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Determinants of Adoption and Dis-Adoption of Integrated Pest Management Practices in the Suppression of Mango Fruit Fly Infestation: Evidence from Embu County, Kenya

Samuel Jeff Otieno [1,2,*], Cecilia Nyawira Ritho [1], Jonathan Makau Nzuma [1] and Beatrice Wambui Muriithi [2,*]

[1] Department of Agricultural Economics, University of Nairobi, Nairobi P.O. Box 30197-00100, Kenya
[2] International Centre of Insect Physiology and Ecology (ICIPE), Nairobi P.O. Box 30772-00100, Kenya
* Correspondence: jeffsamy4@gmail.com (S.J.O.); bmuriithi@icipe.org (B.W.M.); Tel.: +254-(0)-20-863-2144 (B.W.M.); Fax: +254-(20)-8632001/2 (B.W.M.)

Abstract: This study evaluates the drivers of the adoption and dis-adoption of Integrated Pest Management (IPM) practices in the suppression of mango fruit-fly infestation in Embu County, Kenya. It employs a Correlated Random Effects Probit Model and a Discrete-time Proportional Hazard Model on two-wave panel data of 149 mango farmers selected using a cluster sampling technique. The descriptive results show that 59% and 17% of the respondents were adopters and dis-adopters of mango fruit fly IPM practices, respectively. Empirical findings reveal that the cost of IPM and training on IPM positively and significantly influenced adoption, while the unavailability of the technology had a negative and significant effect on adoption. For dis-adoption, the results indicate that farm size and the quality of IPM positively influenced the hazard of exit from IPM use, and hence, enhanced the sustained adoption of IPM. The study recommends capacity building for mango farmers through training and increased access to extension services to enhance the adoption of this technology and prevent dis-adoption.

Keywords: fruit fly; integrated pest management; adoption; dis-adoption

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1. Introduction

Fruit flies are considered the most important pests in the horticulture sector, not only in Sub-Saharan Africa (SSA), but also in other parts of the world [1,2]. In particular, they are the most predominant pests in mango production due to the magnitude of the economic losses that they cause [1,2]. Fruit fly infestation attracts quarantine measures that prevent horticultural produce from accessing export markets, reducing foreign exchange earnings and farmers' net income [3]. In Africa, total annual losses in mango production are estimated at USD 2 billion, 40% of which are due to fruit fly infestation [3]. In Kenya, farmers find it difficult to control fruit fly infestation because of the ecology of the pest constraint [4]. The pupa stage of these pests in the soil offers them protection from insecticides that are applied on the surface [4,5].

For many years in Kenya, mango farmers have relied on the conventional use of synthetic pesticides to control fruit flies [6]. However, the method is unsustainable because synthetic pesticides are not only expensive, but they also pose negative risks to human health and the environment [7]. Historically, farmers have also used indigenous control methods which they consider more cost-effective and environmentally friendly but less effective, such as "smoking herbs" [8]. In response to these challenges, the International Center for Insect Physiology and Ecology (*icipe*) located in Nairobi, Kenya, and other partners have developed and promoted an Integrated Pest Management (IPM) package as a more sustainable approach to managing mango fruit fly infestation over the last decade [3].

IPM is a decision-based process involving the coordinated use of multiple different techniques to effectively manage pests [9]. *icipe's* fruit fly IPM package consists of five components; the male annihilation technique, spot spraying of food bait, Metarhizium anisopliae-based bio-pesticide application, releases of the parasitoid, and use of orchard sanitation [10,11,12]. The male annihilation technique (MAT) entails the use of pheromones combined with toxicants to reduce the male fruit fly population [3]. Since immature female fruit flies require protein for their eggs to develop, they are attracted to food baits containing toxicants placed at specific locations in the orchard. Bio-pesticides are fungus-based formulations that target the fruit fly at the larva and emerging adult stages [3]. The release of parasitoids is a biological control strategy where beneficial insects are introduced to feed on the mango fruit flies [3]. Orchard sanitation comprises a number of practices, including systematically collecting and disposing of all infested fruits found on trees and the ground [3].

The adoption of fruit fly IPM in mango production (defined in this study as the use of at least one of the five practices) has been reported to both directly and indirectly yield positive and significant benefits [6,8,10]. The major direct benefits are: reduced expenditure on pesticides; higher yields and income from mangoes; decrease in mango losses; and reduced negative effects on human health and the environment [6,7,10]. Some of the indirect benefits are improved household diets and women's empowerment from higher incomes [11,12]. In spite of the direct and indirect benefits from the adoption of fruit fly IPM, it has been found that some farmers make the decision to dis-adopt the technology; e.g., Wangithi et al. [8]. In this study, the dis-adoption of IPM was defined as the choice of farmers to voluntarily stop using all fruit fly IPM components that they had used in at least the last three mango production seasons [8]. In addition to dis-adoption, it has also been observed that the adoption of fruit-fly IPM technology is slow [8,10,13–15].

Some of the factors which have been shown to explain the variation in the adoption of fruit fly IPM among farmers are: technology-specific characteristics, such as cost and unavailability; farm and farmer characteristics, particularly education of the household head; household size; training; farm size; and membership to groups related to mango production [8,10,13–15]. On the other hand, variation in dis-adoption of the technology has been explained by the unavailability of the required inputs in the market and their high cost [8]. Sahin [16] attributed technology dis-adoption to the emergence of superior technologies and the dissatisfaction of some farmers with the performance of specific IPM technologies. While these past studies have provided useful insights into IPM adoption, they do not consider the partial, seasonal, or scale of use of IPM technology.

Using three mango production seasons between the baseline and endline surveys (that is, 2019/2020, 2020/2021, and 2021/2022), we defined continuous users of IPM as farmers who used IPM in all three of the production seasons, while seasonal users were farmers who used fruit fly IPM in one or two of the described seasons. In order to assess of use of IPM on their mango orchards in terms of scale, farmers were classified as partial farm users or whole-farm users of the technology. Whole-farm IPM users were farmers who used fruit fly traps (MAT) throughout their entire mango orchard, while partial farm users were those that only used the traps in a section of their mango orchards. Seasonality and scale of use have not been evaluated in previous studies on fruit fly IPM, even though they contribute to the understanding of the reasons for the different decisions made by IPM users.

Even though a significant portion of the literature on technology adoption has focused on factors influencing adoption, there exists limited evidence on the factors influencing technology dis-adoption, since most studies have treated dis-adopters as non-adopters [8,10–15,17]. Similarly, there is limited information on fruit fly IPM dis-adoption. Wangithi et al. [8] assessed the determinants of fruit fly IPM dis-adoption in Kenya using cross-sectional data, but did not fully examine the drivers of adoption or explore the dynamics of adoption. In addition, previous studies on fruit fly IPM adoption [8,10–15,17] have not considered IPM-technology-specific factors, such as cost of IPM, quality of IPM, and unavailability of IPM when assessing the determinants of adoption of the technology. This study fills these gaps by assessing the determinants of fruit fly IPM adoption, as well as their dis-adoption using duration analysis. In addition, we test the hypothesis that "the perceived benefits of IPM technology do not influence adoption and dis-adoption of the technology".

2. Study Methods

2.1. Theoretical Framework and Empirical Approach

The decision to adopt or dis-adopt an IPM technology in this study is modeled following the random utility theory, which posits that decision-makers are rational and will seek to maximize utility based on the available choices [18]. Farmers facing a set of available alternatives will choose the alternative that maximizes their utility [19]. Following Greene [20], the utility function for the adoption of mango fruit fly control IPM technology was specified as follows:

$$U^a = X' \beta_{ipm} + \varepsilon_{ipm} \quad (1)$$

$$U^n = X' \beta_{ipm} + \varepsilon_{ipm} \quad (2)$$

where U^a is the utility derived from adopting the mango fruit fly IPM strategy; U^n is the utility derived by the farmers using alternative control strategies, such as synthetic pesticides and indigenous methods. β are the parameter estimates and ε is the error term. Subsequently, the observed measure of adoption equals one (1) if $U^a > U^n$ and equals zero (0) otherwise.

When the utility of adopting IPM diminishes, farmers discontinue the use of this technology [21–23]. Following the random utility theory, we assume that farmers choose to adopt the IPM technology because of the higher benefits they derive from the adoption of IPM technology, and they choose not to adopt based on the benefits they derive from using other strategies, such as synthetic pesticides and indigenous methods in managing mango fruit flies.

Assessment of the determinants of technology adoption is guided by the nature of the dependent variable. In cases where a discrete choice is made, a Probit or Logit model is used depending on whether a normal or a logistic distribution is appropriate [14]. Multinomial logit is used in cases where the dependent variable has many choices [8]. Other models used are the negative binomial regression, logistic regression, and Poisson [17]. These models use cross-sectional data and are not suitable for the current study, which uses panel data.

The decision to adopt fruit fly IPM over time can be modeled using binary choice panel data estimators, such as a Fixed Effects Logit Model (FEL) and a Correlated Random Effects Probit Model (CREP) [21]. The fixed effects logit model is based on a within-transformation that would drop any time-constant explanatory variables, such as distance to the input market and farm size, and, on variations in the dependent variable over time, which would reduce the number of observations to be used for estimation [22]. Due to these limitations of a fixed effects logit model, the correlated random effects probit model was used.

The decision by farmers to dis-adopt IPM technology can be modeled using duration analysis models, such as a Cox Proportional Hazard Model (CPHM) and a Discrete-time Proportional Hazard Model (DPHM) [23]. Duration analysis is concerned with the timing of events where the event variable represents the transition from one state to another; for instance, from the adoption to the dis-adoption of IPM [24]. The CPHM model is based on a continuous time analysis and cannot deal with unobserved individual heterogeneity, such as mango farmers' skills and motivation. Thus, it was not appropriate for the current study because the duration between adoption to dis-adoption of fruit fly IPM is characterized by discrete distribution and not continuous distribution [21,25].

The Correlated Random Effects Probit was used to model mango farmers' decision to adopt IPM technology. The model is appropriate for use in panel data as it can be used to test the random effects (RE) assumption that heterogeneity, such as mango farmers' skills and motivation, is independent of time-varying covariates; for example, age, education of the household, and household size [21]. Following Alem et al. [21], the latent benefit of IPM adoption was specified as follows;

$$n_{it}^{*} = X'_{it}\beta + \varepsilon_{it} \quad i = 1,2 \ldots N; \; t = 1 \ldots T \tag{3}$$

$$\varepsilon_{it} = \alpha_i + \mu_{it} \tag{4}$$

$$n_{it} = \begin{cases} 1 & \text{if } n_{it}^{*} > 0 \\ 0 & \text{if } n_{it}^{*} \leq 0 \end{cases} \tag{5}$$

where n_{it}^{*} is the latent dependent variable; X_{it} is a vector of time-variant and time-invariant variables, such as age and gender; β is a vector of parameters to be estimated; ε_{it} is the composite error term; α_i unobserved individual heterogeneity; μ_{it} the random error term; n_{it} is the observed binary outcome variable showing the adoption of fruit fly IPM; i and t are the smallholder mango farmers and periods, respectively.

In estimating the parameters, the unobserved individual heterogeneity (α_i), such as mango farmers' motivation and skills, was assumed to be correlated with the observable variables (X_{it}) and time [26]. The transformation is made on the unobserved individual heterogeneity term in Equation (4), and the averages of independent variables are generated and included as additional regressors

$$\alpha_i = \varphi + \bar{X}_i\epsilon + a_i, a_i/{\sim}N(0, \delta_a^2) \tag{6}$$

where $\bar{X}_i$ is the average time-varying variable in X_{it}; δ_a^2 is the variance of unobserved individual heterogeneity (α_i).

To model the decision to dis-adopt IPM technology, the Discrete-time Proportional Hazard Model was used. The model is used in duration analysis in evaluating factors that have a significant effect (both positive and negative) on the hazard of exit from adoption and entry into dis-adoption [27].

The hazard rate represents the risk of exit from adoption to dis-adoption in the current study and shows the proportion of households remaining in the adoption state at the time of observation [21,23]. Jenkins [23] specifies the discrete-time hazard rate h_{it} as;

$$h_{it} = \text{prob}(T_i = \frac{t}{T_i} \geq t; \; X_{it}) \tag{7}$$

where; T_i is a discrete random variable representing the time at which adoption duration ends; X_{it} represents a vector of explanatory variables [23]. The proportional hazard specified by Jenkins [23] was used to analyze IPM adoption as follows;

$$h_{it} = h_0(t)\exp\,(X'_{it}\beta) \tag{8}$$

where h_{it}= pr(y_{it}=1/X_{it}); y_{it}=1 if a farmer dis-adopts IPM at time t; h_{it} is the hazard rate of adoption; $h_0(t)$ is the baseline hazard function which is common to all farmers within the sample [21]; X'_{it} is the vector of regressors; β is the vector of parameter estimates. The exponential specification of the hazard function is adopted, since the form ensures that the hazard function is non-negative without imposing restrictions on β coefficients. In addition, it facilitates the interpretation of the results as the estimated β coefficients show the direction and magnitude of influence of the covariates on the hazard rate [28]. To control for the unobserved individual heterogeneity, a random error term that is assumed not to be correlated with any of the regressors is multiplicatively introduced into the model in Equation (8), as shown below [23].

$$h_{it} = h_0(t)\vartheta_i \exp\,(=h_0(t)\exp\,[X'_{it} + \log\,(\vartheta_i)] \quad (9)$$

Consequently, the discrete-time function in the *j*th interval that is in concordance with Equation (10) above is specified as follows;

$$h_j\left(X'_{ij}\right) = 1 - \exp\,[-\exp\,(\,X'_{ij}\beta)\ + \gamma_j + \log\,(\vartheta_i)] \quad (10)$$

γ_j ; The parameter of the baseline hazard.

2.2. Definition and Measurement of Variables

The use of the male annihilation technique (MAT) was applied in the current study as a proxy for fruit fly IPM adoption as it is the most commonly used and commercialized component of the IPM package and generates significant benefits when used by itself [10,29]. The variable was specified as a dummy variable; a farmer using MAT was assigned one and zero otherwise for the adoption model, while one who used the technology before and stopped was assigned one and zero otherwise in the dis-adoption model (Table 1). The choice for independent variables included in the adoption and dis-adoption models was informed by the literature on agricultural technology adoption and, particularly, the adoption of fruit fly IPM and, in the context of our study [8,10–15,17], includes demographic characteristics, household resources, access to information, social capital, and networking and technology attributes.

Table 1. Description of variables used in the Correlated Random Effects Probit and Discrete-time Proportional Hazard Models.

Dependent Variable	**Definition and Measurement**		
IPM Adoption	Are you currently/in the previous mango season used the male annihilation technique; 1 = yes, 0 = No		
IPM Dis-adoption	If not using/did not use the male annihilation technique in the previous mango season, were you using and stopped? 1 = yes, 0 = No		
Independent Variables	**Definition and Measurement**	**Expected Sign**	
		Adoption	**Dis-adoption**
Household demographic characteristics			
Gender of household head	Gender of household head (1 = male 0 = Female)	−/+	−/+
Size of household	Household size in count	−/+	−/+
Education of household head	Number of schooling years of the household head	+	−
Age of household head	Age of the household head in years	−/+	−/+
Household resources			
Farm size	Total owned land in Acres	+	−/+
Farm income	Proportion of farm income out of total annual household income (%) for the last 12 months	+	−
Market and institutional information access			
IPM training	Attended training on Fruit Fly Integrated Pest Management (1 = yes, 0 = No)	+	−
Distance to input market	Minutes taken by a farmer to walk to the nearest source of input market	−	+
Contact extension officer	Visited by an extension officer in the last 12 months 1 = yes, 0 = No	+	−
Social capital			
Mango group membership	Membership in a mango production/marketing group (1 = Yes, 0 = No)	+	−

Access to credit services	Accessed agricultural credit services in the last 12 months (1 = yes, 0 = No)	+	−
	Fruit fly IPM attributes		
Unavailability of IPM	Whether unavailability of male annihilation technique is a constraint to its adoption (1 = yes, 0 = No)	−	+
Cost of IPM	Whether cost of male annihilation technique is a constraint in adoption (1 = yes, 0 = No)	−	+
Quality of IPM	Whether quality of male annihilation technique is a constraint in adoption (1 = yes, 0 = No)	+	−

The gender of the household head was measured as a dummy (1 = Male, 0 = Female) variable, and was hypothesized to have a positive effect on adoption and a negative effect on the dis-adoption of IPM. The size of the household was measured as the total count of persons who live and eat together from the same pot (share food) and was hypothesized to have a positive effect on adoption and a negative effect on the dis-adoption of fruit fly IPM. We hypothesized the education of the household head to have a positive influence on the adoption of IPM and a negative effect on dis-adoption. Education was measured as the total number of years of formal education. The direction of influence of the age of the household head is indeterminate on both the adoption and dis-adoption of IPM. The age of the household head was measured in years. Farm size was hypothesized to have a positive and negative influence on IPM adoption and dis-adoption, respectively. Farm income was measured as the proportion of income generated from the farm out of the total annual household income, and its direction is indeterminate.

IPM training is likely to have a positive influence on IPM adoption and a negative influence on dis-adoption. IPM training was specified as a dummy variable (farmer who had attended IPM training was assigned one and zero otherwise). Distances to the input market (the number of minutes a mango farmer takes to walk to the nearest mango input market) was hypothesized to have a negative influence on the adoption of IPM and a positive effect on dis-adoption. Extension contact was hypothesized to have a positive influence on the adoption of IPM and a negative effect on IPM dis-adoption. It was quantified as a dummy variable if a farmer was visited by an extension officer 12 months before the survey. Mango group membership (dummy variable equal to one if a farmer belonged to a mango production and marketing group, and zero otherwise) was expected to positively influence IPM adoption. Technology attributes may positively or negatively influence a farmer's decision to adopt a technology. In this study, we controlled for the unavailability, the perceived cost, and the quality of the most commercialized fruit fly IPM component (that is MAT); all variables were measured as dummy variables. While the cost and unavailability of the technology are likely to inhibit farmers from adopting the technology, quality is likely to induce them to take it up, while a contrasting effect is expected for the dis-adoption decisions.

We implemented the Correlated Random Effects Probit Model by first generating the means for all the continuous explanatory variables such as age, household size, education of the household head, and distance to the input market, and then included them as additional covariates. The model was then fitted using the xtprobit command in STATA. In addition, the Random Effects Probit Model (REP) was also run to test for the robustness of the different determinants of adoption. Estimation of the Discrete-time Proportional Hazard Model involved the creation of three new additional covariates, including an interval identification variable, a period-specific censoring indicator, and the definition of variables as a function of time [30]. The interval identification variable captured the duration of IPM adoption; i.e., years from initial use to the survey (the year 2022). The period-specific variable was constructed to capture whether a mango farmer had left the IPM adoption state and entered the dis-adoption state. The model was then fitted using the pgmhaz command in STATA [30].

2.3. Data Sources and Sampling Procedure

The data for the current study were obtained from mango farmers in the Runyenjes and Manyatta sub-counties of Embu County, Kenya. The county (Figure 1) was purposively selected by the African Fruit Fly Program of *icipe* as a benchmark project site, since it is one of the leading mango-producing counties in Kenya.

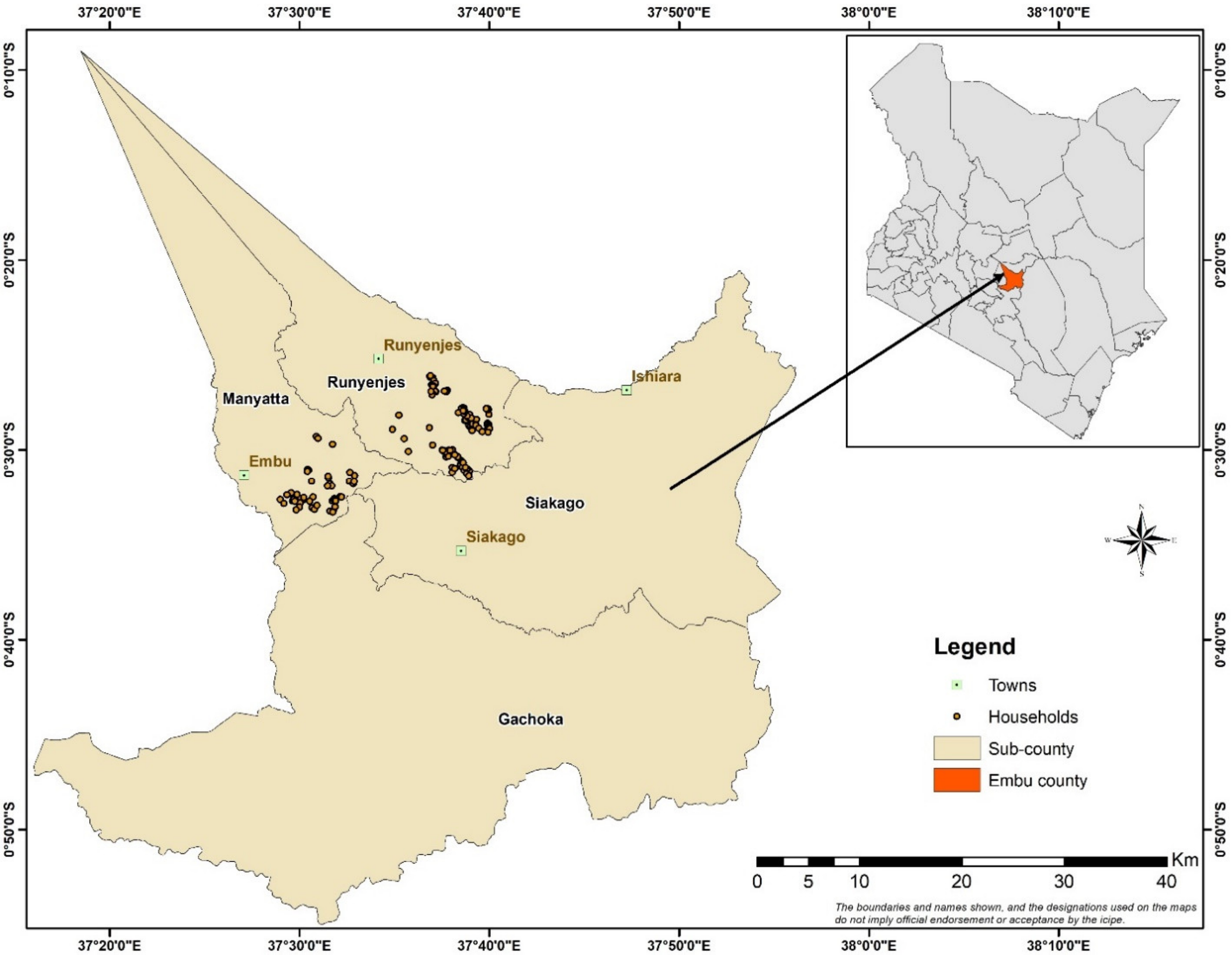

Figure 1. Map of the study area; **Source**: Wangithi et al., 2021 [8].

The data were collected in two phases; a baseline survey conducted in 2019 by Wangithi et al. [8] and a follow-up survey conducted in 2022. The baseline survey used a cluster sampling technique to select 165 mango farmers in Embu County (8). In the first stage, the Runyenjes and Manayatta sub-counties were purposively selected since they lead mango production in the county. The sampling frame was a list of mango-growing households generated by sub-county agricultural officers. In the second stage, a simple random sampling technique was used to select 165 households from the two sub-counties following [31]. The follow-up survey targeted the same households interviewed during the baseline survey, but only 149 households were accessed (approximately 11% attrition) due to relocation from the county. The current study used a balanced panel dataset of 149 households. More detailed descriptions of the study area, target population, sampling frame, and sample size are provided by Wangithi et al. [8].

The baseline and follow-up datasets were collected using semi-structured questionnaires programmed in the Census and Survey Program System (CSPro) and collected through face-to-face interviews by enumerators trained and supervised by the research team. Data were analyzed using STATA 16.

3. Results

3.1. Descriptive Analysis

3.1.1. Farms, Farmers, and IPM Technology Characteristics of Mango Growers in Kenya

Different classifications of farmers by IPM adoption were achieved by first asking the respondents whether they were using or had used the male annihilation technique (MAT) in the last mango production season. The classification generated three different adoption categories—adopters or dis-adopters of IPM; seasonal or continuous users of IPM; and, partial or whole farm users of IPM.

Adopters and dis-adopters were further divided into three different sub-categories: farmers who were using the male annihilation technique (MAT) at the time or had used in the previous mango production season were classified as *IPM* adopters; farmers who had never used MAT were classified as *IPM* non-adopters, while farmers who had used MAT earlier but had discontinued the use were classified as *IPM* dis-adopters. Based on this classification, 59% of the respondents were IPM adopters, 24% were non-adopters, and 17% were dis-adopters. Table 2 presents a comparison of the farms, farmers, and IPM technology attributes. A statistical F test was conducted to test for differences in the variables across the different farmer categories.

Table 2. Comparison of the farms, farmers, and fruit fly IPM technology attributes of mango-growing households across different adoption profiles in Embu County Kenya.

Explanatory Variables	Mean				F-Test
	Pooled	IPM Adopters	IPM Non-Adopters	IPM Dis-Adopters	
	n = 298	n = 176	n = 72	n = 50	
Household demographic characteristics					
Gender of household head (1 = Male, 0 = Female)	0.74	0.78	0.62	0.74	3.67 **
Size of household(count)	3.57	3.66	3.43	3.48	0.49
Education of household head (years of schooling)	9.32	9.81	8.33	9.00	3.75 **
Age of household head (years)	63.44	63.99	60.36	65.98	3.83 **
Resources					
Proportion of annual farm income (percentage)	65.38	68.31	60.94	61.44	2.39
Farm size (acres)	4.13	4.62	3.21	3.73	2.61 **
Market and institutional information access					
IPM training (1 = Yes)	0.49	0.65	0.26	0.28	24.40 ***
Distance to input market (minutes taken when walking)	34.46	36.32	29.51	35.06	1.71
Contact extension officer(1 = Yes)	0.43	0.55	0.27	0.26	12.40 ***
Access to credit services (1 = Yes)	0.10	0.13	0.8	0.4	2.18
Social capital					
Mango group membership(1 = Yes)	0.10	0.16	0.01	0.02	8.94 ***
Fruit fly IPM attributes					
Unavailability of IPM	0.45	0.48	0.51	0.56	9.01 ***
Cost of IPM	0.57	0.56	0.55	0.58	3.76 **
Quality of IPM	0.41	0.44	0.4	0.38	6.70 ***

Source: Author’s survey data (2022); ** $p < 0.05$, *** $p < 0.01$.

The results (Table 2) show that about a third of the fruit fly IPM non-adopting households were headed by females. The education of the household heads was statistically different across the adoption profiles. Fruit fly IPM adopters had relatively higher education (10 years) compared to both the non-adopters (8 years) and dis-adopters (9 years). The average age of the household heads across the three different groups was significantly different. The average age of heads of fruit fly IPM dis-adopters (66 years) was relatively higher compared to both the adopters (64) and non-adopters (60) of the technology. Fruit fly IPM adopters had relatively bigger farm sizes (4.62 acres), compared to non-adopters (3.21 acres) and dis-adopters (3.73 acres). Further results indicated that a bigger proportion of fruit fly IPM adopters (65%) received training on IPM, compared to non-adopters (26%) and dis-adopters (28%). The majority of the dis-adopters perceived the availability (56%) and cost of fruit fly IPM (58%) to be constraints that hindered adoption and continuous use of the technology.

Figure 2 presents the additional reasons reported by the fruit fly IPM dis-adopting households. The major reason reported by 41% of the households was lack of money to buy IPM inputs. These results are consistent with those of Wangithi et al. [8], who found unavailability of IPM inputs in the market to be the main driver of dis-adoption.

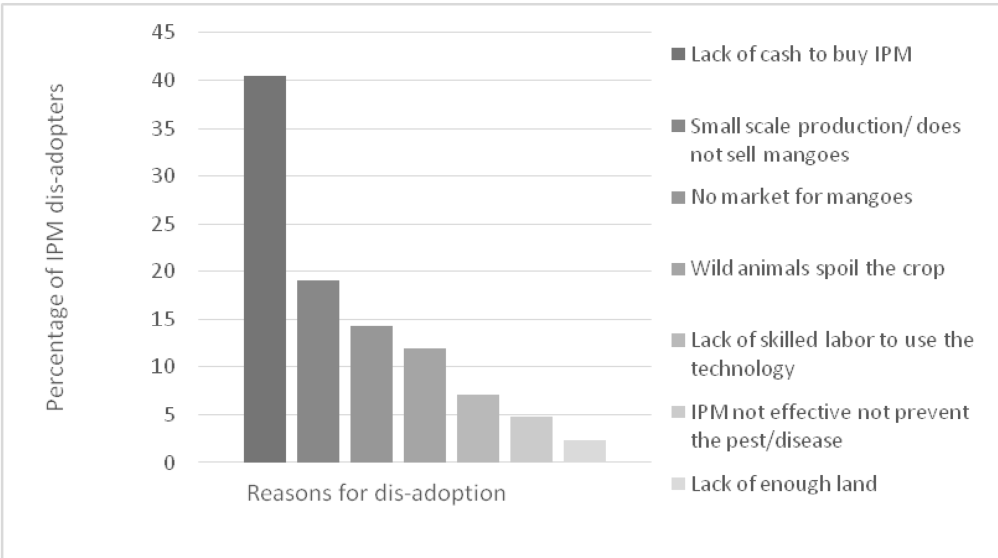

Figure 2. Reasons for fruit fly IPM dis-adoption in Embu, Kenya; **Source**: Author's survey data (2022).

3.1.2. Seasonal Use of Fruit Fly IPM

The second classification of IPM users was IPM use by season, where adopters were categorized as either seasonal users or continuous users. A comparison of seasonal and continuous users showed that 71% of IPM adopters were continuous users, while 29% were seasonal users. The main constraint for the seasonal use by IPM users was limited awareness or knowledge on the replacement of the lures, reported by 52% of the seasonal IPM users (Figure 3). Mango farmers also cited a lack of cash to buy and maintain IPM, and the unavailability of IPM to be the second and third reasons, respectively, leading to the seasonal use of the technology.

Figure 3. Reasons for seasonal use of fruit fly IPM in Embu, Kenya: **Source**: Author's survey data (2022).

3.1.3. IPM Use by Scale of Application in the Mango Orchards

Even when the benefits of technology have been proven, the adoption of most introduced agricultural technologies is often partial, possibly to reduce the uncertainty in performance associated with innovations [32]. A total of 60% of IPM adopters were whole-farm IPM users, while 40% were partial-farm IPM users. A lack of money to buy and service fruit fly traps was cited as the main constraint leading to partial-farm use of the technology (Figure 4). Other constraints cited were the small-scale nature of production, lack of a ready market for the mangoes, crop destruction by wild animals, and a lack of technical support in handling the technology. The perceived non-effectiveness of the IPM reported by a few respondents could be attributed to the incorrect timing of the replacement of the traps, suggesting the need for further training and technical support for enhanced adoption of the technology.

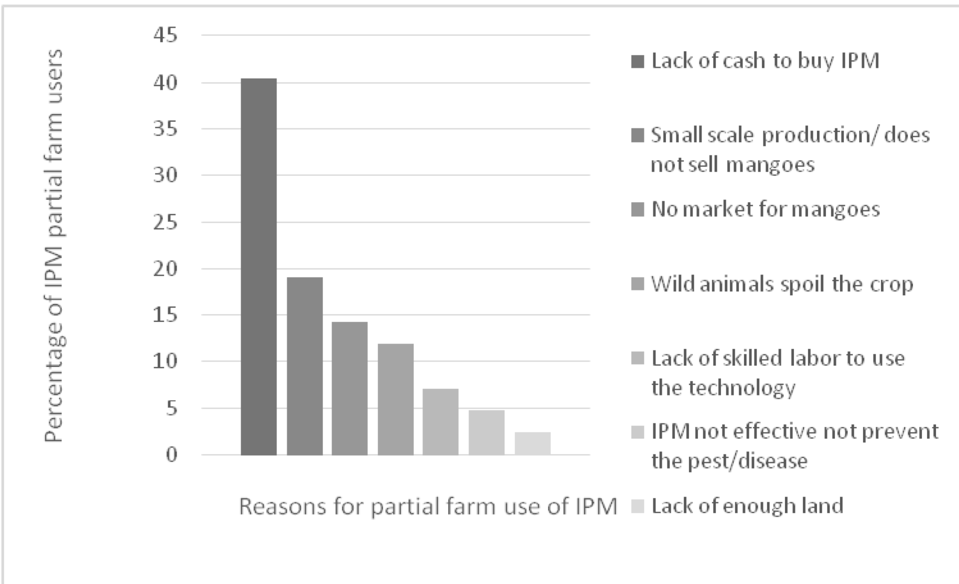

Figure 4. Reasons for partial-farm use of fruit fly IPM in Embu, Kenya: **Source**: Author's survey data (2022).

3.2. Empirical Results

The empirical analysis is based on adoption and dis-adoption of fruit fly IPM grouping because adequate data was not available for the other groups.

3.2.1. Determinants of the Adoption of Fruit Fly IPM

Table 3 presents the maximum likelihood effects (MLE) of the factors influencing the adoption of IPM practices in controlling fruit fly infestation among mango growers in Embu County.

Table 3. Factors influencing the adoption of fruit fly IPM among mango farmers in Embu, Kenya.

IPM Adoption	Correlated Random Effects Probit	Random Effects Probit
Gender of household head	0.16 *** (0.06)	0.12 ** (0.06)
Size of household (count)	0.01 (.03)	0.01 (0.02)
Education of household head	0.05 (0.01)	0.01 (0.01)
Age of household head (years)	−0.06 *** (0.01)	−0.01 * (0.02)
Farm size (acres)	0.01 (0.01)	0.04 (0.06)
Proportion of annual farm income	0.00 (0.01)	0.00 (0.01)
IPM training (1=Yes)	0.27 *** (0.56)	0.29 *** (0.06)
Distance to input market in walking minutes	0.08 (0.03)	0.08 ** (0.03)
Contact extension officer (1 = Yes)	0.13 ** (0.05)	0.11 ** (0.06)
Mango group membership(1=Yes)	0.22 ** (0.09)	0.20 ** (0.09)
Access to credit services (1 = Yes)	0.04 (0.84)	0.01 (0.85)
Unavailability of IPM	−0.19 *** (0.05)	−0.23 *** (0.06)
Cost of IPM	0.11 **(0.05)	0.11 ** (0.06)
Quality of IPM	−0.07 (0.05)	−0.05 (0.54)
Overall r-squared	0.35	0.30
Number of obs	298	298
Chi-square	142.17	111.56
Prob > chi2	0.00	0.04

Significance at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$**. Source:** Author's survey data (2022).

The results show that age and the unavailability of IPM have statistically significant negative effects on the adoption of the technology, while gender, IPM training, access to extension, mango group membership, and quality of IPM have positive and statistically significant influences on adoption.

3.2.2. Determinants of Fruit Fly IPM Dis-Adoption among Mango Growers in Embu, Kenya

Table 4 presents the results for the dis-adoption decisions. The risk of exit from adoption to dis-adoption is shown by the hazard rate, which shows the number of mango farmers found in the adoption state at the time of observation [21,23]. The gender, education, and age of the household head, the farm size, and the perceived quality of MAT have positive and statistically significant effects on the hazard rate.

Table 4. Determinants of fruit fly IPM dis-adoption among mango growers in Embu, Kenya.

IPM Dis-adoption	Coefficient	Standard Error
Gender of household head (1 = Male, 0 = Female)	0.89 *	0.47
Size of household(count)	−0.01	0.11
Education of household head (years of schooling)	0.18 ***	0.06
Age of household head (years)	0.04 **	0.02
Farm size (acres)	0.20 ***	0.01
Proportion of annual farm income (percentage)	0.01	0.05
IPM training (1 = Yes)	0.77	0.31
Distance to input market (minutes taken when walking)	−0.13	0.30
Contact extension officer(1 = Yes)	0.01	0.56
Mango group membership(1 = Yes)	−0.91	0.98
Access to credit services (1 = Yes)	−0.52	0.64
Unavailability of IPM	−0.52	0.33
Cost of IPM	0.02	0.31
Quality of IPM	0.71 **	0.33
Constant	−6.01 ***	1.41
Log-likelihood	−81.12	
Number of obs	298	
Chi-square	155.40	
Prob > chi2	0.00	

Standard errors in parenthesis; significance at *** p <0.01, ** p <0.05, * p < 0.1; **Source**: Author's survey data (2022).

4. Discussions

4.1. Adoption of Fruit-Fly IPM by Scale and Seasonality of Use

The partial fruit fly IPM adopters only applied the technology on a few of their mango sub-plots or sections of the orchard, and limited resources to buy and service the traps were cited as the main challenge. Other reasons included the lack of a ready market to sell high-quality fruits to compensate for their efforts to implement the technology in other sections of their orchards. Lack of technical support contributing to lack of knowledge was also highlighted as one of the reasons contributing to the partial adoption of the technology. As noted by Wangithi et al. [8], the partial adopters did not use the recommended rates for the replacement of the lures, and hence, reported the ineffectiveness of the technology in controlling the fruit fly pest.

Seasonal users of the fruit fly IPM reported limited awareness or knowledge on the replacement of the lures as the main constraint followed by the unavailability of IPM inputs in the market and their high prices. These findings corroborate those of Wangithi et al. [8]. In addition, the lack of technical skills in using IPM products was also a contributing factor to the seasonal use of the technology. These constraints are similar to those reported by previous studies on the adoption of agricultural technologies (Quisumbing et al. [33], and Feyisa [34].

4.2. Determinants of Fruit Fly IPM Adoption among Mango Growers in Embu, Kenya

Age of the household head negatively influences the adoption of the fruit fly IPM, suggesting a lack of receptivity among older farmers toward newly introduced technologies [35]. Older farmers who have spent more time growing mangoes may be reluctant to take the risk of adopting new unfamiliar technologies for the management of mango fruit flies, as found by Kafle [36], who associated the negative effect of age on adoption with the risk averseness and unwillingness of older farmers to accept change in the production techniques that they have previously used.

Contact with agricultural extension service providers, a proxy for access to information, was positively related to the adoption of IPM. As reported by Kafle [36], regular contact with extension agents enhances awareness of new technologies and the skills needed to use them. Fisher [37] also reported that farmers who received information on modern technologies were more likely to adopt them as compared to those who did not. IPM training seeks to increase awareness and impart skills needed in the adoption of IPM technology. Parsa et al. [38] noted that insufficient training and technical support are the major obstacles to IPM adoption in developing countries. Quazi [39] and [40] noted that training and extension contact are important predictors of the perception and acceptance behavior of individuals toward new technologies.

Social capital through membership in the mango group positively influences the adoption of IPM technology. Manda [41] reported that farmer groups provide avenues that enhance easy training and dissemination of new technologies, as well as access to credit services that farmers use to purchase new technologies. Our findings are in line with the findings of Onyeneke [42], who reported that group membership facilitates easy access to agricultural production inputs, thereby enhancing adoption. In addition, group membership aids farmers to access credit services, extension information regarding the crop, and access to output markets [40].

Technology characteristics, including awareness, accessibility, application, benefits, and operating costs, determine the sustainable adoption of technology [43]. The perceived unavailability of IPM technology negatively influences the adoption of the technology. This is plausible as farmers adopt technologies that they can easily access. These results support the findings of Andrade et al. [44], who reported that technologies need to be available for enhanced adoption by smallholders. The results of the perceived operational costs of the IPM technology corroborate the findings of Asieduh-Ayeh [45], who reported that the perceived cost of new technology is not a hindrance to its adoption, as farmers consider whether the intended benefits outweigh the associated costs when making the adoption decision.

4.3. Determinants of Fruit IPM Dis-Adoption among Mango Growers in Embu, Kenya

Larger farm sizes were found to positively influence the continued use of IPM and to discourage the dis-adoption of the technology. The farm size is a proxy of household resources and larger farm sizes are attributed to the adoption of modern technologies [46]. Years of formal education has a positive impact on the hazard of exit from IPM adoption. The educational level of the farmers is often associated with the continued use of agricultural technologies, as it increases the ability to obtain, process, understand, and interpret agricultural information acquired from different sources [46]. The gender of the household head had a positive impact on the hazard of exit from the adoption state of IPM, suggesting that women are more likely to dis-adopt IPM compared to men. Men were the majority among plot managers, and had greater access to resources as compared to women; therefore, male-headed households are likely to adopt and continue using technologies as compared to female-headed households [8].

For the technology characteristics, the perceived quality of IPM was positively associated with the hazard of exit from adoption. The perceived quality of IPM enhances the adoption decisions and sustained use of the technology by mango farmers. Most farmers do not perceive the quality of IPM as a constraint to the continued use of the technology. This finding is consistent with that of Fedeyi [43], who reported that farmers' awareness of technology's quality, use, and benefits enhance its adoption.

5. Conclusions and Policy Recommendations

This study evaluated the determinants of the adoption and dis-adoption of IPM practices in the suppression of mango fruit fly infestation in Embu County, Kenya. The descriptive results showed that 59% of the respondents were adopters of IPM practices in the suppression of mango fruit fly infestation, 24% were non-adopters, and 17% were dis-adopters. Additionally, 40% of the adopters were partial farm users, while 29% were seasonal users of the IPM technology. Farmers who had discontinued the use of IPM technology cited the unavailability of the technology as the main reason for dis-adoption. Seasonal users of the technology reported limited awareness with regard to the timing on when to replace the lures as the main grounds for seasonal use, while partial farm use of the technology was attributed to a lack of capital to procure and maintain the technology. Thus, IPM technology should be made easily accessible to promote sustained adoption and discourage dis-adoption, seasonal use, and partial farm use.

The empirical results showed that training, the perceived cost of IPM, contact with extension officers, group membership, and the gender of the household head positively influenced the adoption of IPM practices in the suppression of mango fruit fly infestation. Furthermore, the age of the household head and the unavailability of IPM products had a negative influence on the adoption of IPM technology. On the other hand, the education of the household head, age of the household head, farm size, and the perceived quality of IPM positively influenced the hazard of exit from the adoption of IPM practices. This study, therefore, recommends building the capacity of mango farmers through training and access to extension services to enhance the adoption of this technology and discourage dis-adoption. This can be achieved through the intensification of information dissemination by extension officers and farmer groups on the importance of the technology. In addition, IPM products should be made easily accessible to farmers to enhance the sustained adoption of the technology.

While our findings provide useful insights into the different classifications of IPM adoption, we lacked enough data for empirical analysis of the last two classifications (seasonality and scale of IPM use in mango orchards). Therefore, further research should consider the empirical assessment of the determinants of the two IPM definition approaches.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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References

1. Badii, K.B.; Billah, M.K.; Afreh Nuamah, K.; Obeng Ofori, D.; Nyarko, G. Review of the Pest Status, Economic Impact and Management of Fruit-Infesting Flies (Diptera: Tephritidae) in Africa. *Afr. J. Agric. Res.* **2015**, *10*, 1488–1498. https://doi.org/10.5897/AJAR2014.9278.
2. Boulahia-Kheder, S. Advancements in Management of Major Fruit Flies (Diptera: Tephritidae) in North Africa and Future Challenges: A Review. *J. Appl. Entomol.* **2021**, *145*, 939–957. https://doi.org/10.1111/jen.12938.
3. Ekesi, S.; De Meyer, M.; Mohamed, S.A.; Virgilio, M.; Borgemeister, C. Taxonomy, Ecology, and Management of Native and Exotic Fruit Fly Species in Africa. *Annu. Rev. Entomol.* **2016**, *61*, 219–238. https://doi.org/10.1146/annurev-ento-010715-023603.
4. Heve, W.K.; El-Borai, F.E.; Carrillo, D.; Duncan, L.W. Biological Control Potential of Entomopathogenic Nematodes for Management of Caribbean Fruit Fly, Anastrepha Suspensa Loew (Tephritidae). *Pest Manag. Sci.* **2017**, *73*, 1220–1228. https://doi.org/10.1002/ps.4447.
5. Dias, N.P.; Zotti, M.J.; Montoya, P.; Carvalho, I.R.; Nava, D.E. Fruit Fly Management Research: A Systematic Review of Monitoring and Control Tactics in the World. *Crop Prot.* **2018**, *112*, 187–200. https://doi.org/10.1016/j.cropro.2018.05.019.
6. Midingoyi, S.G.; Kassie, M.; Muriithi, B.; Diiro, G.; Ekesi, S. Do Farmers and the Environment Benefit from Adopting Integrated Pest Management Practices? Evidence from Kenya. *J. Agric. Econ.* **2019**, *70*, 452–470. https://doi.org/10.1111/1477-9552.12306.
7. Health and Environmental Effects of Adopting an Integrated Fruit Fly Management Strategy among Mango Farmers in Kenya. *Afr. J. Agric. Resour. Econ.* **2020**, *15*, 14–26. https://doi.org/10.22004/ag.econ.307614.
8. Wangithi, C.M.; Muriithi, B.W.; Belmin, R. Adoption and Dis-Adoption of Sustainable Agriculture: A Case of Farmers' Innovations and Integrated Fruit Fly Management in Kenya. *Agriculture* **2021**, *11*, 338. https://doi.org/10.3390/agriculture11040338.
9. Ehler, L.E. Integrated Pest Management (IPM): Definition, Historical Development and Implementation, and the Other IPM. *Pest Manag. Sci.* **2006**, *62*, 787–789. https://doi.org/10.1002/ps.1247.
10. Korir, J.K.; Affognon, H.D.; Ritho, C.N.; Kingori, W.S.; Irungu, P.; Mohamed, S.A.; Ekesi, S. Grower Adoption of an Integrated Pest Management Package for Management of Mango-Infesting Fruit Flies (Diptera: Tephritidae) in Embu, Kenya. *Int. J. Trop. Insect Sci.* **2015**, *35*, 80–89. https://doi.org/10.1017/S1742758415000077.
11. Gichungi, H.; Muriithi, B.; Irungu, P.; Diiro, G.; Busienei, J. Effect of Technological Innovation on Gender Roles: The Case of Fruit Fly IPM Adoption on Women's Decision-Making in Mango Production and Marketing in Kenya. *Eur. J. Dev. Res.* **2021**, *33*, 407–426. https://doi.org/10.1057/s41287-020-00282-z.
12. Nyang'au, P.N.; Muriithi, B.W.; Nzuma, J.M.; Irungu, P.; Gichungi, H.M.; Diiro, G. Impact of Integrated Fruit Fly Management Strategy on Food Security among Smallholder Mango Farmers in Kenya. *Afr. J. Food Agric. Nutr. Dev.* **2020**, *20*, 15431–15454.
13. Kabir, M.H.; Rainis, R. Adoption and Intensity of Integrated Pest Management (IPM) Vegetable Farming in Bangladesh: An Approach to Sustainable Agricultural Development. *Environ. Dev. Sustain.* **2015**, *17*, 1413–1429. https://doi.org/10.1007/s10668-014-9613-y.
14. Muriithi, B.W.; Gathogo, N.G.; Diiro, G.M.; Mohamed, S.A.; Ekesi, S. Potential Adoption of Integrated Pest Management Strategy for Suppression of Mango Fruit Flies in East Africa: An Ex Ante and Ex Post Analysis in Ethiopia and Kenya. *Agriculture* **2020**, *10*, 278. https://doi.org/10.3390/agriculture10070278.
15. Muriithi, B.W.; Gathogo, N.; Rwomushana, I.; Diiro, G.; Mohamed Faris, S.; Khamis, F.; Tanga, C.; Ekesi, S. Farmers' Knowledge and Perceptions on Fruit Flies and Willingness to Pay for a Fruit Fly Integrated Pest Management Strategy in Gamo Gofa Zone, Ethiopia. *Int. J. Agric. Sustain.* **2021**, *19*, 199–212. https://doi.org/10.1080/14735903.2021.1898178.
16. Sahin, I. Detailed Review of Rogers' Diffusion of Innovations Theory and Educational Technology-Related Studies Bsed on Rogers' Theory. *Turk. Online J. Educ. Technol.* **2006**, *5*, 10.
17. Muriithi, B.; Kabubo-Mariara, J. The Dynamics and Role of Gender in High-Value Avocado Farming in Kenya. *Eur. J. Dev. Res.* **2022**, *34*, 2272–2304. https://doi.org/10.1057/s41287-021-00484-z.
18. Cascetta, E. *Transportation Systems Analysis: Models and Applications*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2009; ISBN 978-0-387-75857-2.
19. Baltas, G.; Doyle, P. Random Utility Models in Marketing Research: A Survey. *J. Bus. Res.* **2001**, *51*, 115–125. https://doi.org/10.1016/S0148-2963(99)00058-2.
20. Greene, W.H. *Econometric Analysis 5th Edition*; 5th Ed.; Pearson Education India: Delhi, India, 2002;.
21. Alem, Y.; Hassen, S.; Köhlin, G. Adoption and Disadoption of Electric Cookstoves in Urban Ethiopia: Evidence from Panel Data. *Resour. Energy Econ.* **2014**, *38*, 110–124. https://doi.org/10.1016/j.reseneeco.2014.06.004.
22. Stammann, A.; Heiß, F.; McFadden, D. Estimating Fixed Effects Logit Models with Large Panel Data; ZBW-Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg: Kiel, Germany, 2016.
23. Jenkins, S.P. Easy Estimation Methods for Discrete-Time Duration Models. *Oxf. Bull. Econ. Stat.* **1995**, *57*, 129–136. https://doi.org/10.1111/j.1468-0084.1995.tb00031.x.
24. An, H.; Butler, L.J. A Discrete-Time Duration Analysis of Technology Disadoption: The Case of RbST in California. *Can. J. Agric. Econ. Can. Agroeconomie* **2012**, *60*, 495–515. https://doi.org/10.1111/j.1744-7976.2012.01255.x.
25. Gao, Y.; Zhao, D.; Yu, L.; Yang, H. Duration Analysis on the Adoption Behavior of Green Control Techniques. *Environ. Sci. Pollut. Res.* **2019**, *26*, 6319–6327. https://doi.org/10.1007/s11356-018-04088-9.
26. Mundlak, Y. On the Pooling of Time Series and Cross Section Data. *Econometrica* **1978**, *46*, 69. https://doi.org/10.2307/1913646.

27. Burton, M.; Rigby, D.; Young, T. Modelling the Adoption of Organic Horticultural Technology in the UK Using Duration Analysis. *Aust. J. Agric. Resour. Econ.* **2003**, *47*, 29–54. https://doi.org/10.1111/1467-8489.00202.
28. Khataza, R.R.B.; Doole, G.J.; Kragt, M.E.; Hailu, A. Information Acquisition, Learning and the Adoption of Conservation Agriculture in Malawi: A Discrete-Time Duration Analysis. *Technol. Forecast. Soc. Chang.* **2018**, *132*, 299–307. https://doi.org/10.1016/j.techfore.2018.02.015.
29. Muriithi, B.W.; Diiro, G.M.; Affognon, H.; Ekesi, S. Economic Impact of Integrated Pest Management Strategies for the Suppression of Mango-Infesting Fruit Fly Species in Africa. In *Fruit Fly Research and Development in Africa-towards a Sustainable Management Strategy to Improve Horticulture*; Ekesi, S., Mohamed, S.A., De Meyer, M., Eds.; Springer International Publishing: Cham, Switzerland, 2016; pp. 755–770, ISBN 978-3-319-43226-7.
30. Jenkins, S.P. Discrete Time Proportional Hazards Regression. *Stata Tech. Bull.* **1998**, *7*, 39.
31. Taherdoost, H. Determining Sample Size; How to Calculate Survey Sample Size. *Int. J. Econ. Manag. Syst.* **2017**, *2*, 1–3.
32. Doss, C.R. Analyzing Technology Adoption Using Microstudies: Limitations, Challenges, and Opportunities for Improvement. *Agric. Econ.* **2006**, *34*, 207–219. https://doi.org/10.1111/j.1574-0864.2006.00119.x.
33. Quisumbing, A.R.; Pandolfelli, L. Promising Approaches to Address the Needs of Poor Female Farmers: Resources, Constraints, and Interventions. *World Dev.* **2010**, *38*, 581–592. https://doi.org/10.1016/j.worlddev.2009.10.006.
34. Feyisa, B.W. Determinants of Agricultural Technology Adoption in Ethiopia: A Meta-Analysis. *Cogent Food Agric.* **2020**, *6*, 1855817. https://doi.org/10.1080/23311932.2020.1855817.
35. Arellanes, P.; Lee, D.R. The Determinants of Adoption of Sustainable Agriculture Technologies: Evidence from the Hillsides of Honduras; 2003. In Proceedings of the International Association of Agricultural Economists, Durban, South Africa, 16–22 August 2003. Available online: https://ageconsearch.umn.edu/record/25826/ (accessed on 12 August 2021).
36. Kafle, B. Determinansts of Adoption of Improved Maize Varieties in Developing Countries: A Review. *Int. Res. J. Appl. Basic Sci.* **2010**, *1*, 1–7.
37. Fisher, M.; Abate, T.; Lunduka, R.W.; Asnake, W.; Alemayehu, Y.; Madulu, R.B. Drought Tolerant Maize for Farmer Adaptation to Drought in Sub-Saharan Africa: Determinants of Adoption in Eastern and Southern Africa. *Clim. Chang.* **2015**, *133*, 283–299. https://doi.org/10.1007/s10584-015-1459-2.
38. Parsa, S.; Morse, S.; Bonifacio, A.; Chancellor, T.C.B.; Condori, B.; Crespo-Pérez, V.; Hobbs, S.L.A.; Kroschel, J.; Ba, M.N.; Rebaudo, F.; et al. Obstacles to Integrated Pest Management Adoption in Developing Countries. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 3889–3894. https://doi.org/10.1073/pnas.1312693111.
39. Quazi, A.; Talukder, M. Demographic Determinants of Adoption of Technological Innovation. *J. Comput. Inf. Syst.* **2011**, *52*, 34–42. https://doi.org/10.1080/08874417.2011.11645520.
40. Biniam, T.; Rahmeto, N.; Amanuel, S. Determinants of Adoption of Improved Jalenea Potato Variety: The Case of Chencha Woreda, Southern Ethiopia. *J. Dev. Agric. Econ.* **2019**, *11*, 170–185. https://doi.org/10.5897/JDAE2018.1041.
41. Manda, J.; Khonje, M.G.; Alene, A.D.; Tufa, A.H.; Abdoulaye, T.; Mutenje, M.; Setimela, P.; Manyong, V. Does Cooperative Membership Increase and Accelerate Agricultural Technology Adoption? Empirical Evidence from Zambia. *Technol. Forecast. Soc. Chang.* **2020**, *158*, 120160. https://doi.org/10.1016/j.techfore.2020.120160.
42. Onyeneke, R.U. Determinants of Adoption of Improved Technologies in Rice Production in Imo State, Nigeria. *Afr. J. Agric. Res.* **2017**, *12*, 888–896. https://doi.org/10.5897/AJAR2016.11737.
43. Fadeyi, O.A.; Ariyawardana, A.; Aziz, A.A. Factors Influencing Technology Adoption among Smallholder Farmers: A Systematic Review in Africa. *J. Agric. Rural. Dev. Trop. Subtrop.* **2022**, *123*, 13–30. https://doi.org/10.17170/KOBRA-202201195569.
44. Andrade, J.F.; Rattalino Edreira, J.I.; Farrow, A.; van Loon, M.P.; Craufurd, P.Q.; Rurinda, J.; Zingore, S.; Chamberlin, J.; Claessens, L.; Adewopo, J.; et al. A Spatial Framework for Ex-Ante Impact Assessment of Agricultural Technologies. *Glob. Food Secur.* **2019**, *20*, 72–81. https://doi.org/10.1016/j.gfs.2018.12.006.
45. Asiedu-Ayeh, L.O.; Zheng, X.; Agbodah, K.; Dogbe, B.S.; Darko, A.P. Promoting the Adoption of Agricultural Green Production Technologies for Sustainable Farming: A Multi-Attribute Decision Analysis. *Sustainability* **2022**, *14*, 9977. https://doi.org/10.3390/su14169977.
46. Kehinde, A. A Probit Analysis of Factors Affecting Improved Technologies Dis-Adoption in Cocoa-Based Farming Systems of Southwestern Nigeria. *Int. J. Agric. Econ.* **2017**, *2*, 35. https://doi.org/10.11648/j.ijae.20170202.12.