advice and on future adoption decisions.

4.7. Conclusion

A significant challenge is the long-term adoption of digital extension technology. Even though several studies have shown and demonstrated the impact of adopting digital extension, the adoption is still low due to low e-literacy, the lack of knowledge of digital tools, lack of access, and adequate infrastructure. Most of those constraints can be reduced by the paid extension service. Farmers can take advantage of the technology without directly using it, knowing how to use it, or owning an IT tool. Farmers can then pay for a service provided to them using the technology. This is an indirect strategy that not only addresses farmer adoption issues but also presents an opportunity for agribusiness entrepreneurs. This study analyzed rice farmers' behavior in adopting three business profiles (extension services) and the intention to adopt farmers not exposed to the new adoption approach. The two new constructs, "perceived payment method" and "perceived price," which are the critical components of the new adoption approach, were added to an expanded version of the TAM. The result of the study led us to three main conclusions. First, this study confirms that the two most crucial constructs in the TAM model are "perceived ease of use" and "perceived usefulness." These two constructs positively impact attitude, adoption, and intention to adopt, especially when they have a direct or indirect relationship. This result concerns agribusiness entrepreneurs, in particular when designing strategies to concentrate on farmers' comprehension of the proposed service and its applicability and clearly highlighting its utility by defining the potential impact. Second, the payment and price options, which make up the bulk of the extension service proposal, favorably impact farmers' adoption and intent to adopt. Additionally, the perceived payment method and price positively influence how frequently farmers use the digital extension service. Although farmers were not given a choice in the experiment regarding the type of service provided to them, the results demonstrated that the combination of payment and price options is an adequate remedy for the lack of financial resources, which subsequently justifies the favorable impact on actual use. Third, there are differences between business profiles in how "perceived ease of use", "perceived usefulness", and "adoption" affect "attitude" and "adoption". This demonstrates that the pricing and payment options that defined the business profiles favorably affected farmers' adoption of and attitudes toward the suggested service. The adoption of the proposed paid extension service and the intention of adopting farmers show farmers' interest in using digital technology in agriculture. However, all actors, including researchers, development partners, and Agri-investors, must work together to first analyze smallholder farmers' behavior and perception based on their socio-economic realities in order to define appropriate and sustainable ways to make the technology accessible but also define strategies and adequate policies to ensure its sustainable adoption. This study is considered to be a step and a contribution to finding the most preferred adoption approach for digital extension technologies.

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5. Digitized Extension Service Business Model: An Experimental Evidence in Nigeria

Adapted from: Amoussouhoui, R., Arouna, A., Akpa, A., Yergo, W., Banout, J., Digitized Extension Service Business Model: An Experimental Evidence in Nigeria. Will be submitted.

Credit author statement: Rico Amoussouhoui: Data curation, Formal analysis, Original draft, Writing - review & editing, Methodology. **Aminou Arouna**: Conceptualization, Investigation, Funding acquisition, Writing - review & editing. **Aristide Akpa**: Formal analysis, Writing - review & editing, Methodology. **Wilfried Yergo**: Data collection, Data curation, Conceptualization, Review-editing. **Jan Banout**: Conceptualization, Supervision; Writing - review & editing; Validation.

Abstract

Technologies for digital extension emerged to ease smallholder farmers' constraints throughout the production chain. However, its adoption by smallholder farmers is still challenging. This study assessed the adoption and impact of a digital paid extension service using a randomized controlled trial approach. Data were collected from a sample size of 1560 rice farmers in Nigeria, including 1200 treated and 360 control farmers. The findings show that more than 61% of the exposed rice farmers adopted and paid for the digital extension services. In addition, we found evidence that the digital paid extension service implying payment after harvest at US$13/ha is the most adopted, and the service suggesting cash payment at delivery has the highest impact on farmers' economic performance unexpectedly. We did, however, find evidence that the digital paid extension service with payment after harvest link to the quantity sold does not impact farmers' economic performance but has the highest impact on their profit. This result suggests that farmers should be advised of this business partnership even if it is the second most preferred. This paper contributes to the literature with evidence of smallholder farmers' adoption and impact of paid digital extension services. Agri-business entrepreneurs and policymakers should consider this adoption approach to disseminate and ensure a sustainable adoption of digital extension technologies.

Keywords: Digital Extension; Paid extension service; Technologies; Rice farmers; Nigeria

5.1. Introduction

The rice sector in Sub-Saharan Africa (SSA) is facing important constraints that need to be addressed to ensure sustainable economic development of the sector. Although progress has been made, especially in terms of increasing production volumes, rice consumption is still increasing. Rice consumption has become important for food and nutrition security in many developing countries, including Nigeria. The rice value chain development requires technological advances to improve rice yield and valorize local rice production [1]. As a solution, digital technologies were developed to improve the rice value chain. Among them is RiceAdvice, a decision support tool developed by AfricaRice and partners to provide digital and personalized recommendations to African rice farmers. Several studies assessed technology acceptance and its impact on productivity and food security. However, the sustainable adoption of the technology by rice farmers is still a challenge when considering farmers' low access to IT infrastructure, low e-literacy, and financial constraints. The solution could be an indirect adoption approach through a business model implying a paid service provided to rice farmers using the technology. The literature showed that in the last decade, the private and paid extension services had risen instead for two main reasons: (i) the expensive cost of the public extension service, which leads the government to opt out, especially in developing countries [2,3], and (ii) the inefficiency of the public extension service [4]. While the literature provides information on the reasons and needs for transition, it does not provide information on creating and developing a framework for adopting private and paid extension services. Therefore, business models for private and paid extension services are required and seem to be effective ways to sustain the adoption of technology such as RiceAdvice. Moreover, considering the increase in the unemployment rate from 20.4% in 2017 to 23.1% in 2018 [5] and the youth unemployment rate, which increased from 13,96% in 2017 to 14,17% in 2020 [6], this study aims to test the RiceAdvice as a tool for the private extension sector to support the development of the rice sector and to provide business framework for young people or investors willing to invest in the private extension.

Although recent studies were conducted by Amoussouhoui et al. [7] to assess farmers' willingness to pay for extension advice provided using RiceAdvice and evaluate the profitability of such business, Arouna et al. [8] have assessed the impact of free personalized advice using RiceAdvice on rice productivity and income, and Zossou et al. [9] assessed the opportunities and constraints in scaling up the RiceAdvice. None of the previous studies proposed a framework for scaling up the technology or a sustainable diffusion process. This study aims to fill this gap by testing different business models based on key factors that ensure the sustainable adoption of RiceAdvice. While the term ''Business model'' is defined as a 'business which describes the rationale of how an organization creates, delivers, and captures value [10], it also implies how the organization makes a profit from the value creation [11–13].' In this study, a business model means a set of services proposed and delivered to rice farmers in return for a defined price and payment method. The proposed business models are based on two facts: (i) in the production chain, rice producers are not used to private extension and paid agricultural extension services; (ii) farmers face liquidity constraints during the production season when there is a need for RiceAdvice. Based on this context and the literature, we proposed to test business models with three different prices and payment methods: 1) payment for the service is deferred to the harvest period; 2) payment for the service is included in the price of the rice (no separate fee), and 3) payment in cash when the service is delivered. This study asks three essential research questions:

- What are the adoption rates of the digital paid extension services?
- What are the determinant factors of farmers' willingness to adopt and the adoption of the digital paid extension service?
- How does adopting the digital paid extension service impact rice farmers' economic efficiency and production profitability?

The contribution of the study to literature is twofold. First, contrary to the literature, we assessed the impact of an indirect adoption approach, implying that even if farmers do not have smartphone or internet access to download the application and have no IT skills, they can still benefit from the advantages of using digital extension tools. We consider as adopters the farmers who, in addition to their willingness to adopt, paid accordingly for the service assigned to them. Second, this study provides the first experimental evidence of the impact of adopting a digital paid extension service approach as a strategy for adopting digital extension tools.

In the following lines, the study context and the experimental design. We presented the preliminary and primary results, and we discussed the results. The closing section presents the conclusion and policy implications.

5.2. Context and Experimental Design

5.2.1. Study's background

This study focuses on the new digital extension tool,"RiceAdvice" developed by AfricaRice, to provide personalized extension advice to African rice farmers. As stated above, several studies have been conducted on the technology. However, there is a lack of information and practical framework to ensure sustainable technology adoption. After the validation of the "RiceAdvice", the Competitive African Rice Initiative (CARI) project in Nigeria has initiated a semi-business approach with rice value chain actors for the scaling of the application. The idea was to make the technology accessible for rice farmers by providing personalized extension services using the RiceAdvice tool. CARI has partnered with Rice Millers who work on a rice trading contract with rice farmers. The new initiative consisted of providing a free digital extension service to rice farmers, and CARI and the rice Millers covered the cost of the service. CARI has involved three rice millers for the project: ATAFI, Green Sahel, and Seed First. Predictability, as good and impactful as it was, the initiative stops at the end of the project. The lesson learned from that experience is that what is needed is an independent adoption approach that can be adapted and used by other digital technologies and can be freely conceptualized and used by private and government institutions. This approach ensures that even when farmers cannot directly use digital technology, they can still have access to and use it through a well-designed framework, and that is where the initiative of this study comes from.

The experiment was conducted in collaboration with CARI and rice farmers, and we chose the best two rice millers' business actors, ATAFI and Green Sahel. The choice was made together with CARI based on their productivity in the field, their results, and their efficiency in the previous collaboration with CARI. Business models that provide personalized extension services to rice farmers in return for payment from them were developed. Based on the rice farmers' financial constraints and the idea of making the approach profitable for the service provider (youth or rice millers), we defined three business models based on the service price and the payment method. The defined service prices are based on the business profitability study conducted by Amoussouhoui et al. [11] who stimulated the service prices and defined the appropriate price for the business to be profitable for the service provider. The business models offer rice farmers the possibility of benefitting from personalized advice using the RiceAdvice tools schedule on six visits during one rice season.

5.2.2. Field interventions, Experimental design, and Sampling

Field intervention

The intervention includes the treatment arms with three business models, which in this study differ by service price and the payment method. In our study, the business model includes three main internal actors in the rice value chain and one external support:

- Millers were the first buyers of paddy rice. Millers already do business with a network of rice farmers. They propose trading contracts to rice farmers, including access to credit (cash or in-kind) and extension advice in exchange for rice farmers' production.
- The agents - provide extension services to rice producers throughout the production process. They have IT skills and collaborate with the millers.
- Rice producers - despite their experience, need more accurate and personalized information to operate more efficiently with the challenge of climate change.
- External stakeholders - CARI/Giz project is supporting rice sector development in Nigeria through various interventions with rice millers.

The main idea of this research is to find a sustainable business model where there is no external support, and the service provider is either *(a)* dependent: employed by the miller and paid based on his work (how many rice producers he convinces and signs a contract with for the miller) or *(b)* independent: as young freelance who uses the business model designed and the application RiceAdvice to build his own network of millers and rice producers.

The first treatment (BM1) foresees contract farming and digital personalized extension service with payment of US$13/ha after harvest. The concept of contract farming is categorized by three factors, which are (i) fixed price, (ii) production management, and (ii) input of supply [14]. The rice producers have already been using contract farming with credit proposed to them in terms of input supply or cash, so the additional service here is the personalized extension service. The service provider will assist the rice producer during the production process by providing advice on good agricultural practices. The intervention is done in six visits scheduled with the rice farmers. Based on the targeted yield, personalized services are provided upon advice on the quantity of seed needed, the amount of fertilizer, crop calendar, and related practical advice for rice farm management. The rice producer is invited to make payment after harvest. This payment option is delayed, reflecting that farmers face cash constraints during the production process and can receive payment either at rice maturity (even before harvest) or after harvest and sale, depending on the contract with their buyer.

Treatment 2 (BM2) provides the same service as presented in treatment 1, but the payment method is after harvest and incorporated in the price of rice that the farmer is willing to sell to the miller. For this experiment, the price is set at US$0.66 per 200kg of rice paddy. Therefore, to ensure transparency, we recommend that at the time of the agreement, the price of the rice (US$/kg) must be set, and the agreement of both parties must be obtained. A written contract is signed between both parties specifying the fixed rice price incorporating the cost of the service, the services to be provided by the agent, and the timing and duration.

Treatment 3 (BM3) offers the same service but with a cash payment of US$8.8/ha. The rice farmer must pay the agent in cash for each consultation. We expected a lower adoption rate for this treatment because of farmers' liquidity constraints during the cropping season. However, during the discussion with actors, rice farmers insisted on incorporating this option because some farmers who have multiple off-farm incomes may be able to afford a cash payment.

In addition to the treatment groups, there is a control group (C), with no digital extension advice or business model proposition.

The prices and the payment methods were determined jointly with business promotors (ATAFI and Green Sahel) and rice farmers to ensure the profitability of the activity for the business promotors and an affordable price for the rice farmers. We collect qualitative data to estimate rice farmers' willingness to pay for the advice. In addition, we organized a business-to-business workshop to which all the parties were invited. We used the participative approach and asked the different actors to give their minimum and maximum prices for each business model based on the service and the payment method. The result of this participative exercise enables us to have an interval of price for each business model.

Experimental design and Sampling

To achieve the study's objective, the experimental design randomly assigned the treatment and control groups to rice farmers (Figure 5.1). The experimental design is composed of three treatment arms based on the price of the service and payment method, along with a control group that did not benefit from RiceAdvice services. We consider the control group has received the usual blank advice from the government institution.

Three hypotheses were tested:

Hypothesis 1: The adoption of business models positively affects farmers' economic efficiency and profitability.

Hypothesis 2: Household head sex, age, Education level, Training, Household size, Access to credit, Ownership of phone, Experience in rice Production, Rice area, and Distance to the market are the main factors that determine the business model adoption and payment.

Hypothesis 3: There is at least one business model that increases farmers' economic efficiency and profitability.

The sample size for the experiment was determined using power calculation. Economic efficiency, as the main outcome, was used for the power calculation. To do so, we used data collected in 2021 (data collected for an ex-ante analysis of the acceptability of theoretical businesses) in Kano State, Nigeria, to estimate the mean of economic efficiency for the treatment and control groups. The mean of the control group was estimated at 0.557 and 0.471 for the treatment group. Using the power command in Stata version 16, we have a minimum effect size of 216 at a power of 0.99 and a minimum detectable effect size of 0.38. We go beyond that with a total sample size of 1560 farmers.

For the selection of the households to be surveyed, we received an official list of the Local Government Area (LGA) in which ATAFI and Green Sahel operate. From the list, we randomly selected 1560 rice farmers for the survey. Note that a first sampling was done with a total of 1440 rice farmers, with

360 rice farmers per treatment and control. We conducted the baseline in June 2021, and the follow-up was scheduled to be conducted after the intervention at the end of the season. However, we encountered two major issues. First, there was a very big flooding in the selected areas, which led to the loss of production fields for up to 80 % of the farmers to be surveyed. Second, one of the partners was not able to follow up on the study and participate in the follow-up activities for logistic reasons. This has caused a disruption in the experiment, so we have rescheduled and conducted a new sampling by reducing the area of substantial risk of flooding and increasing the sampling size. This led us to a total of 1560 farmers with whom we conducted a new baseline in June-July 2022 and the follow-up survey after the intervention in July 2023 (Appendix 5.3).

A multistage stratified sampling approach was used to identify the Local Government Areas (LGAs), villages, and households to be surveyed. First, we select LGAs based on the following characteristics: a minimum of 20 rice farmers in the village, accessibility, distance to the farm, and security. Second, we use the same criteria to randomly select villages within the LGA. The villages were randomly assigned into the treatment and control groups. Finally, we randomly selected 20 rice farmers per village selected.

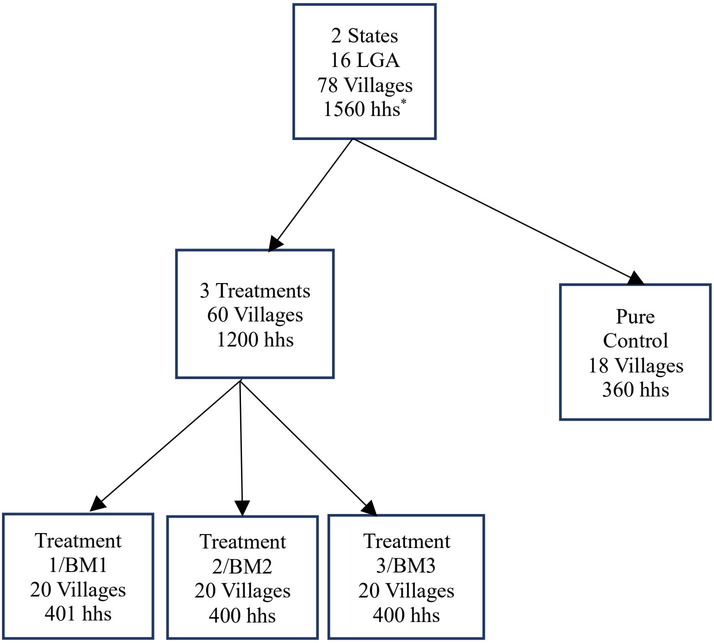

Figure 5.1. Experimental design, *Households.

5.2.3. Data collection and outcomes variables measurement

The data collection was done in three phases. First, the focus group was done with the main actors of the digital extension chain: rice producers, extension agents, and rice millers. The second data collection was the baseline, during which we collected socioeconomic data, production, and information related to farmers' experiences with extension agents as well as their previous knowledge or experience in digital extension services. Finally, we collected the follow-up data after the intervention.

Contrarily to the impact of free advice using the RiceAdvice application conducted by Arouna et al., [8], farmers have paid for the provided service in this study, and we are interested in measuring the impact on the economic performance and profit, taking into account the additional cost of production (cost of the digital paid extension service). Economic efficiency is a well-known indicator that measures a subject's technical and allocative performance [15,16]. It includes the use of production inputs as well as their price. This is considered an important indicator because we hypothesize that the advice received by farmers will lead them to make efficient use of the production inputs and, therefore, have a higher economic efficiency. Economic efficiency is obtained from a multiplicative interaction between the technical and allocative efficiency, estimated using the Cobb-Douglas frontier technique described by Farrel[1] [17]. On the other hand, the profit was estimated using the gross operating income estimation approach.

[1] The stochastic frontier approach is the one used with the Cobb-Douglas function to estimate technical efficiency. The estimation of the functional form was made using the Ordinary Least Squares technique.

$$\ln(Y_i) = \beta_0 + \sum_{i=1}^{k} \beta_i \ln(X_i) + V_i - I_i$$

With, Y_i the output of producer i, β_0 the constant, β_i the elasticity of production, V_i the purely random variable beyond control, I_i the technical inefficiency of firm i and i represents the producers. X_i represents the independent variables.

Balance test

Table 5.1 presents the coefficients of an OLS regression comparing treatments and the control group. The control group had an economic efficiency lower than the overall treatment group and the BM1 and BM2 before the treatment. Only BM3 has a lower economic performance than the control group, which is significantly different from BM1 and BM2. However, the control group realized a profit higher than the overall treatment and the treatment taken individually, with significant differences with BM3. Among the production factors, the quantity of NPK used is significantly different between the control group and the treatments. The control used around 46kg/ha of NPK, more than the treatments. No significant difference is observed for the other production factors. Regarding the socioeconomic factors, there is an overall good balance, except for four factors. The age of household head and household size, where a significant difference of three years and one member, respectively, is observed between BM2 and BM3. The access to credit is significantly different between BM2 and BM1, and the marital status is also significantly different between the control group and the treatment, with the control group having fewer married household heads compared to the treatments. In general, results indicate good balance, and where differences appear, we used the empirical method to control the differences.

Table 5.1. Balance pre-contamination.

	Treated	T-C	BM1-C	BM2-C	BM3-C	BM2-BM1	BM3-BM1	BM3-BM2
Economic Efficiency EE (0<EE<1)	0.571	0.016	0.049	0.064	-0.065	-0.016	0.114***	-0.129***
	(0.200)	(0.073)	(0.074)	(0.074)	(0.079)	(0.024)	(0.033)	(0.025)
Profit (US$/ha)	2123	113	104	409	-172	-304	277	-582**
	(1587)	(334)	(424)	(366)	(307)	(205)	(343)	(225)
Quantity seed (kg/ha)	70.183	-0.647	1.340	0.452	-3.663	0.887	5.002	-4.115
	(28.330)	(5.527)	(5.523)	(5.479)	(6.765)	(3.731)	(4.504)	(2.630)
Quantity NPK (kg/ha)	142.847	-45.462*	-50.767*	-40.580*	-45.228*	-10.187	-5.539	-4.648
	(102.240)	(19.349)	(23.436)	(18.437)	(22.197)	(12.172)	(20.217)	(14.699)
Quantity Urea (kg/ha)	95.839	-25.037	-23.767	-27.316	-23.985	3.549	0.218	3.331
	(60.284)	(13.994)	(17.499)	(14.148)	(14.953)	(9.653)	(15.007)	(9.780)
Quantity Organic (kg/ha)	0.298	0.273	0.009	0.016	0.785	-0.007	-0.776	0.769
	(3.473)	(0.209)	(0.026)	(0.027)	(0.605)	(0.018)	(0.623)	(0.623)
Quantity herbicide (l/ha)	4.405	1.341	1.422	0.932	1.670	0.490	-0.247	0.738
	(4.798)	(0.897)	(0.910)	(0.958)	(0.988)	(0.481)	(0.676)	(0.488)
Age of rice producer (years)	45.142	0.948	1.288	2.126	-0.569	-0.837	1.858	-2.695**
	(9.599)	(1.179)	(1.560)	(1.387)	(1.508)	(1.313)	(1.861)	(1.029)
Household size (n)	14.982	0.835	0.725	1.710	0.070	-0.985	0.655	-1.640*
	(9.122)	(0.911)	(0.891)	(1.135)	(1.101)	(0.767)	(0.892)	(0.787)
Education (=Primary)	0.432	0.041	0.018	0.066	0.038	-0.048	-0.020	-0.028
	(0.496)	(0.043)	(0.057)	(0.057)	(0.049)	(0.041)	(0.058)	(0.067)

Agricultural as main activity (=1)	0.962	-0.022	-0.041	-0.003	-0.021	-0.038	-0.020	-0.017
	(0.192)	(0.017)	(0.038)	(0.017)	(0.014)	(0.039)	(0.038)	(0.014)
Agricultural Training (Days)	0.552	0.127	0.115	0.148	0.118	-0.033	-0.003	-0.030
	(0.498)	(0.097)	(0.099)	(0.112)	(0.104)	(0.066)	(0.074)	(0.060)
Credit for rice production (=1)	0.054	-0.010	0.023	-0.039	-0.012	0.063**	0.036	0.027
	(0.226)	(0.028)	(0.034)	(0.032)	(0.027)	(0.020)	(0.025)	(0.018)
Marital Status (=Married)	0.975	0.047***	0.052***	0.047**	0.042**	0.005	0.010	-0.005
	(0.156)	(0.014)	(0.015)	(0.017)	(0.015)	(0.012)	(0.012)	(0.015)
Ownership of smartphone? (=1)	0.183	0.017	-0.002	-0.009	0.061	0.007	-0.063	0.070
	(0.387)	(0.044)	(0.056)	(0.058)	(0.037)	(0.019)	(0.044)	(0.047)
Experience in rice production? (years)	21	-2	-1	-1	-4	-0	3	-3
	(12)	(2)	(2)	(2)	(2)	(1)	(1)	(1)
Yield (kg/ha)	4151.287	-427.647	-408.351	-225.315	-648.593	-183.036	240.242	-423.278
	(1752.525)	(618.027)	(628.466)	(653.831)	(636.092)	(276.738)	(293.170)	(252.445)
Rice area (ha)	1.091	0.041	0.070	-0.001	0.054	0.072	0.017	0.055
	(0.744)	(0.087)	(0.115)	(0.095)	(0.087)	(0.066)	(0.095)	(0.095)

5.3. Analysis

5.3.1. Statistical methods and models

Objective 1: is to estimate the overall adoption of business models. In addition, analyzes the behavior of farmers who accepted adopting the assigned business model (Willingness to pay/Adopt) versus farmers who adopted by paying accordingly to the assigned business model (Adopters).

Objective 2: is to estimate the determinant factors, we used the Heckman probit model [18] to estimate the determinants of the willingness to pay/adopt, the determinant of the overall adopters, and finally, the determinant of the adoption of the business model taken separately. The Heckman probit model is composed of two equations. The first is a probit equation where the dependent variable (binary variable) is the adoption of the business model, which takes the value 1 for the overall adoption and the adoption of the assigned business model and the value 0 otherwise. The second is a section equation where the dependent (binary) variable is the farmers' willingness to adopt and pay for the business model. It takes the value 1 for the overall willingness and the willingness for the specific business model and 0 otherwise. For both equations, the independent variables are the socioeconomic variables enumerated in the hypothesis formation.

A single mean difference would give us the required impact for the impact assessment. However, since we have both baseline and end-line information, we used two approaches to estimate farmers' Intention To Treat and the treatment effect on adopters.

- first, we used a simple OLS model to estimate the Intention To Treat (ITT) effect:

$$Y_i = \alpha + \delta_{OLS} T_i + \beta X_i + \in_i \quad (1)$$

Where Y_i is the outcome variable (Farmers' decision to adopt and the adopters) and T_i the rice producer's indicator of whether or not he was invited to the intervention or not, and δ_{OLS} the coefficient of the OLS estimation; and X_i the household characteristics and $\in_i$ the idiosyncratic error term.

- Our second estimator is the covariance analysis (ANCOVA) to estimate the treatment effect:

$$Y_i = \alpha + \delta_{ANCOVA} T_i + \theta Y_{i,PRE} + \beta X_i + \in_i \quad (2)$$

Where $Y_{i,PRE}$ is the pre-treatment (baseline) outcome value and δ_{ANCOVA} is the coefficient of the ANCOVA of ITT estimation. The ANCOVA estimator has more power compared to a difference-in-difference [19].

5.3.2. Multiple outcomes and multiple hypothesis testing

This study implies two outcomes (economic efficiency and profitability index) and three treatments, leading us to a total of six hypotheses tests and then six p-values. This large number of hypothesis tests requires adjustment to control for Type I error and thus increase the power to detect significant differences [20]. Several multiple hypothesis testing approaches have been proposed in the literature to reduce false rejections. In the case of this study, we followed Arouna et al. [14] and Mckenzie [21] by using different and recent approaches. We first adjust the p-value using Clarke et al. [22] approach and estimate the FDR q-value using Anderson's approach.

5.3.3. Heterogeneous effects

In this study, we used the Conditional Average Treatment Effects with interaction to investigate the heterogeneity effect. For this purpose, we used the following regression:

$$Y_i = \alpha + \beta T_i + \rho Z_i + \delta Z_i T_i + \theta Y_{i,PRE} + \epsilon_i \quad (3)$$

Where is β is the estimate of the Average Treatment Effect (ATE); δ is the coefficient of interest and represents the interaction effect and the interaction between treatment and covariate.

Regarding the variables we included in the regression, we followed Arouna et al. [14] and used the following variables from the baseline: experience in rice production, access to credit, age, level of education, yield, training in rice, and household size.

5.4. Results

5.4.1. Preliminary results on adoption and its determinant factors

Willingness to pay and adoption analysis

The first part of the intervention was to explain to each farmer the content of the business model assigned to the household and, in the end, collect his willingness to pay and adopt the business model. For those who said ‘’No,” a second visit was paid to them to see if they had changed their mind with time. At the end of the exercise, Table 5.2 shows that 92.83% of the farmers visited agreed to adopt the business model assigned to them. However, for several reasons (See Figure 5.2), only

61.67 % of farmers who agreed really paid according to the business model assigned to them and are therefore considered adopters.

When considering the business models individually, we observed that business model 1 has the highest adoption rate (86.77%). Business model 1 implies that farmers prefer to receive the service at the highest price (US$13/hectare) but pay after harvest. This is expected to be the most preferred business model because it allows farmers to receive the service even if they do not have financial means when it is provided. However, the price is higher compared to business model 3 because a payment delay is a business risk that service providers must consider. The second most preferred option is the business model 2 (49.08%). Even if this has the highest service cost, it gives farmers the freedom to sell their production to whoever they want at the price they want. This could be the reason that justifies the adoption of this business model. Business model 3 is the least preferred by rice farmers even though it has an expected consistent adoption rate of up to 48.46%. This is not expected because we assumed that this business model would be the least preferred and likely have a low adoption rate because it implies a cash payment, which could be a constraint for farmers. Besides the adoption analysis and the reasons for non-adoption, we also investigate the determinant factors that drive the willingness and the adoption of the business models.

Table 5.2. Adoption Analysis.

	Willingness to Adopt/Pay	Paid / Adopters	Did not pay
BM1	94.50 (378/400)	86.77 (328)	13.23 (50)
BM2	94.75 (379/400)	49.08 (186)	50.92 (193)

BM3	93.94 (357/380)	48.46 (173)	51.54 (184)
Overall (%(n))	92.83 (1114/1200)	61.67 (687)	38.33 (427)

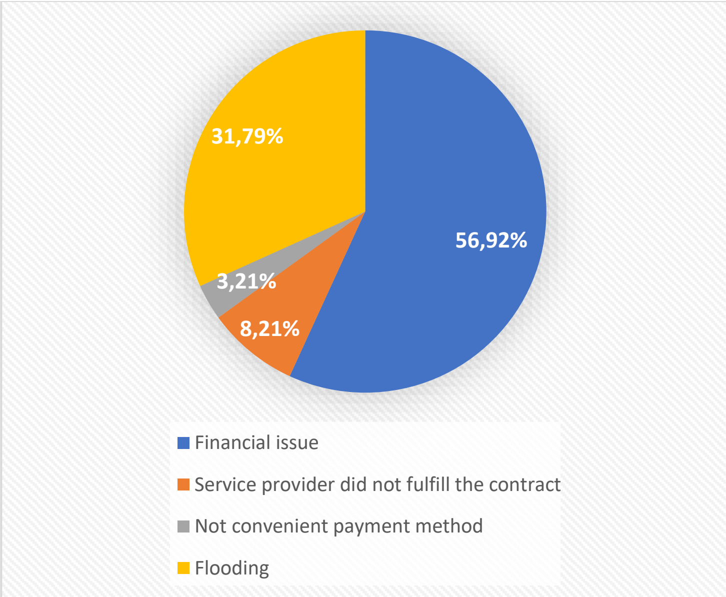

Figure 5.2. Reasons for Non-Payment.

Determinant factors of the willingness to adopt and the adoption

Table 5.3 shows that several socioeconomic factors drive business model willingness and adoption. The result shows an overall significance of the models, with the probability of Wald Chi2 being less than 0.05 for the four models. We included fourteen variables in the probit (adoption) and selection (willingness) models. The result shows that the age of the household head is a significantly positive factor that drives the overall adoption of the business model, especially the adoption of the business model 2. This result implies that the older the farmer, the more likely the farmer is to adopt the business model. However, this variable is significant and negatively drives farmers' decisions regarding the adoption of business model 3. This means that younger farmers are more likely to make the decision to adopt business model 3, which implies a cash payment at delivery. The variable household size is significant and negatively drives the adoption of the overall business model as well as business models 2 and 3. The negative sign implies that the higher the household size, the less likely the household is to adopt the business models, particularly business models 2 and 3. This could be explained by the financial limitation caused by the household size if we consider that all household members do not necessarily contribute. This variable does not intervene in farmers' decision to adopt the business models. The variable education level is positive and significant for the overall business model adoption and the adoption of the three business models. It also intervenes in farmers' decisions to adopt business model 3. This finding means that farmers with a minimum of primary school level are more likely to understand the necessity and utility of the proposed business model, especially when deciding to adopt the cash payment business model. Education level is a determinant factor, particularly in the adoption of business models. The unexpected result is the negative sign of the variable experience in rice production. We assumed that farmers with more experience in rice production would be more open to adopting the business model as well as in their decision-making, but the result revealed otherwise. This could be explained in the way that farmers who have more experience overestimate themselves and think they have enough experience and knowledge and do not need the proposed service. This is the same for the variable information on new rice varieties, which also has a negative effect on farmers' adoption in the overall business model. On the other hand, the variable distance to the market is significant and positively drives the adoption of the overall business model, specifically business model 2. However, a negative effect is registered during farmers' decisions to adopt the business models. As expected, the variable contact with the extension agent is significant and positively drives the overall adoption of the business model and the farmers' decision-making in adopting the business model, especially the business model 2. The proposed extension service through the business model is an improved version of what the traditional extension service provides. Therefore, farmers who already have contact with extension agents are more likely to understand the new service assigned to them and would positively respond to the decision or the adoption. The finding also reveals that agricultural training is a determinant factor in farmers' decision to adopt the business model. Similarly, the duration of agricultural training is negatively significant for the three business models individually. This means that the shorter the training, the more likely it will impact the adoption of the business model. This highlights the importance of agricultural training and the importance of prioritizing quality content instead of duration. We also found that the rice production ecology is a determinant factor in the adoption of the overall business model, especially rice production in the rainy season and in irrigated areas. This is explained by the fact that rice is a water-demanding crop. However, we found that the rainfed ecology is significant but has a negative effect on adopting the business model, implying cash payment at delivery. This could be explained by the unpredictability of the rain, which may be less than needed or too much than expected and, in both cases, negatively impact production. Therefore, farmers who only rely on rain in rice production are less likely to adopt the business model 3.

Table 5.3. Determinants analysis.

	All Model	BM1	BM2	BM3
Adopters				
Household head sex (=1)	-0.197	-4.558	-2.131	-0.329
	(0.218)	(448.606)	(2.759)	(0.418)
Household head age (Years)	0.011**	0.011	0.038***	0.004
	(0.004)	(0.011)	(0.011)	(0.010)
Household size (n)	-0.027***	0.001	-0.069***	-0.050***
	(0.006)	(0.014)	(0.016)	(0.014)
Education Level (=Primary)	0.471***	0.667**	0.563***	0.568***
	(0.092)	(0.286)	(0.198)	(0.188)
Experience in Rice Production (=1)	-0.023***	-0.025**	-0.039***	-0.017*
	(0.004)	(0.010)	(0.010)	(0.009)
Distance to the Market	0.037***	0.027	0.089***	-
	(0.005)	(0.016)	(0.014)	-
Information on New Rice Varieties (=1)	-0.235***	-	-	-
	(0.083)	-	-	-
Contact with Extension Agents (=1)	1.018***	0.305	-	-
	(0.342)	(0.667)	-	-
Agriculture as main Activity (=1)	-0.105	-	-	-
	(0.368)	-	-	-
Rainfed Ecology (=1)	0.332***	-	-	-0.555***
	(0.111)	-	-	(0.198)

Irrigated Ecology (=1)	0.298**	-	-	-
	(0.138)	-	-	-
Training Duration (Days)	-	-0.136**	-0.640***	-0.239***
	-	(0.054)	(0.076)	(0.065)
Do you have phone (=1)	-	-	4.409	-
	-	-	(879.104)	-
Rice area (ha)	-	-	-	0.250
	-	-	-	(0.170)
Constant	-0.886*	5.271	-2.454	1.606**
	(0.536)	(448.607)	(879.108)	(0.627)
Willingness to Adopt / Pay				
Household head sex (=1)	0.044	-0.223	-4.564	-
	(0.282)	(0.484)	(1505.853)	-
Household head age (Years)	-0.005	0.000	-0.011	-0.035**
	(0.006)	(0.013)	(0.013)	(0.017)
Household size (n)	-0.009	0.001	-0.002	-0.021
	(0.008)	(0.019)	(0.019)	(0.023)
Education Level (=Primary)	0.174	0.072	-0.320	0.461*
	(0.143)	(0.274)	(0.239)	(0.275)
Experience in Rice Production (=1)	-0.024***	-0.001	-	0.018
	(0.006)	(0.013)	-	(0.014)
Distance to the Market	-0.003**	0.002	-0.019	-0.006
	(0.002)	(0.005)	(0.013)	(0.012)
Information on New Rice Varieties (=1)	-0.018	-	-	-
	(0.113)	-	-	-
Contact with Extension Agents (=1)	1.507***	-4.410	2.095**	-
	(0.267)	(1450.094)	(0.954)	-
Agricultural Training (=1)	0.921***	1.615***	0.367	1.825***
	(0.132)	(0.458)	(0.262)	(0.705)
Agriculture as main Activity (=1)	0.537	-	-	-
	(0.341)	-	-	-
Rainfed Ecology (=1)	-0.175	-0.056	-	0.348
	(0.175)	(0.510)	-	(0.343)
Irrigated Ecology (=1)	-0.266	-	-	-
	(0.202)	-	-	-

Access to Credit (=1)	0.029		-0.606	-
	(0.211)		(0.415)	-
Training Duration (Days)		-0.079	-0.005	-0.063
		(0.098)	(0.021)	(0.216)
Constant	-0.402	5.577	4.888	1.761*
	(0.505)	(1450.094)	(1505.853)	(0.918)
Athol	1.847***	0.546	0.061	14.445**
	(0.457)	(0.885)	(0.487)	(6.620)
N	1246.000	400.000	400.000	316.000
Wald Chi2	154.86	22.19	122.95	40.99
Prob > chi2	0.000	0.004	0.000	0.000

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

5.4.2. Impact assessment on economic efficiency and profit

Prior to the results of the impact, we first present in a graph the simple means of outcomes of the treatment and the control groups. Figure 5.3 shows a distribution of our outcomes with their means represented by the vertical lines. The graphs show the difference between the business models. However, the difference is not pronounced for profit. In the next section, we present the OLS and the ANCOVA estimates for the post-treatment data. The results with covariates are presented in columns (2) and (4), while the results without covariates are in columns (1) and (3).

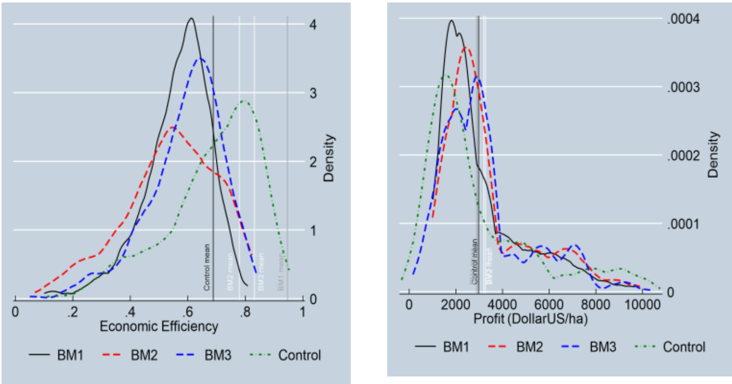

Figure 5.3. Outcomes by treatment group.

Treatment effect on Economic Efficiency (EE)

Table 5.4 presents the result of the treatment effect on farmers' economic performance measured by economic efficiency. The result shows evidence that the adoption of the business models has significantly increased rice farmers' economic performance. For rice farmers who were randomly assigned to business model 1, the result shows an increase in their economic performance between 0.078 and 0.182 when we consider both OLS and ANCOVA estimations. The effect is relatively higher for business model 3, with an increase of 0.114 in ANCOVA estimation with and without covariates. The results imply that the digital paid extension service for which farmers pay cash US$8 /ha at delivery has unexpectedly the highest impact on farmers' economic performance. The effect of the OLS result is low compared to the ANVOCA result. When comparing the treatment and the control, we found a positive and statistically significant difference between the overall treatment and the control group, with an impact between 0.172-0.174 for the ANCOVA estimation. This finding implies a positive and significant impact on the adoption of business models compared to the control group. The comparison between business models reveals a positive and significant difference between business model 3 and business models 1 and 2, which is explained by the high impact of business model 3 compared to the business models 1 and 2. The difference in the impact between business models can mainly be explained by the price of the service and the payment method. Since the provided recommendations are tailor-made, we could hypothetically argue that farmers who paid cash received better treatment and quality service compared to the farmers who committed to pay after harvest. In addition, even if business model 3 represents an additional cost of production during the production phase, it proposes the lowest cost of service compared to the two other business models, which may have contributed to their economic performance. Besides the economic performance, we also investigate the impact on farmers' rice production profit.

Table 5.4. Treatment effects on Economic efficiency.

	(1)	(2)	(3)	(4)
Variables	OLS	OLS	ANCOVA	ANCOVA
BM1	0.182***	0.181***	0.078***	0.079***
	(0.024)	(0.022)	(0.023)	(0.023)
BM2	0.027	0.033	-0.019	-0.017
	(0.023)	(0.025)	(0.032)	(0.030)
BM3	0.112***	0.121***	0.114***	0.114***
	(0.024)	(0.024)	(0.022)	(0.022)
EE0			0.322***	0.320***
			(0.033)	(0.035)
Combined treatment [T-C]	0.321***	0.334***	0.172**	0.174***
	(0.049)	(0.049)	(0.069)	(0.066)
Difference between treatments [BM2-BM1]	-0.154***	-0.148***	-0.097***	-0.096***
	(0.029)	(0.029)	(0.020)	(0.019)
Difference between treatments	-0.069***	-0.060**	0.036**	0.034*

[BM3-BM1]				
	(0.026)	(0.025)	(0.018)	(0.019)
Difference between treatments [BM3-BM2]	0.084***	0.087***	0.133***	0.130***
	(0.0313)	(0.032)	(0.023)	(0.023)
Mean dependent variable in control	0.678(0.172)			
Observations	1,349	1,349	2,769	2,769
R-squared	0.388	0.442	0.365	0.374
LGA FE	Yes	Yes	Yes	Yes
Household Covariates	No	Yes	No	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Treatment effect on profit (US$/ha)

Farmers can be economically performant with a non-consistent profit. That is why we find it useful to also estimate the impact of adopting the business models on the profitability of rice production. Table 5.5 presents the OLS and ANCOVA regression results with and without covariates. The result shows a significant and positive impact of adopting business models on the profit for both estimations OLS and ANCOVA with and without covariate. This implies an overall increase in the profit when adopting the business models. When considering ANCOVA estimation with covariates, we find a significant profit increase for the three business models, and farmers who adopted business model 2 have the highest impact of US$1148/ha. This is an unexpected finding because business model 2 has not only the most expensive cost but also puts farmers in some uncertainty of the market since it does not guarantee a buyer. However, the good side, which may have been to the advantage of farmers who adopted business model 2, is that it gives them the freedom to sell their production at a price of their choice or at least at the market price, which is not the case with the business models 1 and 2 in which the price is pre-defined and cannot be changed. Ultimately, the selling price is a determinant factor of the profit, which may lead farmers to either a significant loss or a consistent profit regardless of the yield. We also find a consistent positive and significant impact when comparing the overall adoption of the business model with the control group. The finding reveals an increase of US$/ha 2559 for the treated compared to the control farmers when considering the ANCOVA estimation with covariates.

Table 5.5. Treatment effect on profit (US$/ha).

	(1)	(2)	(3)	(4)
Variables	OLS	OLS	ANCOVA	ANCOVA
BM1	196**	197**	775***	699***
	(87)	(87)	(158)	(135)
BM2	326***	349***	1,243***	1,148***
	(115)	(119)	(262)	(227)
BM3	463***	530***	747***	710***
	(136)	(128)	(217)	(176)
RBE0			0.38***	0.35***
			(0.12)	(0.09)
Combined treatment [T-C]	986***	1077***	2766***	2559***
	(230)	(232)	(571)	(481)
Difference between treatments [BM2-BM1]	130	152	467***	448***
	(140)	(146)	(168)	(153)
Difference between treatments [BM3-BM1]	267*	332**	-27	11
	(149)	(142)	(147)	(116)
Difference between treatments [BM3-BM2]	137	180	-495**	-437**
	(153)	(140)	(220)	(186)
Mean dependent variable in control	2009 (1416)			
Observations	1,349	1,349	2,769	2,769
R-squared	0.775	0.795	0.280	0.408
LGA FE	Yes	Yes	Yes	Yes
Household Covariates	No	Yes	No	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Heterogeneity analysis

Table 5.6 presents the result of heterogeneity analysis from ANCOVA regression. The result shows the interaction of each household covariate (row) with our two dependent variables, ‘’Economic Efficiency’’ and ‘’Profit’’ (column). The finding shows almost no evidence of a heterogenous effect on the baseline characteristic. However, a statistically significant (10%) heterogeneity was found for the variables ‘’Age of household head” and the ‘’Household size’’. The result implies that larger households are more economically efficient than smaller households. Note that economic efficiency indirectly involves the labor requirement for the production (technical efficiency) and its cost (allocative efficiency). Therefore, a larger household size, which converts its members into labor, would have more workforce and lower the cost of workforce, and therefore, it is likely to be more efficient. Regarding the outcome ‘’Profit’’, the marginal effect of producers’ age is negative, implying that younger rice farmers have more profit than older farmers. Younger farmers are susceptible to being more open to new technologies more dynamic and informed compared to older farmers. Figure 5.4 provides an overview of the interaction of each covariate with the two outcomes. We found very little evidence of heterogeneity that does not impact our impact analysis result.

Table 5.6. Heterogeneity of treatment effects.

	Economic Efficiency (EE)	Profit (US$/ha)
Household head age (years)	0.001	-15.075*
	(0.002)	(8.690)
Household size (n)	0.004*	10.601
	(0.003)	(8.567)
Education (=Primary)	-0.002	75.526
	(0.039)	(195.122)
Agricultural is main activity (=1)	0.116	641.599
	(0.158)	(502.490)
Agricultural training? (=1)	0.079	285.004
	(0.053)	(192.162)
Credit for rice production (=1)	0.089	382.766
	(0.084)	(322.277)
Marital Status (=Married)	-0.028	-639.776
	(0.082)	(404.993)
Ownership of smartphone? (=1)	-0.021	333.698
	(0.072)	(303.608)
Experience in rice production? (Years)	0.002	-3.038
	(0.002)	(7.055)
Rice area (ha)	0.020	247.300
	(0.033)	(163.483)

*** p<0.01, ** p<0.05, * p<0.1

Columns present ANCOVA regressions with covariates and village fixed effects for the two outcome variables as the dependent variable. Cells report the coefficient and standard error on the interaction term of the covariate (row) and treatment indicator on the dependent variable (column).

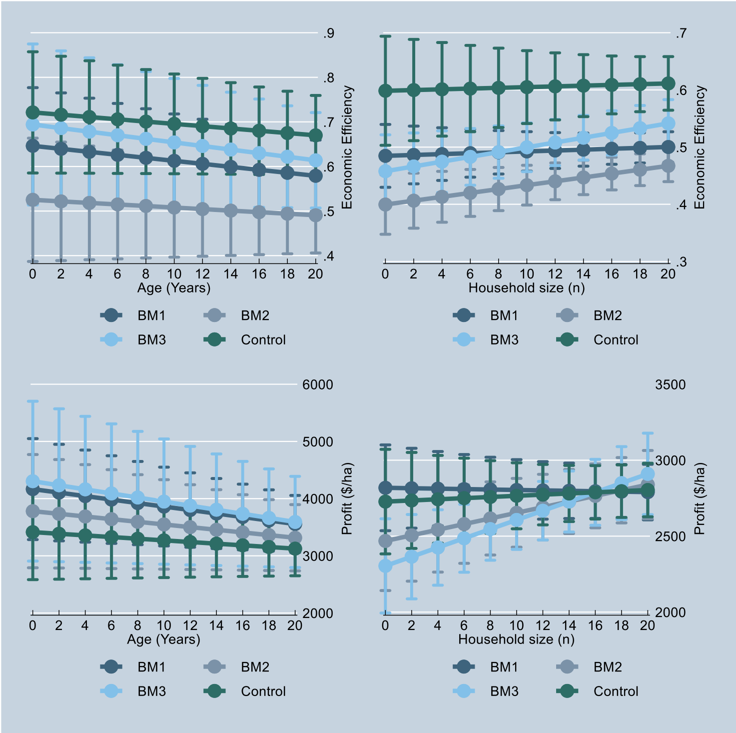

Figure 5.4. Heterogeneity of treatment effects of Age and Household size.

Robustness checks

Farmers will likely be exposed to the same external factors in a cluster randomized controlled trial, making it necessary to examine disparity across the clusters [23]. For this reason, we used the intra-cluster correlation coefficient (ICC) to investigate the clusters' differences and reliability. The ICC has a value between 0 and 1 and is indicated as ‘’poor reliability” when the value is below 0.5, ‘’moderate reliability” when the value is between 0.5 and 0.75, ‘’Good” when the value is between 0.75 and 0.9, ‘’Excellent reliability” when the value is higher than 0.9 [24]. The estimates of the ICC presented in appendix 5.1 indicate a value of ICC above 0.5 and between 0.5 and 0.75, implying evidence of moderate reliability. Our sampling unit (household) is clustered within the randomization unit (village), even though the value of ICC is not as small as anticipated. We checked the robustness of our results to the missing data from farmers who could not produce rice in the follow-up season. The Lee bounds’ [25] results presented in appendix 5.2 show that the treatment effects are different from zero, suggesting that the potential bias caused by the missing data is small compared to the estimated effects sizes. In addition, appendix 5.4 presents the unadjusted *p-values* as well as the adjusted sharpened *q-values*. We find the unadjusted *p-values* less than the *q-values,* indicating the robustness of our *p-values*.

5.5. Discussion

Using a randomized controlled trial approach, the study aims to assess farmers’ adoption of three digital paid extension services and their impact on farmers’ economic performance and profitability. The preliminary finding reveals that 92.83% of farmers accepted adopting and paying for the digital extension business assigned to them. However, after the intervention, only 61.67% of them really adopted and paid according to the assigned business model. Overall, over 1200 rice farmers, 427, accepted and agreed to pay. However, for the reasons stated in Figure 5.2, they could not pay. The finding shows that the extension service with payment after harvest at

US$13/ha (BM1) is the most preferred paid extension service, with 86.77% adoption versus 94.50% prior intervention. This is an expected result since we hypothesized that the payment option ‘’after harvest’’ removes farmers’ financial constraints and enables them to receive the service and then pay for it after harvest. Even though the BM1 is the most preferred by rice farmers, service providers confessed during the follow-up meeting (during intervention) that farmers to whom the BM3 (cash payment at delivery) was assigned are the most serious and reliable farmers, which explained the unexpected adoption rate of 48.46% adoption versus 93.94% prior intervention. However, noted that the BM2 was revealed to be the second most adopted by farmers. This result shows the interest of rice farmers in receiving paid personalized advice using the technology RiceAdvice, and if they could have the opportunity to negotiate or choose the service price and the payment method by themselves, we could have a higher adoption rate.

While a positive impact is expected, it is important to consider the characteristics of the proposed service, farmers’ socioeconomic characteristics, farmers’ needs, the end-users' purchasing power, and the activity's profitability for the service provider. All these considerations should result in an appropriate business model from which we can expect a high sustainable adoption rate. For these reasons, we seek to understand the determinant factors behind farmers’ willingness to pay/adopt and the adoption/payment.

The result shows that several socioeconomic variables drive both farmers’ intention to adopt and their final decision to adopt. We found that the older the farmer gets, the more likely the farmer is to adopt the paid extension service with a payment option linked to the quantity to be sold. This could be explained by the ability to understand business model 2, which older farmers better understand. Also, not necessarily related, but older farmers may have more experience in the rice market and prefer the option of defining the price of rice after harvest following the market trend or other external factors that positively or negatively affect the rice price. It is a risk that older farmers seem to be more comfortable taking.

The finding also suggests a significant and positive interaction between farmers with minimum education level as primary school. These findings are similar to Rajkhowa & Qaim [26] who also established a positive correlation between the adoption of personalized extension services and the Age, and education level. However, contrary to our finding, the author found that household size positively drives the decision to adopt a personalized extension service. It is important to highlight that the reason why the household size negatively affects farmers' decision to adopt a paid personalized extension service, in this case, could be explained by the fact that the service is paid and a high number of non-productive mouths to feed in the household could reduce the household's purchase power and therefore limited the financial capacity to afford a paid extension service. A study by Li et al. [27] investigates the use of a mobile App in adopting fertilization technology. However, the author failed to establish a relationship between household head age, education level, and training but instead established a positive relation between male household heads and the adoption of the technology. Our findings are also similar to those of Amoussouhoui et al. [28] who found a positive and significant relationship between the adoption's decision of paid extension service and the age, household head's education level, but contrary to our finding a positive relationship between the adoption and experience in rice production. Akudugu et al. [29] also established a positive effect of age on the adoption of digital extension technology. However, a negative relationship is observed for the age of the household head in the pre-intervention. This could be explained by the fact that younger farmers are probably more ''tech-savvy'' than older farmers and, therefore, are more open to adopting digital technology services. The age of decision-makers has widely been used as a key valid predictor in the adoption of digital agricultural technologies [30]. It is very often hypothesized that younger farmers are more likely to be open to adopting digital agricultural technology. However, an opposite effect is generally found regarding the adoption [31,32]. We also found that farmers with more experience in price production are less likely to be willing to adopt or adopt the proposed service. This can be explained in a way that farmers who have enough experience in rice production assume that they have enough knowledge and do not need any further advice to succeed in their production.

The impact analysis finding shows that adopting a paid extension service has increased rice farmers' economic performance. The result shows a significant and positive impact of the adoption of business models 1 and 3. In addition to being the most preferred, business model 1 has a positive impact (0.079) on rice farmers' economic performance. However, even if the business model involves a cash payment at delivery, it has the highest impact on farmers' economic performance. Furthermore, adopters' economic performance compared to the control group is significant (up to 0.174), implying evidence of the positive impact of adopting a paid extension service on farmers' economic performance. Our result aligns with the finding of Li et al. [27] who also found a positive impact of adopting a smartphone-based digital extension service on farmers' performance in the use of production input. Furthermore, a literature review conducted by Maffezzoli et al. [33] also reveals a positive impact of using Agriculture 4.0 on farmers' efficiency in terms of cost reduction and farm productivity. Similarly, a study by Rajkhowa & Qaim [26] on adopting digital extension services reveals a positive farm performance with higher input intensity, crop productivity, and incomes than non-adopters.

We also found a significant and positive impact on the profit for the three business models. Unexpectedly, business model 2, which has the highest service cost, impacts farmers' profits most. Even though the service cost is high, this business option allows rice farmers to sell their production to whomever they want at a price not pre-defined by the service provider. Business model 3, which has the lowest cost of service, has a greater impact than business model 1. This result may be explained by the two factors that characterize the business models. First is the cash payment option, which does not directly impact the profit. Second, the cost of the service (US$8/ha), which is lower than the other business models, may have contributed to reducing the cost of production compared to farmers who pay, for example, US$13/ha in business model 1 and higher in business model 2. This difference in price of US$5/ha may be significant based on the farm size. Although the cash payment after harvest offers a solution to farmers' lack of financial means during the production process, it has a risk that service providers need to consider. This justifies why, economically, a farmer paying cash at delivery and another paying after harvest cannot pay the same amount. The difference in price (US$5/ha) is the cost of risk the service providers take. Although cash payment after harvest enables farmers with limited financial means to get the extension service, the cash payment on delivery is still a payment option widely used and preferred by both customer and supplier for security reasons, to avoid fraud, cheaper for the customer, and it reduces the risk of non-payment for the service provider [34–36]. However, in our case, cash payment could be seen as an additional cost in the production process, which could have been used to increase farm size or other production factors to increase performance. Business model 1 not only enables farmers to not pay cash, but it also gives them time to find buyers and sell their production to be able to pay for the service. In some cases, rice farmers have farming contracts with the service provider who will buy the production after harvest. Therefore, rice farmers do not worry about a buyer for their product and then focus on production and maximizing the yield. However, this may not necessarily give them an open view of the global market, and they may sell the production at a price under the market price, which is the advantage that business model 3 offers. Smallholder farmers can use and should be encouraged to use digital extension technology to overcome their constraints, but they mostly lack information on the usefulness of the technology and its potential impact [37,38]. This finding provides experimental evidence on three main constraints of the adoption of digital technologies by smallholder farmers highlighted in the literature [7,11,37,39]. First, farmers' financial and limited access to finance is revealed to be an insignificant barrier to the adoption of digital extension services if the interest, as well as the impact, are proven and explained to the end-user, followed by an adequate solution or alternative to bypass their limited access or lack of financial means during production. The second evidence is that smallholder farmers' low e-literary does not represent a significant barrier to adopting digital extension technology. Third, we have evidence that an indirect adoption approach for smallholder farmers will not only have a significant probability of success in terms of adoption rate (when we consider that service providers are business entrepreneurs, and a high adoption rate would positively impact their profitability and therefore ensure a sustainable business) but will also positively impact farmers' technical, allocative performance as well as their profit. Finally, although the payment after harvest option is revealed to be the most adopted and therefore preferred by farmers, we found evidence that the cash payment option, even less adopted (compared to business models 1 and 2) and not offering an alternative for farmers' financial issue during production, has a significant and positive impact on both rice farmers' economic performance and profit. Obviously, the finding of this study should not be interpreted as the impact of the adoption of all business models of paid extension services in general. It is important to note that the proposed service needs to consider the end user's needs, purchase power, adapt to the socioeconomic reality of the business environment, and, most importantly, be a profitable business for the service provider to ensure both a sustainable adoption and business.

5.6. Conclusion and policy implications

The adoption of digital extension technologies by smallholder farmers is possible and feasible despite the constraints that farmers face along the production process. This study evaluated the impact of an indirect adoption approach designed to bypass farmers' constraints and enable them to use digital technology indirectly. Using a Randomized Controlled Trial approach, we assigned to rice farmers three different paid extension services characterized by the price of the service, the payment method, and an agreement on the farming contract. This adoption approach offers an alternative to farmers for the adoption of digital tools and represents a business opportunity for Agri-entrepreneurs. That is why the study was conducted with the implication of Agribusiness partners who are the service providers. However, the experiment raised three main challenges. First, convince rice farmers to pay for a service they were not used to. Second, ensure the durability of the service provision through a profitable business for the service provider, and third, the service price needs to be affordable for rice farmers. All these factors were considered in designing the three extension services assigned to farmers. We have found, so far, no similar study that conducts such an experiment to assess farmers' readiness to pay for an extension service and the impact of the adoption. This study is, therefore, the first to conduct such experiments. Contrary to what we may think, the result shows evidence that more than 61% of the exposed farmers adopted and paid for the extension service assigned to them. In addition, we found evidence of the positive and significant impact of the adoption of paid extension services on farmers' economic performance and their profit. Overall, the results of the study lead to five main conclusions:

- Rice farmers are aware of the usefulness and the potential impact of the adoption of digital extension and are ready to adopt it.
- The paid extension service approach is an alternative to bypass farmers' constraints and ensure that farmers use digital tools without direct access to the tool or without any knowledge.
- Household head age, household size, primary education level, rice production experience, training duration, and the distance to the market are the socioeconomic factors driving the adoption of paid extension services.
- Business model 1, implying an after-harvest payment option at a cost of US$13/ha, is the most popular paid digital extension service. Even though this option is the most expensive, we understand the reason why farmers prefer this alternative.
- Although business model 1 is the most preferred choice with a significant impact on farmers' economic performance, business model 2, implying payment after harvest on the quality sold, is surprisingly the option with a higher impact on farmers' profit. Therefore, this should be advised not as farmers' first choice but as the most impactful and beneficial for farmers.

We do not consider that these results imply all paid extension services. However, this study suggests the adoption approach to be designed and implemented in collaboration with the actors, including the end-users. Our study provides evidence of the adoption of paid extension services by smallholders to whom the service was assigned. We believe that if not an experiment and choice were given to farmers to choose their preferred service freely, we would register a higher adoption and payment rate. This approach is an open door and should be taken over by both agri-entrepreneurs and policymakers. Youth and agri-entrepreneurs should see this as a new business opportunity and work together with beneficiaries to design the most suitable service. In most developing countries, extension services are still fully being taken care of by the government. We believe that the government has a key role either by incorporating appropriate digital tools into the extension service or by supporting the development of private extensions willing to invest in the paid digital extension service.

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Conclusions

The findings of this thesis shed light on the adoption of digital agricultural technologies and offer a practical solution to overcome the barriers faced by smallholder farmers in embracing digital tools. Through a case study of digital extension technology, we conducted an in-depth analysis of farmers' acceptance of this technology and developed a new approach to ensure its sustainable adoption.

Acknowledging the obstacles to the direct adoption of the technology, our study proposes an indirect adoption approach. This approach entails providing personalized paid extension advice to rice farmers through the application. While this adoption method involves farmers paying for extension services, thereby adding to their production costs, it also requires service providers to engage in a new type of agribusiness. However, a significant challenge remains in determining the appropriate business profile to ensure an affordable price for farmers while maintaining profitability for the service provider.

The research began with a first chapter employing systematic and meta-analysis methods to highlight the importance of modern solutions, particularly Digital Agricultural Technology, in global agricultural development. This chapter provides a global overview of DAT adoption, examining adoption rates and influencing factors across continents with a focus on socioeconomic variables. Key findings include a strong interest in adopting Digital |Agricultural Technology, with Africa and South America showing the highest adoption rates (39% and 22%, respectively). Also, younger farmers are more likely to adopt Digital |Agricultural Technology, with a positive trend in adoption linked to more recent publications. In addition, gender and income positively influence adoption rates. Finally, socioeconomic factors (age, gender, education, and income) significantly correlate with adopting Digital |Agricultural Technology in various agricultural sectors. This first chapter confirms the trend, albeit low, in adopting Digital Agricultural Technology, particularly in developing countries. However, it also emphasizes the importance of tailoring both the technology and the adoption approaches to the socioeconomic realities. This leads to the second chapter, where we used a case study of Digital Agricultural Technology and initiated a new tailor-made adoption approach: a paid extension service established in a business profile. Additionally, we gathered data on farmers' willingness to adopt the proposed approach and analyzed its feasibility and long-term profitability.

The second chapter explores the effectiveness of the service-based business model for transferring and upscaling new digital agricultural technology to the end-users. Using the business model Canvas approach, this chapter emphasizes the importance of conducting an upstream analysis to assess market conditions and environmental factors. The finding indicates that rice farmers are willing to utilize and pay for a personalized extension service offered through the application. Moreover, rice farmers recognize the tool's utility and demonstrate readiness to formalize short- and long-term extension service contracts. The study concludes that identifying user needs, ensuring customer satisfaction, and addressing business weaknesses are crucial for establishing a sustainable, profitable service-based business in agriculture. Based on the results of this study regarding farmers’ acceptance of the proposed adoption approach, their willingness to pay for it, and its profitability, chapter three of this thesis investigates the business profile most preferred by farmers. To do this, we used an experimental approach, presenting ten theoretical business profiles to farmers so they could choose their preferred profiles based on the characteristics of each profile. Each business profile is characterized by the price of the service, the payment method, the length of the partnership, the agreement on contract farming, the possibility of obtaining credit, the willingness to get additional paid services, and the agreement on the quality and the quantity to be sold. The results showed a preference for cash payment after harvest at US$14.50 per hectare per season. Following the intervention, rice farmers attested that the service price and proposed payment methods significantly influenced their decision to adopt the service. These factors also impact the frequency of adoption among rice farmers.

In the post-experiment phase, the experiment was refined to three business profiles, which were randomly assigned to groups of farmers. After explaining the assigned profiles and obtaining farmers' agreement, the service was provided. Using the Technology Acceptance Model to which we added two new constructs (payment method and price of the service), the fourth chapter analyzed rice farmers' behavior towards three business profiles of extension services and explored new factors, “perceived payment method” and “perceived price” added to the expanded version of the Technology Acceptance Model (TAM). The key findings include that "perceived ease of use" and "perceived usefulness" are crucial for positive attitudes and adoption, emphasizing the need for clear communication of the service’s utility. In addition, the payment and price options significantly influence farmers’ adoption and usage of digital extension services, helping address financial constraints. Furthermore, the pricing and payment options variations affect farmers’ attitudes and adoption rates differently. The study concludes that while farmers are interested in using digital technology, successful adoption requires understanding their socio-economic realities and developing appropriate, sustainable strategies and policies. After analyzing farmers’ behavior in adopting the new adoption approaches using a randomized control trial approach, chapter five explores the adoption of the assigned business profiles and their impact on farmers’ technical efficiency and profitability. The results show that over 61% of farmers adopted and paid for the extension services, indicating their readiness to use digital tools. In addition, the paid extension service model successfully addresses farmers' constraints and improves their economic performance and profit. Furthermore, socioeconomic factors such as age, education, and market distance influence adoption. Above all, the most popular service model charges $13/ha after harvest, while another model based on payment after harvest on quality sold had a higher impact on farmers' profit.

Overall, the adoption of digital extension technology is indeed feasible, as demonstrated by this dissertation thesis. What holds the most significance is not solely farmers' direct utilization of the technology but rather the endeavor to ensure its accessibility to the broadest possible range of farmers. While we do not claim this thesis as the definitive reference for universal knowledge on the sustainable adoption of digital agricultural technologies in developing countries, we see it as a valuable starting point.

APPENDICES

Chapter 3. Analysis of the factors influencing the adoption of digital extension services: Evidence from the RiceAdvice application in Nigeria

Appendix 3.1. Sample of the dataset of two rice farmers.

	Ident	Gender	Age	Nivsco	Exprice	Knricea	Hhinco	BM	BPChoice
1	1001	0	33	Primary	10	1	698250	1	0
2	1001	0	33	Primary	10	1	698250	2	0
3	1001	0	33	Primary	10	1	698250	3	0
4	1001	0	33	Primary	10	1	698250	4	1
5	1001	0	33	Primary	10	1	698250	5	0
6	1001	0	33	Primary	10	1	698250	6	0
7	1002	0	45	None	20	1	2700000	1	0
8	1002	0	45	None	20	1	2700000	2	0
9	1002	0	45	None	20	1	2700000	3	0
10	1002	0	45	None	20	1	2700000	4	1
11	1002	0	45	None	20	1	2700000	5	0
12	1002	0	45	None	20	1	2700000	6	0

Note: Ident (Farmer identification code); Nivsco (Education level); Exprice (Experience in rice production in year); Knricea (Knowledge of RiceAdvice); Hhinco (Household annual income in Naira); BP (Business Profile); BPChoice (Business Profile Choice)

Appendix 3.2. Cronbach's Alpha test.

Business Profiles	Average interitem covariance	Number of items in the scale	Scale reliability coefficient
1 to 5	1.056	6	0.87
6 to 10	0.644	6	0.76

Appendix 3.3. Pairwise correlation test.

Pairwise correlations Group 1

Business profiles	(1)	(2)	(3)	(4)	(5)
(1)	1.000				
(2)	0.642	1.000			
(3)	0.464	0.680	1.000		
(4)	-0.606	-0.446	-0.374	1.000	
(5)	-0.717	-0.694	-0.559	0.577	1.000

Pairwise correlations Group 2

Business profiles	(6)	(7)	(8)	(9)	(10)
(6)	1.000				
(7)	0.673	1.000			
(8)	0.319	0.445	1.000		
(9)	-0.363	-0.243	-0.056	1.000	
(10)	-0.594	-0.562	-0.465	0.236	1.000

Appendix 3.4. Business profiles removed and reasons.

Attributes	Business Profiles					
	1	2	3	4	5	6
Rice Advice Payment method	Cash at delivery	Cash at delivery	Cash payment after harvest	Cash payment after harvest	Payment cash after harvest incorporate	Payment cash after harvest incorporate
Price of service (Naira/quarter of hectare)	2.40	2.40	2.40	4.80	4.80	3.60
Length of partnership	More than 2 seasons	More than 2 seasons	1 season	1 season	More than 2 seasons	More than 2 seasons
Contract farming (Trading contract)	No	No	No	No	No	No
Credit	No	Yes	Yes	No	Yes	No
Additional Paid services (threshing ...)	No	Yes	Yes	No	Yes	No
Agreement on the Quantity	No	Yes	Yes	Yes	No	Yes
Agreement on the Quality	Yes	No	Yes	Yes	Yes	No

Reasons	Profile not feasible: since there is no trading contract, the agreement on quality won't exist	Profile not feasible: since there is no trading contract, the agreement on the quantity won't be possible, and the service provider will have no guarantee by providing credit to the farmer.	Since there is no trading contract, credit, or additional service, agreement on quantity and quality won't be possible	Same as profile 1	Same as profile 3	Same as profiles 1 and 4

Appendix 3.5. Retained business Profiles from the Alternative-specific analysis.

Characteristics/Attributes	BP1 (26.8%)	BP6 (44.7%)	BP3 (49.4%)
Payment Method	Cash at delivery	Cash payment after harvest	Cash payment after harvest
Cost of service per hectare (US$	14.50	14.50	9.70
Length of partnership	1 season	1 season	More than 2 seasons
Credit	No	Yes	No
Additional paid services (land preparation, threshing...)	Yes	Yes	Yes
Contract farming	Yes	No	Yes
Agreement on quantity	No	No	Yes
Agreement on quality	Yes	No	Yes

() Predicted probability

Chapter 4. Analyzing farmers' behavior in the adoption of paid digital extension service: Experimental evidence of RiceAdvice in Nigeria

Appendix 4.1. Technology Acceptance Model for the adoption of RiceAdvice business model.

Section 1: Model evaluation for Treatment

Constructs		Statements
Perceived Ease of Use	PEU1	The collaboration during my RiceAdvice partnership went very well.
	PEU2	I did not have any difficulty in applying the recommendation received from the service provider.
	PEU3	I feel comfortable and confident using the advice from the application.
	PEU4	My interaction with the partner is clear and understandable.

	PEU5	All things considered, I think that the adoption of the partnership required a large effort in training and effort from me.
Perceived usefulness	PU1	Adopting the partnership has made my production easy for me.
	PU2	The adoption of partnership increases my productivity.
	PU3	It has improved my work efficiency and my effectiveness.
	PU4	The recommendation received helped me reduce the quantity of input used.
	PU5	The adoption of the partnership helps me to have more control over the management of my farm.
	PU6	All things considered; I think the adoption of the Partnership was not that useful to my farm management.
Attitude	ATT1	I believe that the use of the RiceAdvice application through the partnership is the best option for rice farmers to adopt the technology.
	ATT2	All things considered; I think that adopting this partnership by rice farmers is not a good idea.
	ATT3	I think that the adoption of such a partnership by rice farmers would be wise.
	ATT4	The credibility of the information and recommendations is high and trustful.
Adoption	ADP1	I will likely continue to adopt RiceAdvice through the partnership proposition.
	ADP2	I intend to make the most use of the partnership I signed for.
	ADP3	I will surely continue to use the partnership if I have access to it.
Actual use	AU1	I have used and adopted the partnership assigned to me.
	AU2	I have fulfilled all my engagements in terms of payment method and price.
	AU3	I have not encountered any difficulties during the partnership period.
	AU4	I did not have any issue applying the recommendation provided by the agent.
Image	IM1	Using the recommendation provided by the RiceAdvice application makes me feel confident.

	IM2	Using the partnership has created a good image for my farm.
	IM3	Using the partnership makes us more visible and on the edge for opportunities.
Perceived usefulness on the payment method	PUPM1	I found appropriate and useful the proposed payment method.
	PUPM2	The payment method was respected according to the partnership.
	PUPM3	I think the payment method should be reviewed to offer more options to farmers.
	PUPM4	I think farmers should be free to choose any payment method without affecting the price.
Perceived price	PR1	I found the price of the service too high for me compared to the service offered.
	PR2	I think the price should be reviewed and put down.
	PR3	I think the proposed prices are realistic and fit with the proposed service.

1-Strongly Disagree; 2-Disagree; 3-Neutral/Uncertain/Partially; 4-Agree; 5-Strongly Agree; *Partnership means the business model

Section 2: Model evaluation for Control

Constructs		Statements
Perceived Ease of Use	PEU11	I could adopt the partnership based on RiceAdvice application
	PEU21	I would not have any difficulty applying the recommendation received from the service provider.
	PEU31	I would feel comfortable and confident using the advice from the application.
	PEU41	I would not have a problem partnering with the service providers.
	PEU51	All things considered, I think that the adoption of the partnership would require a large effort in training and effort from me.
Perceived usefulness	PU11	Adopting the partnership would make my production easy for me
	PU21	The adoption of a partnership could increase my productivity.
	PU31	It could improve my work efficiency and my effectiveness.

	PU41	The recommendation received could help me reduce the quantity of input used.
	PU51	The adoption of the partnership could help me to have more control over the management of my farm.
	PU61	All things considered; I think the adoption of the partnership would not be that useful to my farm management.
Attitude	ATT11	I believe that the use of the RiceAdvice application through the partnership would be the best option for rice farmers to adopt digital technology.
	ATT21	All things considered; I think that adopting this partnership by rice farmers is not a good idea.
	ATT31	The technology could provide us with accurate and useful information.
	ATT41	I believe that the credibility of the information and recommendation would be high and trustful.
Intention to adopt	IAD1	I'm sure I will likely adopt RiceAdvice through the partnership proposition if it is proposed to me.
	IAD2	Assuming I have access to the system, I intend to use it.
	IAD3	Given that I have access to the system, I predict that I would use it.
Image	IM11	Using the recommendation provided by the RiceAdvice application could make me feel confident.
	IM21	Using the partnership could create a good image for my farm.
	IM31	Using the partnership could make us more visible and on the edge for opportunities.
Perceived usefulness on the payment method	PUPM11	The payment method is a very important factor for the adoption of the partnership.
	PUPM21	I would make the necessary effort to respect the payment method according to the business model.
	PUPM31	I think a better payment method option should be given to farmers.
	PUPM41	I think farmers should be free to choose any payment method without affecting the price.
Perceived price	PR11	The price is a very important factor in the adoption of the business model.

	PR21	I think the price should be an open option to be reviewed with the agent based on how many visits.
	PR31	I think a fixed-price option is more realistic and fits with the proposed service.

1-Strongly Disagree; 2-Disagree; 3-Neutral/Uncertain/Partially; 4-Agree; 5-Strongly Agree; *Partnership means the business model

Appendix 4.2: Internal consistency of the treated and Control farmers.

Appendix 4.2.1. Internal consistency of the treated farmers.

N=1200	Perceived ease of use	Perceived usefulness	Attitude	Adoption	Actual use	Image	Perceived usefulness PM	Perceived price
PEU1	0.727							
PEU 2	0.787							
PEU 4	0.804							
PU1		0.760						
PU 3		0.819						
PU 5		0.785						
ATT1			0.794					
ATT 3			0.731					
ATT 4			0.700					
ADP1				0.747				
ADP 2				0.709				
ADP 3				0.722				
AU1					0.706			
AU 2					0.763			
AU 4					0.799			
IM1						0.814		
IM 2						0.702		
IM 3						0.732		
PUPM1							0.701	

PUPM 2							0.795	
PUPM 4							0.795	
PR1								0.863
PR2								0.921
Cronbach's Alpha	0.663	0.701	0.620	0.552	0.626	0.605	0.632	0.749
Dillon-Goldstein's Rho	0.817	0.831	0.783	0.769	0.801	0.785	0.804	0.887
Average R square=0.390		Absolute GoF = 0.476		Relative GoF = 0.922				

Appendix 4.2.2. Internal consistency of the control farmers.

N=360	Perceived ease of use	Perceived usefulness	Attitude	Intention to Adoption	Image	Perceived usefulness PM	Perceived price
PEU11	0.841						
PEU 21	0.859						
PEU 31	0.842						
PEU 41	0.893						
PU11		0.841					
PU 21		0.835					
PU 31		0.870					
PU 41		0.815					
PU 51		0.866					

ATT11			0.850				
ATT 31			0.897				
ATT 41			0.875				
IAD1				0.885			
IAD 2				0.819			
IAD 3				0.858			
IM11					0.891		
IM 21					0.852		
IM 31					0.871		
PUPM11						0.849	
PUPM 21						0.847	
PUPM 31						0.841	
PUPM 41						0.883	
PR11							0.862
PR21							0.829
PR31							0.882
Cronbach’s Alpha	0.882	0.900	0.846	0.814	0.842	0.877	0.820
Dillon-Goldstein’s	0.918	0.926	0.907	0.890	0.905	0.916	0.893
Average R-squared = 0.771		Absolute GoF = 0.75395		Relative GoF = 0.99533			

Appendix 4.3. Discriminant and convergent validity.

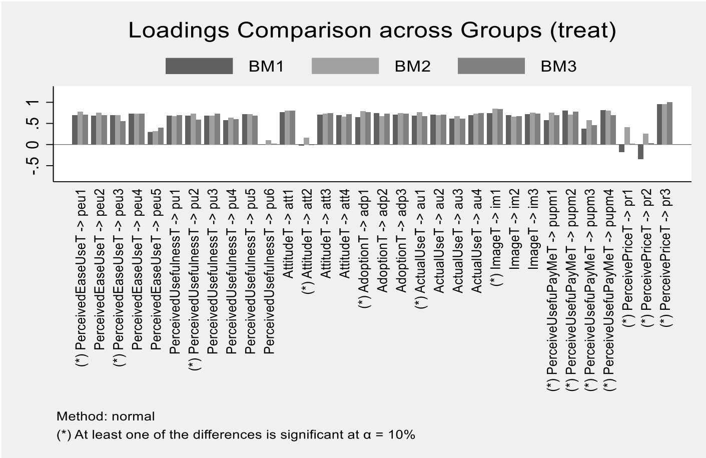
Appendix 4.3.1. Discriminant and convergent validity - Squared interfactor correlation versus Average variance extracted (AVE) HTMT for treated farmers.

	Perceived ease of use	Perceived usefulness	Attitude	Adoption	Actual use	Image	Perceived usefulness PM	Perceived price
Perceived ease of use	1.000							
Perceived usefulness	0.301	1.000						
Attitude	0.323	0.331	1.000					
Adoption	0.345	0.322	0.453	1.000				
Actual Use	0.361	0.282	0.391	0.446	1.000			
Image	0.352	0.310	0.395	0.485	0.379	1.000		
Perceived usefulness PM	0.328	0.273	0.330	0.397	0.398	0.450	1.000	
Perceived price	0.140	0.118	0.179	0.176	0.177	0.227	0.189	1.000
Convergent Validity AVE	0.598	0.621	0.546	0.527	0.573	0.550	0.578	0.339
Pseudo R^2	0.399	0.389	0.452	0.446	0.668	0.525	0.476	0.311

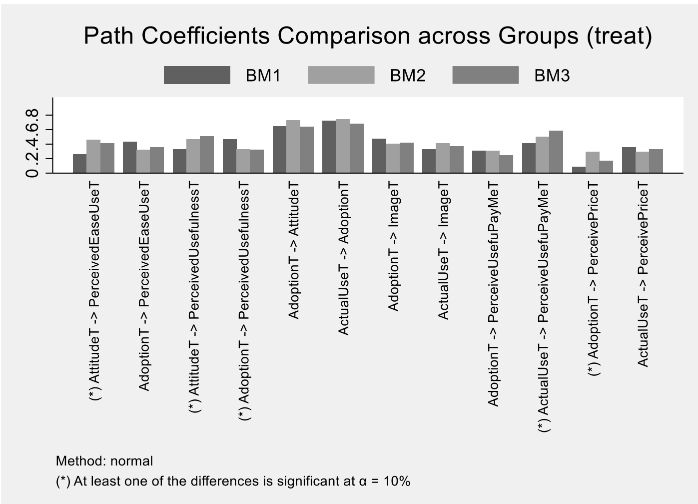
Appendix 4.3.2. Discriminant and convergent validity - Squared interfactor correlation vs. Average variance extracted (AVE) HTMT for control farmers.

	Perceived ease of use	Perceived usefulness	Attitude	Intention to Adopt	Image	Perceived usefulness PM	Perceived price
Perceived ease of use	1.000						
Perceived usefulness	0.788	1.000					
Attitude	0.706	0.783	1.000				
Intention to Adopt	0.737	0.792	0.658	1.000			
Image	0.723	0.746	0.695	0.744	1.000		
Perceived usefulness PM	0.739	0.802	0.682	0.789	0.805	1.000	
Perceived price	0.668	0.708	0.598	0.747	0.744	0.771	1.000
Convergent Validity AVE	0.738	0.715	0.764	0.730	0.760	0.731	0.736
Pseudo R^2	0.819	0.869	0.657	0.811	0.744	0.789	0.746

Appendix 4.4. Multi-group Analysis.



Source: Graphical output designed by authors



Source: Graphical output designed by authors

Chapter 5. Digitized Extension Service Business Model: An Experimental Evidence in Nigeria

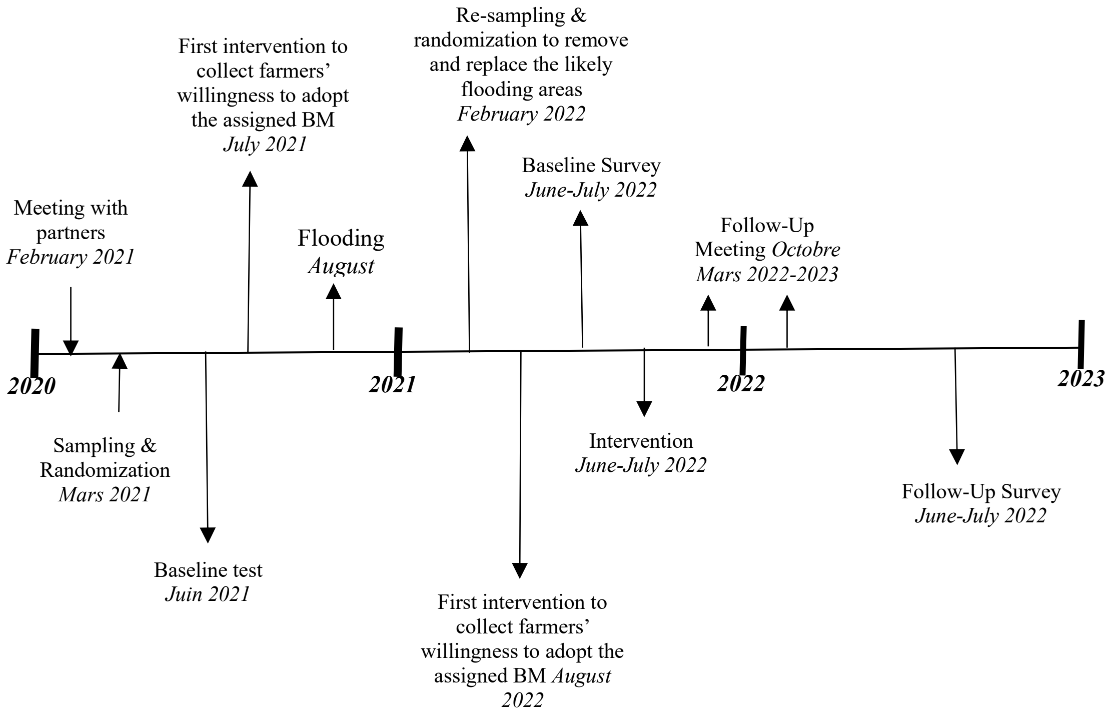
Appendix 5.1. Intra-cluster correlation coefficients for the outcome's variables.

	ICC	SE
Economic Efficiency (EE)	0.502	0.043
Profit (US$/ha)	0.503	0.044

Appendix 5.2. Lee bounds on the treatment effect.

		Lee Bounds	
	OLS	Lower	Upper
Economic Efficiency	-0.104***	-0.136***	-0.083***
	(0.014)	(0.010)	(0.010)
Profit (US$/ha)	156.838	-28.090	688.877***
	(173.995)	(131.486)	(155.017)

Appendix 5.3. Experiment timeline and field activities plan.



Appendix 5.4. Multiple hypothesis testing *(T-C)*.

	OLS	OLS_C	ANCOVA	ANCOVA_C
	1	2	3	4
Outcome 1: Economic Efficiency				
Unadjusted *p*-value	0.000	0.000	0.000	0.555
Bonferroni adjusted p-value	0.001			
Holm adjusted p-value	0.001			
Sharpened q-value	0.001	0.001	0.001	1.000
Outcome 2: Profit (US$/ha)				
Unadjusted *p*-value	0.286	0.065	0.952	0.785
Bonferroni adjusted p-value	0.039			
Holm adjusted p-value	0.019			
Sharpened q-value	0.167	0.034	0.909	1.000

Note: The results with covariates are presented in columns (2) and (4), while the results without covariates are in columns (1) and (3).