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Does Using Digital Platforms Impact Irish Potato Productivity? The Case of Smallholder Farmers in Molo and Njoro Sub-Counties, Kenya

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Abstract

This study examined the effects of using digital platforms, specifically Viazisoko and Mzizi apps, on Irish potato productivity among smallholder farmers in Molo and Njoro sub-counties, Kenya. A multistage sampling technique was used to sample 402 farmers. The Multinomial Endogenous Treatment Effect (METE) model was used for analysis. The model consists of two components: Treatment and Outcome models. The results from the treatment model revealed that factors that significantly influenced the likelihood of farmers being in one of the two treatment categories, "Know but non-user" or "Know and User" relative to the base category, "unaware of the platform" were sex, training, education, and need for production and marketing information. The outcome model revealed that both treatment categories had a higher potato productivity relative to the base category. Farmers in the "Know but Non-users" category had a 0.741 unit increase in productivity ($p < 0.01$), while farmers in the "Know and User" category had a 0.532 unit increase in productivity ($p < 0.01$). Based on the findings, the study suggests that the digital platform developers should prioritize extensive training and improve awareness campaigns in order to facilitate enhanced knowledge and usage of such digital platforms. These efforts will promote an increase in potato productivity among smallholder farmers.

Keywords

Digital Platforms, Irish Potato, Multinomial Endogenous Treatment Effect Model, Productivity

1. Introduction

Irish potato (*Solanum tuberosum* L.) is a key contributor to world food and nutrition security and ranks fourth after maize, wheat, and rice [1]. In Sub-Saharan Africa, the largest amount of potatoes is produced in Eastern Africa (71%), Southern Africa (21%), and Western Africa (8%) [2]. Kenya is the second major potato producer, producing 8.36 t/ha after Tanzania (8.43 t/ha) in Eastern Africa [3]. In Kenya, potatoes are the second-most important food crop after maize and are produced mainly in two rainy seasons, the long rains (April to August) and short rains (September to January), with the length of the season changing from one region to another [4]. Potato production is done in different counties such as Meru, Nyeri, Nyandarua, Taita-Taveta, Nakuru, Narok, Bomet, Elgeyo Marakwet, and West Pokot, among others.

In Kenya, the potato value chain employs over 3.5 million actors, contributing over 50 billion Kenyan shillings (Ksh) to the economy per annum [5]. Nakuru is one of the leading counties in potato production, and the Nakuru County Integrated Development Plan (CIDP) 2018-2022 identifies potatoes as one of the main cash crops produced in the county and the second most important staple food crop after maize. Potato farming is one of the enterprises that has increased in Kenya due to its benefits. The subsector creates income and employment for many smallholder farmers, which also makes a major contribution to the nation's food security [6]. The majority of households in Nakuru County depend on agriculture as their primary source of income, with the potato being the second most widely cultivated crop in the county.

For the past five years, the potato has emerged as one of the leading value chains in food, nutrition, and income security, but the industry still faces several challenges, which include low productivity, access to high-quality seed, unstructured marketing, inadequate investment, and coordination of the industry [5]. According to [6], the potato industry tends to perform below its potential due to poor farming practices, leading to current productivity of an average of 7 - 10 tons per hectare, against the potential of 30 - 40 tons per hectare. Nevertheless, in recent times, there have been introductions of digital platforms such as *Viazisoko and the Mzizi* app. These platforms have been introduced across the country, including Nakuru County, to provide agricultural information to farmers. However, the impact of using these platforms on farmer productivity has not been empirically evaluated.

The *Viazisoko* platform was developed by the National Potato Council of Kenya (NPCK) and its partners, notably the International Potato Centre (CIP) and GIZ, and launched in May 2017 [7]. It became functional in 2021 [8]. The platform provides an efficient way of accessing quality farm inputs and services such as certified seeds, potato-specific fertilizer, approved agrochemicals, spray services, soil testing, and mechanization services, among others. It is also used to connect farmers to market outlets. There are 114,454 farmers registered in the *Viazisoko* database from Meru, Nyeri, Nyandarua, Kiambu, Nakuru, Narok, Bomet, and Elgeyo Marakwet in Kenya. However, only 20,621 (18%) farmers are using the *Viazisoko* platform, with 1,668 (1.5%) farmers from Nakuru.

The *Mzizi* app was developed in June 2023 by the Mzizi private company. Its mission is to transform potato production in rural Sub-Saharan Africa through innovative technology to cultivate food security and prosperity [9]. The app acts as a one-stop shop where smallholder farmers can get all production services, such as inputs and agronomic support, from its pool of experts. Additionally, farmers who have farm records in the *Mzizi* app can be easily linked to their preferred market. So far, more than 15,000 smallholder potato farmers have been reached in Kenya [9], with 1,547 (10.3%) farmers using the platform from Nakuru County.

Despite the strategy of the digital platforms (*Viazisoko* and *Mzizi* app) to reach a huge number of smallholder potato farmers, a substantial number of farmers do not use the digital platforms to access agricultural information for potato production and marketing. As a result, this study was conducted to evaluate the effects of using such platforms on productivity among smallholder potato farmers.

2. Methodology of Study

2.1. Study Area

The study was conducted in Molo and Njoro sub-counties in Nakuru County, which are major potato-producing areas in the county [10]. Molo sub-county is located in the Rift Valley along the Mau Forest, which runs on the Mau escarpment at 0.25˚ South latitude, 35.73˚ East longitude, and 2,534 meters above sea level [11]. The sub-county is approximately 478.79 square kilometers with a population of 156,732 persons, and the average farm size for food crops is less than a hectare per household [11]. Njoro sub-county is located 18 kilometers southwest of Nakuru Town and lies between Longitude 35˚45'0" and 36˚10'0" East and Latitude 0˚15'0" and 0˚42'30" South at approximately 1,800 m above sea level. The sub-county covers an area of 713.3 square kilometers with a total population of approximately 238,773 people [11].

2.2. Sampling Technique

A multistage sampling technique was employed in the study. In the first stage, Nakuru County was purposively selected because it is one of the major potato-producing counties in Kenya. This was followed by the purposive selection of two sub-counties in the county, namely Molo and Njoro, since they are among the major producing areas of potatoes in Nakuru. In the third and last stage, systematic random sampling was used to sample the n^{th} potato farmers using digital platforms. A list of farmers who were using the platforms was obtained from NPCK and Mzizi Company to identify the respondents. Simple random sampling was used to sample the potato farmers who were non-users of the platforms.

The determination of the sample size for this study followed the coefficient of variation formula [12] since the population of smallholder potato farmers who are using the *Viazisoko* and *Mzizi* app was known.

$$n = \frac{NC^2}{C^2 + (N-1)e^2} \tag{1}$$

$$n = \frac{376(0.3)^2}{(0.3)^2 + (376-1)0.02^2} = 141 \quad (2)$$

where: n = sample size; N = population; c = coefficient of variation; e = standard error. Nassiuma (2000) states that in most surveys, a coefficient of variation in the range of $21\% \le c \le 30\%$ and a standard error in the range of $2\% \le e \le 5\%$ is acceptable. The study therefore used a coefficient of variation of 30% and a standard error of 2%. The lower limit of the standard error is selected to ensure low variability in the sample and minimize the degree of errors [10].

The derived sample size for the study was $141 \times 3 = 423$ respondents for three groups: "know and users of the digital platforms," "know but non-users of digital platforms," and "control group, unaware of the digital platforms." However, due to the unavailability of other farmers, the study managed to interview 402 smallholder farmers. In this study, knowledge was defined as the awareness and understanding of digital platforms acquired either through formal training or informal exposure and familiarity gained from fellow farmers.

2.3. Empirical Models

Determining the effects of using digital platforms on productivity could be achieved using Propensity Score Matching (PSM) and Endogenous Switching Regression models (ESR). Productivity was measured in terms of output per unit area and is affected by numerous factors such as land size, fertilizer use, type of crop variety, farmer experience, and weather conditions, among others. The PSM is a quasi-experimental impact evaluation approach that commonly uses counterfactuals to match individuals receiving treatment with control individuals [13]. This study did not use the PSM model because the model assumes that all variables that influence treatment assignment and potential outcomes simultaneously must be observed by the researcher [14]. Therefore, factors affecting the treatment assignment and outcome that could not be observed would not be accounted for directly, and overlooking the unobservable factors during analysis could cause inconsistent estimates.

The ESR model is more robust in tackling potential endogeneity and deals with selection bias while consistently measuring the dependent variable using actual and counterfactual outcomes [15]. However, the ESR model was not used because it is typically designed for binary treatment (*i.e.*, two groups such as treated vs. untreated). In this study, we focused on three treatments: 1) unaware of the platform, 2) know but non-user, and 3) know and user. As a result, a Multinomial Endogenous Treatment Effect (METE) model was used to analyze the impact of a treatment on an outcome (log productivity), while accounting for the endogeneity of the treatment decision. The model was estimated under both exogenous and endogenous treatment assumptions, with the endogenous model correcting for selection bias using selection terms (lambda- λ).

The METE framework uses a two-stage estimation method; in the first stage, the treatment model estimates the factors influencing the likelihood of farmers being in one of the two treatment categories ("Know but non-user" or "Know and User") relative to the base category (unaware of the platform) using a mixed multinomial logit (MMNL), and in the second stage, the outcome model estimates the effects of being in one of the two treatment categories ("Know but non-user" or "Know and User") relative to the base category (unaware of the platform) on log productivity.

In empirical analysis involving endogenous treatment variables with multiple categories, such as multinomial endogenous treatment models, the use of valid and relevant instrumental variables (IVs) is crucial to obtain unbiased and consistent estimates. This study used an exclusion restriction instrument: internet access, which affects treatment choice but does not directly affect the outcome; log productivity after conditioning on observed variables that affect both the treatment and outcome, such as the number of contacts with extension officers, training received, potato land size, experience in potato farming, and so on.

Let Y_i denote the potato productivity of farmer i and $\mathrm{T}_j \in \{1,2,3,\cdots,j\}$ the treatment level.

Treatment category 1 = Unaware of the digital platform.

Treatment category 2 = Know but non-user of the digital platform.

Treatment category 3 = Knowledge and use of the digital platform.

2.3.1. First Stage: Treatment/Selection Model

Theoretically, a farmer decides to use a digital platform when the expected utility received from using the platform is greater than the utility received from not using the digital platform. Following [16], each farmer i chooses one treatment from a set of three or more choices, which naturally includes a control group, implying a multinomial choice model. Let EV_{ij}^{*} denote the indirect utility that would be obtained by selecting the j^{th} treatment.

$$EV_{ij}^{*} = X'_j\alpha_j + \delta_j l_{ij} + \varepsilon_{ij} \tag{3}$$

where X_i denotes exogenous covariates with associated parameters α_j and ε_{ij}, which are independently and identically distributed error terms. Also, EV_{ij} includes a latent factor l_{ij} that incorporates unobserved characteristics common to farmer i' s treatment choice and outcome. Let $j = 0$ denote the control group and $EV_{ij} = 0$. Let d_j be binary variables representing the observed treatment choice and $d_j = \left(d_{i1}, d_{i2}, \cdots, d_{ij}\right)$. Also let $l_j = \left(l_{i1}, l_{i2}, \cdots, l_{ij}\right)$. Then, the probability of treatment can be represented as:

$$\Pr\left(d_i \mid X_i l_i\right) = g\left(X_i'\alpha_1 + \delta_1 l_{i1}, X_i'\alpha_2 + \delta_2 l_{i2}, X_i'\alpha_j + \delta_j l_{ij}\right) \quad [4]$$

Where g is an appropriate multinomial probability distribution, assuming that g has a mixed multinomial logit (MMNL) structure, defined as:

$$\Pr(d_i \mid x_i l_i) = \frac{\exp\left(X_i'\alpha_j + \delta_j l_{ij}\right)}{1 + \Sigma_{k=1}^{j} \exp(\left(X_i'\alpha_k + \delta_k l_{ik}\right)} \quad [5]$$

2.3.2. Second Stage: Outcome Model

In the second stage of METE, we estimated the effects of being in one of the two treatment categories ("Know but non-user" or "Know and User") relative to the base category (unaware of the platform) on log productivity. The expected outcome equation for farmer i, $i = 1, 2, \cdots, n$ is expressed as:

$$E(Y_i = y_i \mid d_i, x_i, l_i = x_i^{'}\beta + \sum_{j=1}^{j}\gamma_j d_{ij} + \sum_{j=1}^{j}\lambda_j l_{ij} \quad (6)$$

where Y_i is the productivity for a farmer i, x_i is a set of exogenous covariates with associated parameter vectors β; d_{ij} represents binary variables for observed treatment choice; and γ_j denotes the treatment effects relative to the control (unaware of the digital platform). $E\left(y_i \middle| d_i, x_i, l_i\right)$ is a function of each of the latent factors l_{ij}, *i.e.*, the outcome is affected by unobserved factors that affect selection into treatment.

3. Results and Discussion

3.1. Descriptive Statistics of Farmer Status

The results of farmer status characteristics with respect to sex, farmer group membership, ownership of the smartphone, and marital status are presented in Table 1. Regarding the sex of the respondents, 60.2% were males, while 39.8% were females, with the majority (86.3%) of the respondents being married. The results also reveal that 63.4% of the respondents were members of a farmers' group. Most farmers said that their groups were involved in many activities other than potato farming. Some were active in village savings and loans (VSL) groups where they shared information related to production, marketing, savings, and loans.

From the results, 97.3% of the farmers in Molo and Njoro sub-counties owned a mobile phone, while 2.7% did not. This reveals the high level of phone ownership in the two sub-counties, indicating a high level of (digital/vocal) communication. The findings also indicated that out of the 97.3% of farmers possessing mobile phones, 66.8% owned smartphones, whereas 33.2% used keypad/basic phones. This suggests that farmers utilizing smartphones are more inclined to download digital applications and obtain agricultural information. This aligns with the findings of [17], who specified that smartphone ownership enhances the probability of farmers utilizing digital services for agricultural information.

Table 1. Farmer status characteristics.

Categorical Variables	Frequency	Percentage (%)
Sex		
Male	242	60.2
Female	160	39.8
Marital Status		
Divorced	3	0.8
Married	347	86.3
Single	31	7.7
Widowed	21	5.2

Continued

Farmer Group Membership		
Yes	255	63.4
No	147	36.6
Phone Ownership		
Phone owners	391	97.3
Phone non-owners	11	2.7
Phone Type		
Keypad phone (basic phone)	130	33.2
Smartphone	261	66.8

Source: Authors.

Digital Platform Usage

The results on digital platform usage are presented in **Table 2**. Out of the sampled population of 402 farmers, 35.07% of the respondents used either *Viazisoko* (42.55%) or the *Mzizi* app (57.45%). The majority of respondents (64.93%) had never used any of the digital platforms. Out of those who had never used the platforms, the majority (51.34%) had knowledge of the digital platforms either by attending a training or being told by a friend. This suggests a low adoption and usage of the digital platforms, which may be due to practical and structural challenges emanating from poor internet connectivity, high data costs, and low technical know-how. This is consistent with the findings of [18], who reported that there has been a noticeable reluctance among farmers to adopt and utilize digital platforms. The majority of the digital platform users (53.19%) had used the digital platforms for 1 year, probably due to the fact that these digital platforms were developed recently. According to [8], *Viazisoko* became functional in 2021, and the *Mzizi* app was developed in 2023 [9], thereby rendering their usage 1 to 2 years only.

Table 2. Knowledge and usage of various digital platforms.

Variable	Frequency	Percentage (%)
Use of Digital Platforms		
"Know and users"	141	35.07
Non-Users	261	64.93
"Know but non-users"	134	51.34
"Unaware-control group"	127	48.66
Digital Platforms Used		
Mzizi app	81	57.45
Viazisoko	60	42.55
Duration of Usage of Digital Platforms		
Viazisoko		

Continued

Above 2years	14	9.93
For 2years	5	3.55
For 1year	29	20.57
Less than 1year	12	8.51
***Mzizi* app**		
For 1 year	46	32.62
Less than 1year	35	24.82

Source: Authors.

3.2. Effects of Using Digital Platforms on Irish Potato Productivity

To analyze this objective, a Multinomial Endogenous Treatment Effect (METE) Model was used. Following [19], the model was estimated under both exogenous and endogenous treatment assumptions, with the endogenous model correcting for selection bias using selection terms (lambda).

3.2.1. Treatment Model

Table 3 presents the results for the first stage of the METE model: the treatment (selection) model, which estimated the factors influencing the likelihood of farmers being in one of the two treatment categories ("Know but non-user" or "Know and User") relative to the base category ("unaware of the platform").

Sex statistically and positively influenced the likelihood of farmers being in both treatment categories relative to the base category. The results revealed that males are significantly more likely to be in the "know but non-user" category in the exogenous and endogenous models, and slightly more likely to be in the "know and user" category in the exogenous and endogenous models compared to females. This might indicate a potential gender gap in digital usage or exposure. The findings are in line with [20], who also found that male farmers are more likely to know and use agricultural technologies than female farmers.

Training had a positive and significant influence on both knowledge and actual usage of the digital platforms. From the results, it is shown that trained farmers are 2.7 units more likely to know about the digital platforms, and 5.1 units more likely to be users of the platforms, a stronger effect than the farmers who did not receive any training. This suggests that training programs are crucial for digital adoption. This aligns with the findings of [21], who reported that training positively influences farmers' decision to adopt digital agricultural services.

Sub-county level variation had a significant negative influence on knowledge and actual usage of the digital platforms. The results revealed that Njoro sub-county has significantly lower digital engagement than Molo sub-county, perhaps due to differences in infrastructure between the sub-counties. According to [22], adoption and usage of digital technologies vary across different regions, with the highest adoption rate in the Highlands region and the lowest adoption rate in the low-lying regions. He further attributed the variations to local factors, availability of infrastructure, and access to support services. These results agree with the findings of this study; Molo is located at 2534 meters above sea level, while Njoro is located at 1800 meters above sea level [11].

Production and marketing information statistically and positively influenced the likelihood of farmers being in the "Know and User" treatment category. The results revealed that farmers needing information on potato production and marketing were more likely to use (know and users) the digital platforms in both exogenous and endogenous models. This implies that digital platforms meet critical information needs for farmers. Ref. [23] confirms the findings, stressing that the perceived economic and operational benefits of having the production and marketing information at their fingertips serve as a strong motivator for farmers to adopt and use digital agricultural platforms.

Internet access strongly increases the likelihood of using digital platforms ($p < 0.01$) in both models. The results revealed that farmers who had access to the internet both at the household and village levels were more likely to use digital platforms than farmers who had no access to the internet, indicating the importance of improving rural internet infrastructure to enhance digital inclusion. According to [24], farmers using the internet to acquire timely agricultural technology information are more likely to use digital technologies. The usage rate might be further enhanced through improved training and the accessibility of digital infrastructure [25].

Education statistically and positively influenced the likelihood of farmers being in the treatment category of "Know but non-user" at the 5% significance level in the exogenous model and was weakly significant ($p < 0.1$) after correcting for selection bias in the endogenous model. However, it was not significantly associated with actual usage of the digital platforms in both models. This suggests that while education may help farmers become aware of digital platforms, it does not necessarily translate into adoption/use, possibly due to other barriers such as digital literacy or perceived usefulness. This agrees with the findings of [26], who confirm that education influences farmers' knowledge of digital technologies, but did not clearly indicate whether it necessitates the use of the digital technology. However, [27] observed that education level directly correlates with digital literacy.

Extension contact was negatively associated with being in the "know but non-user" treatment category (coef. = −1.3, $p < 0.01$) in both models. The results revealed that limited extension contact reduces the likelihood of farmers knowing about the digital platforms. For this variable, the study looked at the number of extension visits/contacts that farmers had in a year. From the study, 48.76% of the farmers did not have any contact with the extension officers, while among those who had contact with the extension officers (51.24%), the majority of them (22.82%) had three (3) contacts/visits in a year. This suggests a low extension worker to farmer ratio, which affects service delivery, thereby limiting the likelihood of farmers knowing about digital platforms. This finding raises policy concerns regarding the need to incorporate digital platform training into existing extension service programs. Ref. [28] somewhat agrees with the findings by pointing out that information awareness through extension contact directly and significantly influences actual usage of digital platforms, further highlighting that information on the use of digital technology is necessary to enable smallholder farmers to actually adopt the technology into their farming practices. Ref. [29] also points out that access to extension services is positively associated with farmers' usage of digital platforms.

Table 3. Determinants of know-how but non-use, or knowledge and use of digital platforms.

	Exogenous		Endogenous	
Variable	**Know but Non-User**	**Know and User**	**Know but Non-User**	**Know and User**
Age	0.026 (0.018)	−0.008 0.027	0.023 (0.017)	−0.009 (0.026)
Sex (1 = male)	0.981** (0.411)	1.134* (0.584)	0.984** (0.412)	1.133* (0.582)
Internet access_enc	0.510 (0.531)	2.316*** (0.838)	0.543 (0.519)	2.370*** (0.827)
Education (years)	0.107** (0.053)	−0.025 (0.071)	0.095* (0.053)	−0.036 (0.071)
lpotato farming (years)	−0.080 (0.323)	0.069 (0.484)	−0.037 (0.322)	0.094 (0.483)
Credit access	−0.570 (0.410)	0.428 (0.568)	−0.522 (0.406)	0.462 (0.565)
Received training	2.716*** (0.427)	5.119*** (0.598)	2.788*** (0.426)	5.185*** (0.596)
Info: production	−0.362 (0.584)	1.317* (0.763)	−0.301 (0.573)	1.372* (0.750)
Info: marketing	0.826 (0.584)	1.226* (0.646)	0.789 (0.578)	1.187* (0.640)
Farmers group	0.683 (0.424)	0.486 (0.566)	0.604 (0.420)	0.448 (0.563)
Extension contact	−1.292*** (0.400)	−0.239 (0.529)	−1.319*** (0.400)	−0.402 (0.530)
Internet access_village	−0.599 (0.755)	3.502*** (1.078)	−0.468 (0.749)	3.757*** (1.076)
Sub−county_2	−1.004** (0.394)	−1.224** (0.496)	−1.070*** (0.391)	−1.321*** (0.493)
_Constant	−2.176 (1.219)	−8.555 (1.763)	−1.952 (1.214)	−8.321 (1.748)

Note: *, **, *** = significant at the 10%, 5%, and 1% levels, respectively.

3.2.2. Outcome Model

The results in Table 4 show the effects of being in one of the two treatment categories ("Know but non-user" or "Know and User") relative to the base category (unaware of the platform) on log productivity. The results revealed that farmers who know but do not use the digital platforms in the exogenous model had a 0.445 unit increase in log productivity ($p < 0.01$), which rises to 0.741 unit ($p < 0.01$) in the endogenous model. This suggests that even knowledge without actual usage of digital platforms positively impacts productivity, and the effect is stronger when accounting for endogeneity. This may be due to indirect knowledge spillovers. Although these farmers were not direct users of the digital platforms, they appear to have benefited from information transferred by those who did use them. Such spillovers may occur through mechanisms such as farmers sharing information, particularly on good agricultural practices within social or farmer groups, and observing improved practices from others and indirectly adopting them. It is important to note that this represents an interpretation of the statistical results, suggesting possible ways through which awareness alone may contribute to productivity gains. This agrees with [30], who reported that the knowledge spillover effect has a significant effect on productivity as farmers have access to agricultural advisory services indirectly through the spillover effect. Similarly, [31] noted that the spillover effect enhances farmers' agricultural knowledge, improves productivity, and evidently improves food security.

Farmers who know and use the digital platform in the exogenous model had a 0.524 unit increase in log productivity ($p < 0.01$), which slightly increased to 0.532 units in the endogenous model ($p < 0.01$). This indicates that platform usage has a positive effect on productivity, though with a slight increase when correcting for selection bias. This positive effect confirms the role of digital platforms in enhancing productivity, likely due to improved access to information, weather updates, input advice, and market linkages. Compared to farmers who are unaware of the digital platforms ("base category"), both treatment categories are significant ($p < 0.01$), confirming that digital platform knowledge and actual usage are associated with high productivity gains even after correcting for selection bias. The results are in line with those of [32], who found that the use of *Ekisaan*, a digital platform for farmers, not only improved productivity but also ensured cost-effectiveness, reduced input usage, and increased income gains. Similarly, [33] also points out that digital technology usage significantly enhances agricultural productivity across EU countries.

Table 4. Effects on log productivity.

Variable	Exogenous	Endogenous
Know but do not use	0.445*** (0.111)	0.741*** (0.128)
Know and use	0.524*** (0.133)	0.532*** (0.147)

Continued

Sex (1 = male)	0.279*** (0.086)	0.256*** (0.087)
Marital status	−0.197* (0.110)	−0.204* (0.111)
Education (years)	0.009 (0.011)	0.007 (0.011)
Seed type	0.284*** (0.101)	0.280*** (0.101)
Shangi variety	0.345** (0.173)	0.322* (0.172)
Log potato experience (years)	0.263 (0.301)	0.240 (0.301)
Log potato experience_sq (years)	−0.094 (0.068)	−0.093 (0.068)
Shock: floods	−0.834** (0.381)	−0.837** (0.376)
Shock: drought	−0.229 (0.154)	−0.211 (0.154)
Shock: irregular Rain	−0.162 (0.121)	−0.165 (0.120)
Credit access	0.124 (0.089)	0.161* (0.091)
Training received	0.169* (0.098)	0.131 (0.102)
Potato market information	0.129 (0.089)	0.174* (0.093)
Land allocated for potatoes (ha) logged	−0.009 (0.064)	−0.004 (0.063)
Land allocated for potatoes_sq (ha)	0.070** (0.020)	0.072*** (0.020)
Extension contact	−0.171** (0.085)	−0.117 (0.087)
Sub-county (2)	−0.347*** (0.087)	−0.333*** (0.088)
Constant	8.215 (0.390)	8.11 (0.393)
/lnsigma	−0.319*** (0.035)	−0.510*** (0.092)
*/lambda_category*2		−0.426*** (0.090)
*/lambda_category*3		0.080 (0.089)

Note: *, **, *** = significant at the 10%, 5%, and 1% level, respectively.

Other significant covariates that had either a positive or negative effect on productivity included sex, marital status, seed type, Shangi variety, shocks, floods, potato land squared, location, credit access, and potato market information. Much focus was on variables that were significant in both exogenous and endogenous models, and in the endogenous model only (after correcting for selection bias).

Sex had a significant and positive effect on potato productivity. The results revealed that males had higher log productivity by 0.28 units and 0.26 units (coef. = 0.28, 0.26; $p < 0.01$) in exogenous and endogenous models, respectively, than female farmers, confirming gender gaps in agricultural performance. This could be attributed to the fact that males tend to have more control of productive resources like land than females. In a study by [34] on bean production in Kenya, males produced more than females. Ref. [35] also found that male farmers produce more maize than females since females are believed to have limited access to productive resources like land, and that they are time-constrained by reproductive roles and domestic chores.

Marital status had a negative and significant effect on potato productivity in both models. Surprisingly, the results revealed that married farmers were associated with lower potato productivity by 0.19 units and 0.20 units (coef. = −0.197, −0.204; $p < 0.1$) in exogenous and endogenous models, respectively. This could probably be due to differences in risk aversion or off-farm labor allocation, which could reduce the time or resources dedicated to potato production. This is in disagreement with [36], who found that marital status is positively associated with high productivity, where married farmers produced more than unmarried farmers, further arguing that married farmers usually have a larger labour force, probably from the household, than unmarried farmers.

Seed type had a positive association with potato productivity in both models. The results showed that farmers who used certified seed experienced significantly higher productivity than farmers who used farm-saved seed. This suggests that certified seeds typically offer better yields, strengthening their importance in enhancing agricultural performance. This agrees with the findings of [37], who conducted a study on the productivity and food security effects of using certified seed potatoes. Their findings revealed that farmers who used certified seed potato (CSP) obtained higher yields than those who did not use CSP.

Shangi variety statistically and positively affected potato productivity in both models. The results showed that using the Shangi variety increases productivity among smallholder farmers. This is probably because the Shangi variety is a locally preferred and high-yielding cultivar that most farmers planted in the study area. The results are consistent with the findings of [38], who reported that the Shangi variety performed well and had a significant positive effect in increasing potato yields among smallholder farmers. However, the results contradict [6] report, which revealed that although Shangi remains the most widely cultivated potato variety in Kenya, it does not rank highest in terms of yield potential, nor does it perform optimally in areas like mechanization, processing, or post-harvest storage. In addition, the International Potato Center (CIP) has not identified the reason why the Shangi variety has a deep-rooted dominance in the country's potato production system.

Shocks had a significant and negative effect on potato productivity. The results found that exposure to climate-related shocks like floods negatively affects potato productivity among smallholder farmers. Floods had the largest impact (coef. = −0.83 to −0.84, $p < 0.05$) in negatively affecting potato productivity. The results agree with [39], which reported that Nakuru, one of the leading counties for potato farming in Kenya, faces challenges such as drought, intense rainfall, flooding, and rising temperatures, posing challenges to productivity. Similarly, [40] reported that climate-related disasters like drought and floods are the major factors affecting potato production in Uganda.

Access to credit positively and significantly influenced potato productivity in the endogenous model. The results revealed that farmers who had access to credit were associated with a higher log productivity by 0.16 units, suggesting that access to credit enables farmers to purchase inputs, invest in technologies, or manage production risks more effectively. This aligns with [41], who revealed that access to credit increased farmers' potato yield by 45 kilograms in Malawi. Similar results were also observed by [42], who reported that access to credit had a positive effect on cassava productivity among smallholder farmers in Ghana.

The results also indicated that location plays a significant role in influencing productivity. Njoro sub-county (sub-county 2) had a significant negative effect on productivity in both models. Farmers in Njoro recorded significantly lower productivity compared to those in Molo. This could probably be due to unfavourable climatic conditions for potato productivity in Njoro compared to Molo. According to [10], Molo is the main potato-growing sub-county in Nakuru County and is ranked as the second leading producer in Kenya.

Potato market information had a positive and significant effect on log potato productivity. The results showed that farmers who had access to market information were 0.17 units more likely to increase their potato productivity in the endogenous model, after correcting for selection bias. This suggests that access to potato market information may help farmers make better production decisions, boosting productivity. The results are similar to the findings of [43], who confirm that useful agricultural information leads to higher productivity. This further suggests that farmers' access to agricultural information through mobile phones reduces the costs of searching for information, which leads to higher productivity.

Log potato land squared (ha) positively and significantly affected potato productivity in both models. The results revealed that on small land sizes, increasing land size may have a negative effect on productivity, but as land size grows, each additional unit of land contributes more to potato productivity. This is in agreement with [44], who revealed that an increase in land size inversely contributes to productivity or yield, but the net output per each additional fragment of land substantially increases total yield.

3.3. Density of Predicted Log Potato Productivity

The use of digital platform effects is also shown using the kernel density functions of predicted log productivity. Figure 1 shows the density of predicted log potato productivity by digital platform category. As indicated in the figure, farmers who know and use the digital platform had a wider tail, suggesting that the users had a higher probability of having increased potato productivity.

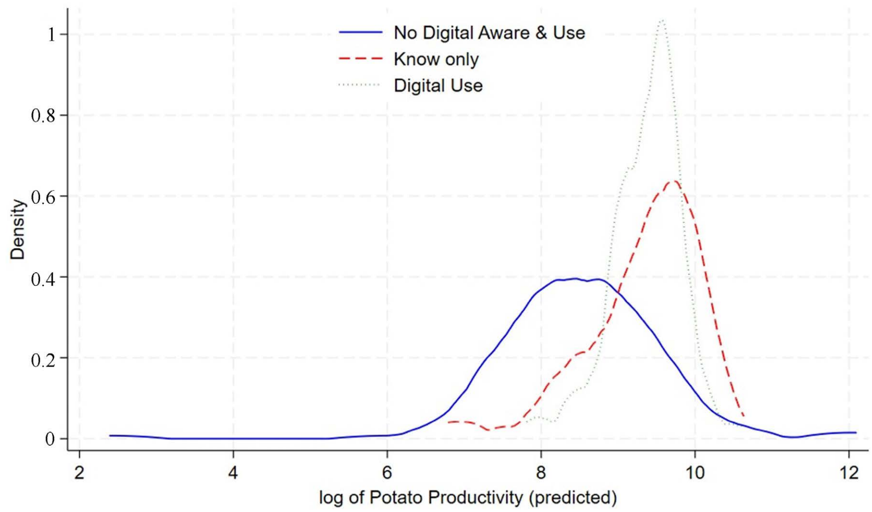

Figure 1. Density of predicted log potato productivity by digital platform category.

4. Conclusions

This study evaluated the effects of using digital platforms on potato productivity among smallholder farmers in Molo and Njoro sub-counties in Kenya using a Multinomial Endogenous Treatment Effect (METE) model. The results revealed that the use of digital platforms is associated with high productivity gains even after correcting for selection bias. Farmers in the treatment categories of "know but non-user" and "know and user" had higher productivity gains compared to farmers who were unaware of the digital platforms. This raises policy concerns regarding the importance of knowledge and usage of digital platforms in increasing potato productivity among smallholder farmers. These results suggest raising awareness campaigns and prioritizing extensive training among smallholder potato farmers on the importance of using digital platforms in order to increase productivity. The results also revealed other covariates that had positive and negative associations with potato productivity among smallholder farmers. From the results, sex, seed type, access to credit, potato market information, Shangi variety, and log potato land squared were positively associated with high productivity; whereas marital status and floods negatively affected Irish potato productivity among smallholder farmers.

However, certain limitations must be considered. The findings of this study are based on self-reported cross-sectional data and, therefore, may not reflect the changing situations over time. Furthermore, the study was limited to two sub-counties within Nakuru County, so the results may not reflect the realities in other potato-growing regions in Kenya such as Nyandarua, Meru, or Elgeyo Marakwet, which have different climatic conditions, infrastructure, and socio-economic contexts.

Future research should consider other digital platforms that potato farmers are using, since this study focused on digital platforms that were solely developed for Irish potato farming. It would also be necessary to study the effects of using these digital platforms on income among smallholder potato farmers.

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Conflicts of Interest

The authors declare no conflict of interest regarding the publication of this paper.

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