IMPACT OF ICT ADOPTION ON THE FOOD SECURITY OF AGRICULTURAL HOUSEHOLDS IN BURKINA FASO

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Abstract

This research evaluates the impact of the adoption of information and communication technologies (ICT) on the food security of farming households in Burkina Faso. Data were collected from 420 farmers in the Centre region, selected by simple random sampling. Descriptive statistics and the propensity score matching (PSM) model were used to compare the results of treated observations with those of no treated observations. The results reveal that farm households that adopt ICTs benefit from a substantial improvement in their food security, reflected by an average treatment effect (ATE) of 0.505, with very high statistical significance ($p < 0.001$). These findings imply that targeted policies to promote digital are needed to maximize the benefits of ICT in the agricultural sector and enhance food security in rural areas.

***Key words**: Adoption, Burkina Faso, ICT, Technical efficiency.*

Introduction

According to the definition adopted at the World Food Summit (1996), food security is achieved when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and preferences, thus enabling them to lead an active and healthy life. Consequently, improving food security is a fundamental pillar of national and international policy frameworks aimed at reducing poverty in developing economies, particularly in sub-Saharan African countries (Gebrehiwot and van der Veen, 2015; Asante et al., 2021). In this context, empirical studies have highlighted that knowledge and information play a decisive role in achieving food security (Nakasone and Torero, 2016; Namubiru et al., 2018; Asante et al., 2021).

In sub-Saharan Africa, farming households, mostly rural, face major structural constraints such as limited access to agricultural information, low yields, insufficient market integration, high vulnerability to climatic hazards and a deficit in advisory support services (Nyoni et al, 2024).

In this context, ICTs are emerging as a particularly effective potential lever for transmitting this information and knowledge to farmers. These tools offer new opportunities for improving productivity, farm management and access to essential strategic information. For example, ICTs make it possible to disseminate information on new agricultural technologies, optimized input management methods and modern production techniques (Namubiru et al., 2018). In addition, they facilitate the identification and exploitation of the best sales opportunities for crops (Asante et al., 2021). They also help to improve the efficiency of agricultural markets, reduce price volatility and enhance food availability, all of which are essential to ensure sustainable food security (Nakasone and Torero, 2016).

However, despite these promising technological advances, the scientific literature still lacks rigorous empirical studies that assess the direct and causal effects of ICT adoption on the food security of farming households particularly in rural areas. In Burkina Faso, although ICTs are increasingly used in rural areas, food security remains a major challenge for many farming households. Most existing research is limited to descriptive analyses or local case studies, without establishing a clear link between ICT use and tangible improvements in food security. This gap raises the following question: What is the impact of ICT adoption on the food security of farm households?

This question is all the more crucial as food security remains a major unresolved challenge in many developing countries (Gebrehiwot and van der Veen, 2015), where ICTs could play a key role in the sustainable transformation of agricultural and food systems. .

In Burkina Faso, as in other sub-Saharan African countries, a large proportion of the population lives in rural areas and depends mainly on subsistence farming. Gross domestic product (GDP) per capita is among the lowest on the continent, with around 40.1% of the population living below the poverty line (INSD, 2022). Agriculture is characterized by low yields and high dependence on rainfall, making harvests particularly vulnerable to recurrent droughts that cause loss of life and increased land degradation (Sawadogo, 2021).

Furthermore, disparities in ICT adoption, due to socio-demographic, economic and institutional factors, limit their effectiveness and risk amplifying food inequalities. These challenges highlight the need for rigorous analysis to better understand the interactions between ICT adoption and food security, while taking into account the contextual specificities of farm households.

This research examines five main ICTs used in the Centre region of Burkina Faso, namely: cell phones, the Internet, mobile money transfer services, radio and television (INSD, 2022). The Diffusion of Innovations Theory (DIT), developed by Everett Rogers in 1962, is the theoretical framework used in this research. Indeed, IDT provides a better understanding of how ICTs can transform agricultural practices, improve access to information and optimize resource management, thereby enhancing food security.

The main objective of this research is to assess the impact of ICT adoption on the food security of farming households in the Centre region of Burkina Faso. Based on this theoretical framework, the hypothesis tested is: ICT adoption contributes to strengthening the food security of farming households in the Centre region of Burkina Faso.

While much previous work in the Centre region of Burkina Faso has focused primarily on the impact of climatic shocks and socio-economic factors on agricultural productivity and household food security (Sawadogo, 2021; Semde et al., 2021, Ouedraogo, 2020), this research adopts an innovative perspective. Indeed, it draws on the regular use of ICTs in this region (INSD, 2022) to explore the existing links between ICT use and the food security of farming households. By shedding light on these interactions, the results of this research will offer strategic

orientations likely to guide public policies and interventions aimed at sustainably strengthening food security.
The following section presents the theoretical framework of the research, while the third part details the methodological approach used, including the data collection method, the empirical model and the analysis methods. The results of the statistical analyses and the propensity score model (PSM) are presented in Part Four and discussed in Part Five. Finally, a conclusion offers recommendations to public decision-makers for the optimal use of ICT to improve food security.

1. Theoretical framework

The analysis of the impact of ICT technologies on the food security of farming households is rooted in a dual theoretical perspective: development economics and the theory of the diffusion of innovations. From an economic point of view, classical theory highlights that improving agricultural productivity is a fundamental lever for rural development and improving household living conditions (Sigué, 2019 : 32). In a context marked by rapid population growth, increased pressure on natural resources and growing climatic variability, farmers must constantly adjust their practices to guarantee food sufficiency and the sustainability of their livelihoods. Access to information, training and technological innovation becomes a decisive factor in strengthening their resilience.
With this in mind, the Diffusion of Innovations Theory (DIT), formulated by Everett Rogers (1962), provides a relevant analytical framework. This theory stipulates that the adoption of an innovation - in this case, ICTs - depends on several perceived attributes: relative advantage, which refers to the expected benefits compared with existing practices; compatibility, i.e. the innovation's suitability to users' values, needs and contexts; complexity, i.e. ease of learning and use; testability, which allows the innovation to be experimented with on a small scale before being fully adopted; and observability, linked to the visibility of the innovation's positive effects on peers.
In the context of this study, ICT represents a strategic innovation that facilitates access to reliable, real-time information on weather conditions, agricultural markets, production techniques, phytosanitary diseases and financing possibilities. In this way, they optimize

agricultural decisions, reduce uncertainty and enhance food security. The adoption of these digital tools, influenced by socioeconomic, demographic and institutional factors, can play a structuring role in the transformation of local agricultural systems (Nakasone and Torero, 2016 : 59; Namubiru et al., 2018 : 10). In sum, innovation diffusion theory provides a robust theoretical framework for understanding not only the dynamics of ICT adoption by agricultural producers, but also their differentiated effect on households' ability to ensure their food security in resource poor contexts.

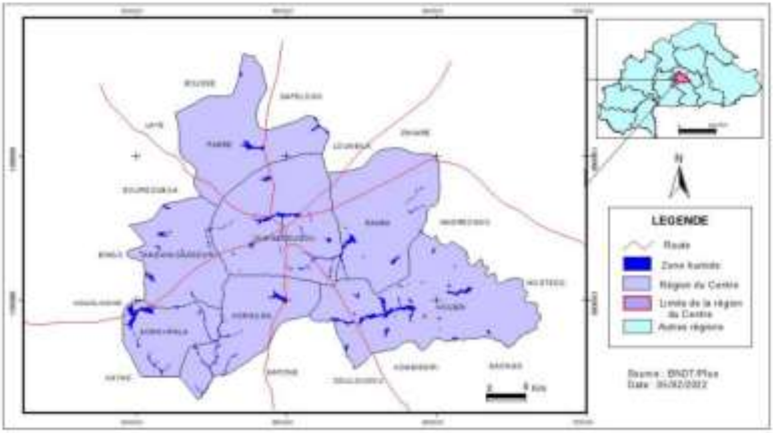
2. Materials and methods

This section describes the research framework, data collection methods, sampling techniques and data analysis approach.

2.1. Study area

The region studied in this research is the Centre, located in Burkina Faso, between 2°00' and 1°15' west longitude, and between 12°45' and 12°00' north latitude. It is bordered by the Central Plateau to the northwest, the Centre-Ouest to the west, and the Centre-Sud to the southwest and southeast (fig 1). The region, with Ouagadougou as its capital, consists of a province that is divided into a special urban commune and six rural communes, which together encompass 187 villages. This research excludes Ouagadougou due to the limited agricultural activities in the area, focusing exclusively on the rural communes.

Figure 1: Map of the Centre Region in Burkina Faso



Source BNDT/Plus (2022)

The main economic sectors in the rural communes of Burkina Faso's Centre region are agriculture, livestock farming, and handicrafts.
In agriculture, the primary cereals produced in the region include millet, white sorghum, red sorghum, maize, and rice. In 2023, maize was the most widely produced cereal, followed by red sorghum, white sorghum, and rice. However, the average cereal yields have declined over the past five agricultural seasons (MARAH, 2021).
In addition to agriculture, the rural communes practice three types of livestock farming: extensive, semi-intensive, and intensive. This sector plays a significant role in meeting the nutritional needs of the local population. The region's proximity to the capital facilitates the sale of products and access to agricultural inputs.
Alongside agriculture and livestock farming, handicrafts play an important role in the region's economy, serving as a major source of employment and income. This sector encompasses various activities such as carpentry, welding, weaving, masonry, leatherwork, pottery, blacksmithing, and sculpture. However, the sector faces two main

challenges : weak organization among actors and a lack of technical expertise in international trade (MEF, 2008).
Finally, the Centre region stands out for its greater use of information and communication technologies (ICT) compared to other regions in the country (INSD, 2022). The most widely used ICTs in rural communes include landline phones, radios, televisions, mobile phones, and the internet.

2.2. Data collection

An initial exploratory survey was conducted using a questionnaire administered to 20 farmers in the study area. The purpose of this survey was to gather preliminary information and test the questionnaire. This phase allowed for adjustments to the questionnaire, including the rewording of certain questions, to improve the quality of the responses. Following this, the main survey was carried out with 420 farmers from across the study area. Villages were selected purposively, while farmers were chosen randomly. It is important to note that the 20 farmers who participated in the exploratory survey were not included in the final sample for the main data collection.
Cette sous-section expose le modèle empirique utilisé dans cette recherche, décrit le processus de sélection et de caractérisation des variables, et présente en détail la spécification du modèle empirique adopté.

2.2.1. Empirical model

Empirical impact assessment, particularly the evaluation of the effect of ICT adoption on farm household food security indicators using non-experimental data, poses a significant challenge for researchers (Habtewold and Heshmati, 2023 : 27). Unlike experimental data, observational data are often subject to biases due to household self-selection, influenced by both observable and unobservable characteristics. This complexity complicates causal inference, which is critical for accurately measuring the true effects of ICT adoption. Failure to properly account for this self-selection bias can lead to inconsistent estimates of ICT adoption's impact.
Heckman et al. (1997 : 654) highlight that causal inference requires constructing a counterfactual scenario, which is an essential but challenging condition in non-experimental research. Becker (2009 : 193)

further points out that one of the main difficulties is the inability to observe both treatment and non-treatment states for the same unit and their corresponding outcomes. Thus, it is crucial to identify a method that can simulate experimental conditions in a quasi-experimental setting.

In this research, the propensity score matching (PSM) model, developed by Rosenbaum and Rubin (1983 : 55), is employed. This non-parametric approach provides reliable estimates by controlling for observable variables and facilitating robust comparisons between groups with similar socio-economic and demographic characteristics.

PSM relies on two fundamental assumptions. First, non-adopters should have mean scores comparable to those of adopters for identical propensity scores (Gebrehiwot and Van der Veen, 2015 : 47). Second, each individual must have a positive probability of being assigned to either the adopter or non-adopter group for the same propensity score value. When these conditions are met, it is possible to accurately estimate the average treatment effect of ICT adoption on farm household food security.

There are several techniques for implementing PSM, including stratification or interval matching, caliper or radius matching, kernel and local linear matching, and nearest-neighbor matching with a caliper (Khandker et al., 2010 : 239). This research uses the nearest-neighbor matching with caliper approach.

To ensure the quality of the matching process, various methods are used to check the balance of covariates. A two-sample t-test (before and after matching) can assess whether there are significant differences in covariate means between the treated and untreated groups (Rosenbaum & Rubin, 1985 : 38). Additionally, Sianesi (2004 : 42) recommends comparing the pseudo R^2 before and after matching to evaluate covariate balance. Finally, covariate balance can be assessed using standardized differences and variance ratios, as proposed by Rosenbaum & Rubin (1985 : 38). This research adopts the latter technique to verify the quality of the matching by comparing the treatment and control groups before and after PSM.

2.2.2. Variable selection

The empirical literature allowed us to categorize the variables selected for this research into three main groups. As the primary objective is to evaluate the impact of information and communication technologies (ICT) adoption on the food security of farming households, the treatment variable chosen is the use of ICT (UTIC), a dichotomous variable. This variable is assigned a value of 1 if the household adopts ICTs, and 0 otherwise.

The outcome variable is the household food security score (FSS). This score was calculated by multiplying the frequency of consumption of various food groups by their respective nutritional weights and then summing the results to obtain an overall score (FAO, 1996 : 43). The use of FSS as an outcome variable is justified by its capacity to capture multiple dimensions of food security, including diversity, quality, and quantity, making it a comprehensive measure for assessing the impact of ICT adoption on food security.

The third category comprises explanatory variables, identified from previous empirical studies on the determinants of ICT adoption by farmers (Aminou et al., 2018 : 88 ; Diendéré, 2019 : 13 ; Ebele et al., 2019 : 397). These variables reflect characteristics identified by Rogers (1962) as determinants influencing ICT adoption. The explanatory variables include gender (Sex), age (Age), level of education (Inst), household size (TailM), distance to the communal market (DistM), membership in a producers' organization (ApOP), regular contact with an advisory support agent (PEAPC), agricultural income exceeding 200,000 CFA francs (RevA), number of agricultural assets in the household (Acta), non-agricultural income exceeding 200,000 CFA francs (RevNA), frequency of supervision (FrEnc), area sown (SupEmb), sufficiency of daily food requirements (SufCj), sufficiency of agricultural production for annual consumption (SufPAC), and number of months covered by food stock (NbMCStock).

All variables selected for this study were subjected to correlation tests, which revealed no issues with multicollinearity.

2.2.3. Empirical model specification

This research employs the propensity score matching (PSM) model, developed by Rosenbaum, P. R., & Rubin, D. B. (1983 : 55). This model contrasts the outcomes of treated observations with those of untreated observations, using the calculated propensity scores of the groups. The propensity score P(X) is defined as the conditional probability that a household will adopt ICT (W = 1), given its observable characteristics X

$$P(X) = Pr(Wi = 1|X) \quad (1)$$

Where :

Wi = 1 if the household adopts ICT, otherwise 0

X = represents the multidimensional vector of explanatory variables such as household characteristics. The score is estimated using a logistic model :

$$P(X_i) = \frac{exp(\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+....\beta_k X_k)}{1+ exp(\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+....\beta_k X_k)} \quad (2)$$

Where :

β_0 is the model constant. It represents the baseline probability of ICT adoption when no explanatory variable is

(Xi =0) is not considered.

β_i (i = 1, 2,… K) represent the regression coefficients associated with the explanatory variables Xi, which measure the marginal effect of a unit increase in the explanatory variable Xi.

X_i (i = 1, 2,… K) are the explanatory variables or covariances that influence the probability of ICT adoption.

Following the estimation of propensity scores, nearest-neighbor matching with caliper is applied to reduce bias due to differences between individuals and maximize comparability between treated and untreated groups. Individuals are matched if the difference between their propensity scores is below a certain threshold (the caliper).

$$|P(X_i) - P(X_j)| < \delta \quad (3)$$

Where :

$|P(X_i)\text{-}P(X_j)|$ represents the absolute value between the propensity scores of individuals i and j

δ represents the caliper, i.e. the predefined threshold that limits the difference between the propensity scores so that two individuals can be matched. A caliper of 0.2 times the standard deviation of the propensity score is used (Rosenbaum & Rubin, 1985 : 38).

After matching, the average effect of treatments on treated (ATT) was evaluated using the following formula :

$$ATT = \frac{1}{N_T}\sum_{i\in T}\left[Y_i(1) - \sum_{J\in C} W_{ij} Y_j Y(0)\right] \quad (4)$$

Where :
N_T represents the number of households treated
W_{ij} represents the matching weight between household i (treated) and j (untreated)
Finally, covariate balance was verified by measuring standardized differences and variance ratios using the following formulas :

$$Standard\ differences = \frac{|X_T - X_C|}{\frac{\sqrt{S_T^2 + S_C^2}}{2}} \quad (5)$$

Where :
X_T represents the mean of covariate X in the treatment group.
$X^2{}_C$ represents the mean of covariate X in the control group (untreated).
$S^2{}_T$ represents the variance of the covariance X in the treated group.
S_C represents the variance of the covariance X in the treated group.

$$Variance\ ratio = \frac{S_T^2}{S_C^2} \quad (6)$$

3. Results

This section presents a summary of the descriptive statistics, and the estimation of the PSM model.

3.1. Summary of descriptive statistics

Table I indicates that the mean score of the outcome variable, the Food Security Score (FSS) for ICT users (UTIC), is significantly higher than that of non-ICT users (NUTIC), with a highly significant mean difference of 0.59. The table also reveals that the means of socio-demographic, economic, and institutional variables, used as explanatory variables—such as farm assets, education level, supervision by an advisory agent, farm income, frequency of supervision, area sown (SupEmb), sufficiency of daily food requirements (SufCj), sufficiency of agricultural production for annual consumption (SufPAC), and the number of months covered by food stock (NbMCStock)—are marginally higher in the UTIC group than in the NUTIC group.

Regarding other variables, the UTIC group is, on average, closer to markets (mean distance of 0.61) compared to the NUTIC group (mean distance of 0.74). Additionally, the average age of the UTIC group (44.36 years) is slightly lower than that of the NUTIC group (45.45 years), suggesting that ICT users are generally younger. The average household size for the UTIC group is also slightly smaller compared to the NUTIC group. Conversely, variables such as gender, membership in a producer organization, and off-farm income are marginally higher in the NUTIC group than in the UTIC group.

Table I : Descriptive statistics and definitions of empirical variables

		Mean			
Description variables		All	UTIC	NUTIC	Diff
	Treatment variable				
UTIC	Farmers use ICT for agricultural production		0,57 (0,50)	0,43 (0,50)	0
Output variable					
FSS		0,364 (0,48)	0,62 (0,48)	0,03 (0,16)	0,59
	Explanatory variables				
Sex	Sex of farmer (1= male, 0= female)	0,62 (0,48)	0,76 (0,42)	0,43 (0,49)	0,33
Acta	Number of farm workers in household	5,64 (3,34)	5,65 (2,95)	5,64 (3,81)	0,01
Age	Farmer's age (year)	44,83 (12,14)	44,36 (11,75)	45,45 (12,64)	-1,09
Inst	Farmer's education (1=educated, 0=uneducated)	0,51 (0,5)	0,64 (0,47)	0,34 (0,47)	0,3
TailM	Number of people in the farmer's household (Number)	9,37 (5,1)	9,27 (4,56)	9,49 (5,75)	-0,22
DistM	Is the farmer more than 5km from his village to the commune's main market? (1=yes, 0=no)	0,67 (0,46)	0,61 (0,48)	0,74 (0,43)	-0,13

		Mean			
Description variables		All	UTIC	NUTIC	Diff
RevNA	Farmer has a non-agricultural income of over 200 thousand (1=yes, 0=no)	0,34 (0,47)	0,41 (0,49)	0,24 (0,43)	0,17
ApOP	Is the farmer a member of a producer organization? (1=yes, 0=no)	0,42 (0,49)	0,46 (0,49)	0,37 (0,48)	0,09
PEAPC	Is the farmer in contact with an advisory agent ? (1=yes, 0=no)	0,77 (0,42)	0,85 (0,35)	0,65 (0,47)	0,2
FrEnc	Frequency with which the farmer is coached	2,85 (3)	3,43 (3,48)	2,09 (2,01)	1,34
SuperEmb	Area sown by farmer (Ha)	1,49 (1,22)	1,35 (0,78)	1,48 (1,24)	-0,02
RevA	Farmer has an agricultural income of over 200 thousand (1=yes, 0=no)	0,34 (0,47)	0,41 (0,49)	0,25 (0,43)	0,16
SufCJ	Your daily household consumption is sufficient for all household members (1=yes, 0=no)	0,84 (0,36)	0,88 (0,31)	0,78 (0,41)	0,1
SufPAC	Does your annual production meet your annual consumption needs (1=yes, 0=no)	0,55 (0,55)	0,65 (0,47)	0,41 (0,49)	0,24
NbMCSto	How many months of the year can your annual stocks cover (Number of months)	9,24 (9,24)	9,96 (2,72)	8,29 (3,27)	1,67

Source : Based on survey data (2024)

Notes : Values are averages. Standard deviation is shown in brackets. Stars *, ** and *** indicate the mean difference (t-test) between the ICT user group (UTIC) and the non-user group (NUTIC) at the 10, 5 and 1% significance levels, respectively.

3.2. PSM estimation results

3.2.1. Propensity score estimation

The conditional probability of the impact of ICT adoption on the food security of farming households was estimated using a logistic regression model. This model incorporates several observable covariates that potentially influence both ICT adoption and food security, for which data were available. The results are presented in Table II.

The model is statistically significant, as indicated by the Chi-square test probability ($p < 0.000$). The pseudo R^2 of 0.226 suggests that the covariates explain a substantial proportion of the variance in ICT adoption. Additionally, certain covariates show significant effects. The estimation results reveal that the probability of ICT adoption is strongly influenced by gender, with a positive and significant coefficient (1.320, $p < 0.001$). Education level also has a significant positive impact (0.897, $p < 0.001$), indicating the critical role of education in ICT adoption. Household size has a significant negative effect (-0.638, $p < 0.05$), suggesting that larger households are less likely to adopt ICT. The distance of households from the communal market, particularly those more than 5 km away, has a marginally significant negative effect (-0.499, $p < 0.10$), indicating that greater distance poses a barrier to ICT adoption. Frequency of supervision has a significant positive impact (0.149, $p < 0.05$), reflecting the importance of regular supervision in fostering ICT adoption. Finally, the number of months covered by food stock shows a significant positive effect (0.152, $p < 0.01$), highlighting the role of food stocks in encouraging ICT adoption.

Other variables, such as age, non-agricultural income, and area sown, do not have a significant effect on ICT adoption.

The results highlight factors influencing ICT adoption among farming households. Gender and education level are critical determinants, while household size and market distance act as barriers. Regular supervision and the availability of food stocks facilitate this adoption. These factors will be used for matching in a subsequent analysis to compare households that have adopted ICT with those that have not.

***Table II** : Estimation of Propensity Scores*

Variables	Coefficient	Std. Err	P>|z|
Sexe	1,320	0,256	0,000***
Acta	0,056	0,048	0,244
Age	-0,014	0,010	0,176
Inst	0,897	0,249	0,000***
TailM	-0,638	0,031	0,043**
DistM	-0,499	0,264	0,059*
RevNA	0,322	0,277	0,245

Variables	Coefficient	Std. Err	P>|z|
ApOP	-0,162	0,255	0,949
PEAPC	0,336	0,355	0,345
FrEnc	0,149	0,061	0,016*
SuperEmb	-0,166	0,100	0,090*
RevA	0,473	0,289	0,102
SufCJ	-0,186	0,368	0,613
SufPAC	0,096	0,354	0,787
NbMCStoc	0,152	0,059	0,010**
Const	-0,167	0,673	0,013**
LR Chi2		129,95	
Prob > chi2		0,0000	
Log likelihood		-222.40	
Pseudo R2		0,226	
N		420	

Notes : The stars *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Source : Based on data from the propensity score estimation (2024).

3.2.2. Estimation of the Average Treatment Effect (ATE)

Table III presents the results of the treatment effect estimation using propensity score matching, highlighting a significant positive impact of ICT adoption (UTIC) on the food security of farming households (FSS). The average treatment effect (ATE) is 0.505, with a p-value of less than 0.001, indicating a robust and statistically significant effect.

These findings confirm that ICT usage substantially enhances household food security by facilitating access to agricultural information, markets, and support services. The use of propensity score matching effectively controlled for selection bias based on observable variables, thereby strengthening the reliability of the conclusions. The histograms of propensity scores by treatment group demonstrate a good common support distribution, validating the success of the matching process (Figure 2).

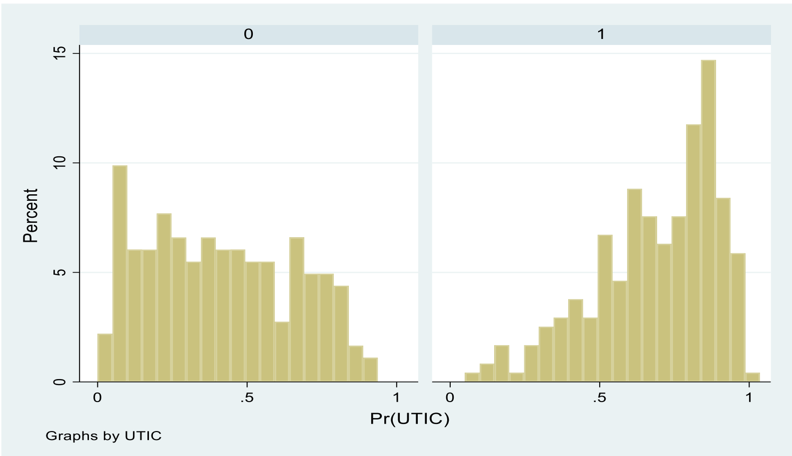
In conclusion, ICT adoption emerges as a promising strategy for improving the food security of farming households, particularly in contexts where access to information and agricultural services remains limited.

***Table** III : Average Treatment Effect (ATE)*

FSS	Coefficient	Sdt.err	z	P>|z|
ATE UTIC (1 vs 0)	0,505	0,045	11,10	0,001

Source : Based on data from the propensity score estimation (2024).

***Figure 2** : Histograms of Propensity Scores by Treatment Group*



Source : Based on data from the propensity score estimation (2024).

3.2.3. Covariate balance check

Table IV presents the analysis of covariate balance before and after propensity score matching, demonstrating a significant improvement in the balance between treated and control groups. Prior to matching, several covariates showed significant imbalances, such as gender (standardized difference of 0.714), level of education (0.642), and frequency of supervision (0.468). Post-matching, these differences were

substantially reduced, with all falling below the acceptable threshold of 0.1 for standardized differences, indicating a good balance.
The variance ratio also improved for most covariates following matching. For example, the variance ratio for gender increased from 0.731 to 1.027, for the level of education it remained close to 1, for the frequency of supervision it decreased from 3.00 to 1.76, and for the area sown it improved from 0.08 to 0.19, indicating homogeneity of variances between groups.
These results confirm the effectiveness of matching in reducing biases related to observable covariates, enhancing the comparability of treated and control groups. This reinforces the robustness of the previously observed average treatment effects (ATE). Ensuring covariate balance is a critical step that validates the methodological rigor of the study's conclusions regarding the impact of ICT adoption on the food security of farming households.

***Table IV** : Covariate Balance*

Variables	Standard différences		Variance ratio	
	No matched	Matched	No matched	Matched
Sexe	0,714	-0,049***	0,731	1,027**
Acta	0,002	-0,111	0,598	0,743
Age	-0,089	0,058	0,864	0,743
Inst	0,642	0,052***	1,015	1,000*
TailM	-0,041	-0,081	0,630	0,625
DistM	-0,280	-0,771	1,248	1,065
RevNA	0,363	0,225	1,303	1,019
ApOP	-0,176	-0,086	1,055	0,972
PEAPC	0,473	0,046	0,544	0,936
FrEnc	0,468	0,054***	3,000	1,762***
SuperEmb	-0,099	-0,994	0,083	0,190**
RevA	0,328	-0,798	1,262	0,950
SufCJ	-0,274	0,077	0,596	0,844
SufPAC	0,490	0,057	0,927	0,987
NbMCStoc	0,553	0,007	0,692	1,055
UTIC	238			
NUTIC	182			
Nbr d'observations	420			

Notes : The stars *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Source : Based on data from the covariate balance verification (2024).

4. Discussion

The descriptive statistics from this research reveal significant differences between ICT users (UTIC) and non-users (NUTIC). In terms of socio-economic and institutional characteristics, UTIC demonstrate advantages over NUTIC, particularly in education level, proximity to markets, support from advisory agents, and frequency of supervision. These observations suggest that access to ICT is associated with better demographic, economic, and institutional conditions. Similar findings were reported by Twumasi et al. (2021 : 65), indicating that ICT users, especially those using the Internet, are more likely to have a higher level of education and more frequent contact with extension agents compared to non-Internet users. However, some variables, such as gender and non-agricultural income, are slightly more favorable among NUTIC, reflecting contextual differences.

The propensity score estimation results highlight the determinants of ICT adoption by farming households and its potential impact on food security. The logistic regression model reveals that gender and education level are key factors promoting ICT adoption, underscoring potential gender disparities and the importance of education in technology integration. The frequency of supervision, which is positively significant, indicates that technical support plays a crucial role in ICT adoption.

The average treatment effect (ATE) results show that ICT adoption has a significant positive impact on the food security of farming households, with an ATE of 0.505, confirming substantial improvements in access to agricultural information and services. Access to agricultural production information via ICT contributes to enhancing food security among farming households in Iran, as confirmed by Lashgarara et al. (2011 : 39), who demonstrated that providing information through ICT positively affects food security, agricultural production, and product marketing. Similarly, Namubiru et

al. (2018 : 10) observed that households in northern Uganda accessing agricultural information through FM radios and mobile phones improve their food security.
The use of propensity score matching effectively reduced selection biases, ensuring a valid comparison between ICT users and non-users. The well-distributed propensity scores after matching strengthen the robustness of the results, suggesting that ICT plays a critical role in improving the food security of farming households. Similar research conducted by Mulugeta and Heshmati (2023 : 27) in Ethiopia confirms these findings, highlighting the positive impact of agricultural technologies on food security. Finally, the covariate balance analysis demonstrates significant improvements after propensity score matching, reducing initial imbalances between treated and control groups. The standardized differences for covariates fell below the acceptable threshold of 0.1, indicating good balance. The improvements in the variance ratio for several covariates confirm increased homogeneity between the groups. Similar results were observed by Wordofa et al. (2021 : 12) in Ethiopia. These findings attest to the effectiveness of matching in minimizing biases, thereby reinforcing the robustness of the conclusions regarding the impact of ICT on food security.

Conclusion

This research assessed the impact of the adoption of information and communication technologies (ICT) on the food security of farming households in the Centre region of Burkina Faso. The results obtained are based on descriptive statistics, a logistic regression model, and propensity score estimation (PSM). Descriptive analyses indicate that ICT users have a significantly higher food security score than non-users, while econometric results confirm this trend by identifying major determinants of adoption, such as gender, level of education, frequency of technical supervision and availability of food stocks. On the other hand, factors such as household size and distance from markets appear to be obstacles to adoption.
The evaluation of the average treatment effect (ATE) by propensity score matching highlights a positive and statistically significant impact

of ICTs on food security, underlining their role in improving the dissemination of agricultural information, the optimization of farming practices and access to markets and advisory services. The hypothesis that the adoption of ICTs contributes to enhancing the food security of farming households in the Centre region of Burkina Faso is therefore verified.

These results underline the strategic importance of ICT in strengthening the food resilience of rural populations, particularly in contexts where access to information remains limited. They call for the implementation of public policies aimed at fostering digital inclusion, specifically targeting vulnerable groups such as women, remote households and the poorly educated, as well as strengthening technical support mechanisms.

The results of this study underline the need for policies and actors in rural development to design ambitious and inclusive programs promoting the adoption of ICTs in the agricultural sector. The positive and significant link between the use of ICTs and improved food security is a signal in favor of integrating them into the conduct of agricultural activities, particularly in rural areas where food vulnerabilities are still very marked. In addition to its economic dimensions, this dynamic has significant social benefits: it helps to empower producers, improve resource management, facilitate decision-making, and promote the inclusion of young people and women in production and marketing channels.

In addition, this research provides a solid empirical foundation to enrich scientific thinking on the transformation of agricultural systems. In future work, it would be particularly relevant to disaggregate effects according to the types of ICT mobilized, and to examine impact mechanisms in different socio-geographical contexts, in order to adapt interventions to local realities and maximize their reach.

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