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Factors influencing adoption of agro-ecological pest management options for mango fruit fly under information constraints: a two-part fractional regression approach

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ABSTRACT
The catalytic effect of climate change on the emergence and prevalence of invasive alien pests along with weak pesticide regulatory frameworks in developing countries calls for a transition towards sustainable pest management. Agro-ecological pest management (APM) offers a nature-based, cost-effective alternative for addressing systemic pest challenges, such as mango fruit fly invasion. We applied a two-part fractional regression to sequentially model APM adoption and intensity decisions among 423 smallholder mango orchard managers from Makueni County, Kenya. Despite APM's potential, we observed moderate adoption rates (56.7%), with the average adopter implementing only 25% of the APM practices concurrently. Farmers' socio-psychological attributes significantly influenced both adoption and intensity decisions. While perceptions of technology attributes and institutional and social factors primarily influenced both the adoption and intensity decisions, information constraints, resource endowment, gender and inter-generational factors significantly influenced only the intensity decision. To support the transition from synthetic insecticides to APM measures, policymakers should create more opportunities for awareness creation, training and knowledge co-creation and co-production, particularly through social networks and gender-disaggregated participatory group approaches.

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Agro-ecological pest management; behavioural change; fruit fly; intensity of adoption; invasive alien pests; mango; two-part fractional regression

1. Introduction

Invasive alien pests pose an increasing threat to human livelihoods, particularly as climate change-induced ecosystem disturbances and transboundary trade pathways expand and intensify (Early et al. 2016; Skendžić et al. 2021). Historically, pest invasions have been known for their association with high economic consequences resulting from yield loss and abatement costs. For instance, between 1970 and 2017, an annual average of USD 18.6 billion was estimated to be lost directly to damage caused by invasive species, including pests, while an additional USD 1.4 billion was estimated to be incurred in management costs globally (Diagne et al. 2021). The economic impacts associated with invasive pests are particularly concerning for sub-Saharan Africa (SSA) economies, where the agricultural sector contributes 20–50% of the gross domestic product (GDP) (Giller 2020) and employs over 53% of the workforce (Srinivasan, Tamò, and Subramanian 2022). These effects are further compounded by the existence of weak regulatory frameworks and inadequate response mechanisms for the containment and eradication of invasive pests (Ndlela, Niassy, and Mohamed 2022).

The conventional management of systemic pest challenges has predominantly relied on the application of synthetic pesticides (Schreinemachers et al. 2017). However, over time, the widespread and intensive use of synthetic pesticides has negatively affected agroecosystems by exacerbating climate change and biodiversity loss (Heimpel et al. 2013; Skendžić et al. 2021). Extensive pesticide use has also contributed to the "pesticide treadmill[1]", which has diminished natural pest control efforts (Bakker et al. 2020). Projections indicate that by 2030, the hidden costs associated with conventional food systems could reach up to USD 13 trillion annually (Rockström et al. 2020).

Agro-ecological pest management (APM) represents a paradigm shift from conventional pest management. Broadly, APM is a systemic approach that prioritises prophylactic control options for

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long-term pest management through the utilisation of contextualised bio-rational strategies that are compatible with existing methods and adaptable to future food production bottlenecks (Belmain et al. 2022). By design, APM practices are hybridised on both indigenous and scientific knowledge (Deguine et al. 2021; Wezel et al. 2009), with emphasis on the utilisation and recycling of on-farm and locally available inputs to reduce reliance on chemical pesticides. Thus, APM is viable, particularly for smallholder farmers in resource-limited settings.

In SSA, mango (*Mangifera indica L.*) is cultivated predominantly by smallholders under rain-fed conditions, constituting up to 90% of the total annual production (Ndlela, Niassy, and Mohamed 2022). The crop ranks second among fruit crops in Kenya, following bananas in both value and volume. In 2020, its annual production value was estimated to be USD 154 million – representing 17.34% of the total fruit value and 8.64% of the horticultural GDP in the country (Horticultural Crops Directorate 2021).

The major impediment to mango productivity and marketing is the oriental fruit fly *Bactrocera dorsalis* (Diptera: Tephritidae). This pest is highly invasive, and its fecund and polyphagous traits endow it with comparative advantages over its intra-specific competitors (Mutamiswa et al. 2021). *B. dorsalis* has been reported to reduce yields by between 30% and 90% (Vayssières, Korie, and Ayegnon 2009). In the African continent alone, approximately USD 2 billion is estimated to be lost annually due to quarantine and self-bans associated with the pest invasion (Korir et al. 2015). Consequently, there is an urgent need to mitigate the impacts of *B. dorsalis* and enhance the sustainability of the mango value chain. Effective control of *B. dorsalis* through eco-friendly practices such as integrated pest management (IPM) has been demonstrated to result in higher revenues (Kibira et al. 2015; Midingoyi et al. 2019; Muriithi et al. 2016a) increased yields (Midingoyi et al. 2019; Mulungu et al. 2023; Muriithi et al. 2016b), reduced mango rejection rates in key markets (Kibira et al. 2015), and increased per capita calorie intake at the household level (Nyang'au et al. 2020).

At the farm level, the decision to transition to sustainable technologies, such as APM, is primarily driven by the economic advantages offered by these alternatives. However, it is also widely recognised that the main relative advantage of environmentally sustainable practices lies in their delivery of public goods in the form of positive externalities, such as ecosystem services. Therefore, decisions to adopt eco-friendly alternatives often have economic consequences and are generally more controlled (Dessart, Barreiro-Hurlé, and Van Bavel 2019). Voluntary adoption under such circumstances is likely influenced by farmer's intrinsic motivations (Ejelöv et al. 2022; Meijer et al. 2015; Runhaar 2017; Schoonhoven and Runhaar 2018). Farmers may also adopt APM as a cost-minimisation strategy by reducing over-reliance on the often-expensive synthetic pesticides. Additionally, some farmers are motivated by ethical concerns regarding the impact of their practices on the environment and society. Furthermore, consumer demand for organic and sustainably produced food is growing, creating market incentives for farmers to transition to more sustainable alternatives.

2. Past related studies

A burgeoning stream of literature explores the determinants of the voluntary uptake of environmentally sustainable pest management technologies by smallholder farmers (see Kirui et al. 2023; Midingoyi et al. 2019; Mwungu et al. 2020; Otieno et al. 2023; Rahman and Norton 2019; Sadique Rahman 2022; Wangithi, Muriithi, and Belmin 2021). However, these studies have largely emphasised external factors, including economic incentives, socio-demographic attributes and institutional support, with limited attention to the intrinsic socio-psychological attributes that influence farmers' decisions. Extant literature on the voluntary uptake of environmentally sustainable pest management technologies by smallholder farmers that accounts for the behavioural attributes of decision makers has predominantly focused on the intention to adopt (Despotović, Rodić, and Caracciolo 2019; Khan et al. 2021; Punzano, Rahmani, and Delgado 2021) and willingness to pay/adopt (Gao et al. 2017; Muriithi et al. 2021; Nyangau et al. 2022; Petrescu-Mag et al. 2019) pest management technologies. Although self-reported intentions and willingness to adopt a technology can predict observed behavioural patterns, farmers may overstate their intentions and willingness in an attempt to report "socially acceptable" behaviours (Khan et al. 2021; Petrescu-Mag et al. 2019). Indeed, behavioural intention is a *necessary* but *insufficient* condition for observed adoption. Our analysis focuses on *actual* adoption and integrates a number of latent covariates that encompass cognitive aspects of farm decision makers.

Several studies have assessed the drivers of the extent of adoption of pest management strategies in various contexts using different empirical models. Kabir and Rainis (2015) applied a step-wise linear regression model to assess the determinants of the intensity of adoption of IPM among a sample of 331 vegetable producers in Bangladesh. Similar to the linear probability model for binary data, linear regression models for fractional outcomes are not guaranteed to yield predicted values within the unit interval and are therefore inappropriate for handling fractional data. Murage et al. (2015) analysed the extent of adoption of push-pull technology for managing lepidopteran stem borers and African witchweed (*Striga spp*.) using a Tobit regression. However, Tobit models assume that the explanatory variables of the censoring mechanism must also impact the adoption intensity when it takes non-zero values. This assumption is clearly invalid in situations where both the adoption and intensity decisions are influenced by separate data-generating processes (DGPs), as assumed in this study. Additionally, if the dispersion in the response variable is limited within the unit interval, or a significant proportion of its values fall at either extremum, the Tobit model becomes constrained (Papke and Wooldridge 1996).

Korir et al. (2015) applied both Poisson and Negative Binomial regressions to analyse the determinants of the intensity of IPM practices adoption for suppressing mango fruit flies in Embu County, Kenya. However, models drawing from the Poisson distribution may be inappropriate and could lead to biased estimates if the DGP is non-memoryless (Plan 2014), such that the probability of being an adopter alters the probability of its level, as commonly observed in uptake of pest control technologies.

Gao et al. (2017) employed a linear regression model to evaluate the factors influencing the intensity of uptake of green control techniques for pest management on family farms in China. However, the study's definition of adoption intensity, based on the difference in the rate of chemical pesticide application before and after adoption, may be an unsuitable measure for evaluating the uptake intensity of sustainable pest management strategies in resource-limited settings. While the adoption of eco-friendly practices is likely to reduce pesticide usage rates, smallholders in SSA might decrease the quantity of synthetic pesticides applied primarily due to financial constraints, rather than the adoption of APM strategies. In fact, the consumption of chemical pesticides in pest management can significantly vary based on other factors such as perceived severity of the infestation. Although the authors accounted for the jointedness in adoption decisions, their adoption decision is based on willingness to adopt, which could have been overstated by respondents.

Midingoyi et al. (2019) analysed the extent of adoption of IPM strategies among a sample of 633 smallholder farmers in Kenya using an ordered probit model. Ordinal regressions, such as ordered probit, rely on the restrictive assumption of parallel lines for identification, a condition frequently violated in practice. When the ordinality assumption is violated, the predicted probabilities may fall below zero, subjecting the model to the common pitfalls associated with linear probability models. Additionally, heteroskedastic errors can create apparent disparities in effects between adoption groups. Moreover, the estimates from ordered regressions can have multiple plausible yet radically different interpretations, complicating the analysis and the derived policy implications.

Misango et al. (2022) employed a fractional response model (FRM) to analyse the determinants of the intensity of adoption of push-pull technology as an IPM practice for controlling stem borer and fall armyworm among 194 small-scale maize farmers in Rwanda. However, the study focuses on a single practice despite the comprehensive nature of IPM. To capture its holism, we focus instead on the uptake of several complementary and synergistic APM options rather than a single practice. Additionally, the authors assume that adoption intensity is a spontaneous decision. However, we permit adoption decisions to be made sequentially by orchard managers, allowing each decision stage to be influenced by separate DGPs. Within this framework, we adopt a nuanced approach by focusing on the orchard manager as the unit of analysis, following Miriti et al. (2021). An orchard manager is defined as the household member responsible for the majority of decisions related to orchard-level activities. This approach relaxes the often-restrictive assumption that the household head is the primary decision maker in agricultural enterprises.

The primary objective of this study was to analyse the determinants of the adoption and intensity of APM practices for mango fruit fly suppression among smallholder farmers under information constraints[2]. Specifically, we test the hypotheses that: (i) socio-psychological factors, including attitudes towards the technology and perceptions of technology attributes as well as social networks, resource endowment, training and knowledge co-creation, impact both the adoption and intensity of APM decisions; and (ii) information constraints, encompassing both the quality of awareness and agronomic knowledge in APM implementation, significantly determine the extent of uptake of APM technologies.

The remainder of the article is organised as follows: In Section 3, we discuss the research methodology, including a brief description of the study area, the sampling procedure and data collection, the variables employed in the study and the analytical framework. We then present and discuss our results in Section 4, before concluding in Section 5 with a brief discussion of the implications of our findings for practice, policy and future research.

3. Data and methods

3.1. Study area

This study was conducted in Makueni County, located in the south-eastern region of Kenya (Figure 1). The county covers a total area of 8176.7 Km^2, 62% of which is classified as arable land. The upper part of the county features fertile soil and experiences an average annual rainfall ranging from 800 to 1200 mm, with annual temperatures ranging from 17 °C to 30 °C (County Government of Makueni 2022). These conditions not only favour the cultivation of horticultural crops such as mango but also contribute to high pest incidences. Makueni County is home to approximately 28,696 smallholder households practising rain-fed farming (Onyango et al. 2023), and is the leading producer of mango in Kenya, contributing up to 19.7% of the annual production in 2020 (Horticultural Crops Directorate 2021).

3.2. Sampling technique and data collection

We employed a cross-sectional survey design with a multistage sampling procedure. In the first two stages, purposive sampling was used to select Makueni County and the sub-counties of Makueni, Mbooni and Kaiti. In the third and fourth stages, simple random sampling procedures were employed to select six wards and twelve sub-wards, respectively, from the three sub-counties. A systematic random sampling approach was implemented at the final stage, during which every third orchard manager was selected from each sub-ward.

The study utilised the Yamane (1967) formula to determine the required sample size n as:

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

Given that the population of smallholder mango farmers in Makueni County, N, was approximately 28, 696, the minimum sample size required at the 95% (i.e., e = 0.05) confidence level was 395, calculated as $n = \frac{28696}{1 + 28696(0.05)^2} \approx 395$. However, we adjusted this value by a factor of 1.10 to 434 (i.e., $1.10 \times 395 = 434$) orchard managers to address potential issues related to incomplete questionnaires and outliers. This adjustment coefficient has been utilised in previous literature (see Ojwang et al. 2021). We encountered two outliers who were omitted from the analysis. From the remaining 432 respondents, we also discarded nine responses from orchard managers who were unaware of the APM practice by

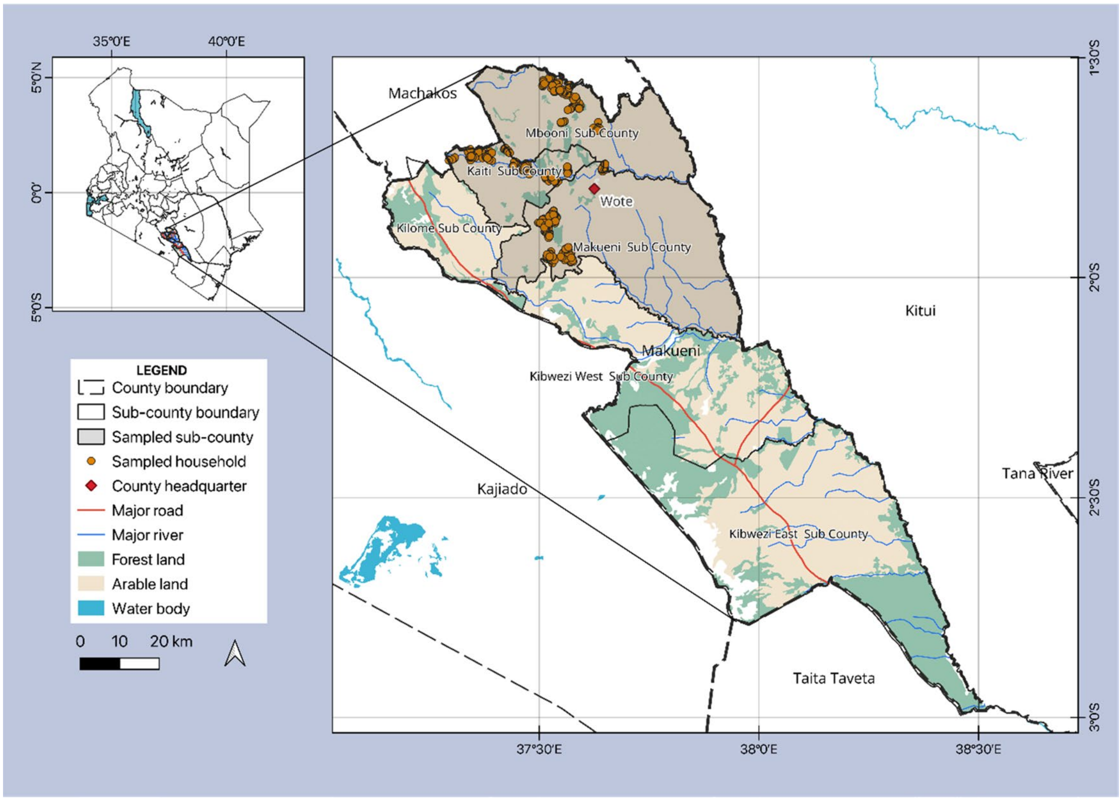

Figure 1. Map of the study sites in Makueni County, Kenya.

conditioning all analyses on positive awareness as discussed in Section 3.4.1. Data were collected between August and September 2023 and involved face-to-face interviews by trained enumerators using a pretested questionnaire. Informed consent was obtained from the respondents prior to the interviews. The questionnaire captured information such as the household and respondent demographics, asset endowment, access to institutional services, awareness, perceptions, attitudes and knowledge, adoption of agro-ecological practices, input use and mango production. All the surveyed orchard managers had observed fruit fly damage in their orchards at least 5 years before the survey.

3.3. Theoretical framework

The study was anchored on the von Neumann–Morgenstern expected utility theory (EUT) (von Neumann, Morgenstern, and Rubinstein 1944), Lancaster model of consumer behaviour (LMCB) (Lancaster 1966) and random utility theory (RUT) (McFadden 1974) to explain smallholder orchard managers' decisions to adopt APM practices. The von Neumann–Morgenstern EUT posits that a decision-making unit (DMU) evaluates the expected utility of potential outcomes to maximise profit when choosing between risky and uncertain prospects (von Neumann, Morgenstern, and Rubinstein 1944). In pest management, risks stem from yield loss and management costs due to pest damage, as well as health and market uncertainties. Given the nature of loss aversion, the uncertainty associated with innovations such as APM makes them less appealing to smallholder farmers than conventional alternatives (Alwang, Norton, and Larochelle 2019). Shifting to APM is often seen as risky (Deguine et al. 2021), especially in regions like SSA, where reliable insurance safety nets for risk transfer are either limited or non-existent (Ngango, Nkurunziza, and Ndagijimana 2022; Ntukamazina et al. 2017). Consequently, decisions to adopt such innovations are primarily based on expectations of future outcomes (Feder 1979). Therefore, prior to adoption and intensity decisions, rational farmers are assumed to evaluate options based on the available information to understand the probability distribution of their outcomes.

Suppose we denote the consequences of adopting a fruit fly management technology by a finite set $C=\{c_{i1},c_{i2},\dots,c_{IN}\}$ and let the set of all available alternatives be represented by another set $A=\{a_{\mathrm{APM}},a_{\mathrm{conventional}},\dots,a_{IN}\}$. Then, adoption is associated with a probability distribution of consequences such that:

$$a:C\to[0,1] \text{ with } \sum_{c\in C} a^*(c) \tag{2}$$

$$\sum_{c\in C} p_i=\sum_{c\in C} q_i=\dots=1 \quad \forall p_i\geq 0, q_i\geq 0$$

where p_i and q_i represent the probabilities of obtaining outcome c_i when APM or other alternatives are adopted, respectively. The von Neumann–Morgenstern utility function $u(\cdot)$ is defined as:

$$u:C\to\mathbb{R}, \text{ such that } \mathbb{E}\left[U(a)\right] = \sum_{c\in C} a(c)u(c) \quad \forall a_{\mathrm{APM}},a_{\mathrm{conventional}},\dots\in A \tag{3}$$

For APM and conventional methods, the expected utility is expressed as:

$$\mathbb{E}\left[U(a_{\mathrm{APM}})\right]=\sum_{c\in C} p_i u(c_i) \; and \quad \mathbb{E}\left[U(a_{\mathrm{conventional}})\right]=\sum_{c\in C} q_i u(c_i) \tag{4}$$

The expected utility function $\mathbb{E}\left[U(\cdot)\right]$ takes the form $\mathbb{E}\left[U\right]:a\to\mathbb{R}$, and A is a closed, bounded and compact subset of $\mathbb{R}^n$, where $n=|C|$. The primary objective of a risk-averse DMU is to maximise the expected utility by adopting a technology from the set A of alternatives if its expected utility is higher than that of other alternatives:

$$a_{\mathrm{APM}}\succ a_{\mathrm{conventional}} \Leftrightarrow \mathbb{E}\left[U(a_{\mathrm{APM}})\right]-\mathbb{E}\left[U(a_{\mathrm{conventional}})\right]>0 \tag{5}$$

However, farmers do not only consider the overall utility of the technology but also evaluate specific attributes of the alternatives, as described by Lancaster's consumer behaviour model (Lancaster 1966). Lancaster argues that consumers derive utility from the attributes of goods or technologies, rather than the technologies themselves. When comparing APM and conventional methods, farmers evaluate attributes such as ease of use, effectiveness, health benefits, environmental impact and cost. The utility function then depends on these attributes:

$$U(a)=f(\lambda(a)),\lambda(a)=\{\lambda_1(a),\lambda_2(a),\lambda_3(a),\dots,\lambda_N(a)\} \tag{6}$$

where $\lambda_1,\lambda_2,\lambda_3,\dots,\lambda_N$ are the attributes of the alternative a. An orchard manager chooses the option that maximises utility based on these attributes.

In addition to considering attributes, adoption decisions involve random, measurable and unobserved factors, which affect individual preferences. These preferences can be explained using the RUT (McFadden 1974). The RUT assumes that the utility $U(a)$ has a deterministic component $V(a)$, and a random component $\epsilon(a)$:

$$U(a) = V(a) + \epsilon(a) \tag{7}$$

From this perspective, the probability $Pr(\cdot)$ of a farmer choosing APM over conventional options can be expressed as:

$$Pr(a_{\text{APM}} \succ a_{\text{conventional}}) = Pr[U(a_{\text{APM}})] - Pr[U(a_{\text{conventional}})] > 0 \tag{8}$$

$$= Pr\left[\begin{array}{l}(V(a_{\text{APM}}) + \epsilon(a_{\text{APM}})) \\ -(V(a_{\text{conventional}}) + \epsilon(a_{\text{conventional}})) > 0\end{array}\right]$$

The adoption decision is dichotomous and is therefore typically modelled using discrete choice models, such as probit or logit, which account for these random factors.

3.4. Empirical framework

3.4.1. Sequential decision process

We considered the adoption and intensity of APM decisions as separate but sequentially made by orchard managers, assuming dissimilar DGPs. Adoption was voluntary, and given the high prevalence of the pest at the study sites, farmers were classified as adopters if they utilised at least one of the six "reactive" APM practices. This study defined reactive APM options as practices that could be applied as stand-alone[3] measures due to their potential for killing, repelling and discouraging the establishment of mango fruit fly within the orchard. These practices included male annihilation, smoking herbs, spraying botanical concoctions, spraying food baits, spraying bio-pesticides and spraying ash and tobacco solutions. The remaining practices were considered synergistic options that reinforced the preventive actions of the reactive options within an integrated framework but could not be relied upon as solitary control measures. Although previous studies on adoption of fruit fly IPM, including Otieno et al. (2023) and Wangithi, Muriithi, and Belmin (2021) utilised the male annihilation technique as a proxy for IPM adoption since it was the main commercialised component of the IPM technology, this categorisation fails to account for the holistic nature of IPM. The APM, just like IPM, is a holistic strategy that incorporates the application of various synergistic practices, with emphasis on traditional and locally available alternatives, such as smoking herbs and dung, and spraying botanical concoctions, ash, and tobacco solutions due to cost considerations in resource-limited settings. Therefore, categorisation of farmers into adoption groups should account for the technology's holism and should not be restricted to a single practice. On the other hand, we measured the intensity of adoption as the proportion of APM practices adopted concurrently during the 2022/2023 mango cropping season out of the 18 APM practices outlined in Table 2.

Awareness is a critical precursor to adoption. It is well known that, to consistently estimate the parameters of the drivers of technology uptake, it is necessary to condition on observed awareness or exposure to the technology. This conditioning ensures that the estimation accounts for the "non-exposure bias" (Diagne and Demont 2007) and the "knowledge deficit problem"[4] (Khan et al. 2021). To account for these problems without explicit modelling of awareness as the initial stage of the decision-making process, both decisions were conditioned on positive awareness. Beginning with adoption and contingent on awareness, if an orchard manager adopted APM technology, then they decided on the extent of its use. In this case, a positive random variable, intensity of adoption y_i, was observed. Naturally, this decision process yields many zeros in y_i for non-adopters. To model this DGP, we employed a two-part FRM (TP-FRM) developed by Ramalho and da Silva (2009).

3.4.1.1. Part I of the decision process: probability of adoption.

The first part of the TP-FRM governs the adoption decision – a binary response determining whether an orchard manager adopts the APM. Conditional on awareness, adoption a_i is defined as:

$$(a_i \mid z_i, \omega_i = 1) = \begin{cases} 1, & if\ a_i^* \in (0,1], \\ 0,\ \text{otherwise} & if\ a_i^* = 0, \end{cases} \tag{9}$$

where a_i^* is the latent adoption, ω_i is a binary variable indicating APM awareness ($1 = \text{aware}$), and z_i denotes a $1 \times K$ set of covariates hypothesised to influence the adoption decision. The probability of adoption is estimated using a probit and specified as:

$$Pr(a_i = 1 \mid z_i, \omega_i = 1) = Pr(a_i^* \in (0,1] \mid z_i, \omega_i = 1) = \Phi(\vartheta z_i) \tag{10}$$

where $Pr(\cdot)$ is the conditional probability function, $\Phi(\cdot) \equiv \int_{-\infty}^{z} \phi(v)dv$ is the standard normal cumulative distribution function (CDF) and ϑ is a $K \times 1$ vector of parameters of interest.

Using the delta method, the average marginal effects (AMEs) for continuous and discrete covariates are estimated, respectively, as (Papke and Wooldridge 2008):

$$\frac{\partial \mathbb{E}\left(a_i | z_i, \omega_i = 1\right)}{\partial x_j} = \vartheta_j \Phi(\vartheta z) \equiv \vartheta_j \mathbb{E}\left[\Phi(\vartheta z)\right] \equiv \breve{\vartheta}_j \left[N^{-1} \sum_{i=1}^{N} \Phi\left(\breve{\vartheta} z_i\right)\right] \quad (11)$$

$$\Phi\left(\vartheta z_{(1)}\right) - \Phi\left(\vartheta z_{(0)}\right) \equiv N^{-1} \sum_{i=1}^{N} \Phi\left(\breve{\vartheta} z_{(1)}\right) - \Phi\left(\breve{\vartheta} z_{(0)}\right) \quad (12)$$

3.4.1.2. Part II of the decision process: intensity of adoption. The second part of the TP-FRM pertains to the intensity decision. Conditional on awareness, adoption and the regressors, the (conditional) expected intensity of adoption, $\mathbb{E}\left(y_i | x_i, a_i^*, \omega_i\right)$ is estimated as a generalised linear model (GLM) with a direct nonlinear transformation of the linear index function as:

$$\mathbb{E}\left(y_i | x_i, a_i^* \in (0,1], \omega_i = 1\right) = G(\boldsymbol{\varphi x}) \quad (13)$$

where $\mathbb{E}(\cdot)$ is the expectations operator, x_i is the $1 \times K$ set of regressors, φ is the $K \times 1$ vector of parameters of interest, and $G(\cdot)$ is the standard normal CDF with a probit link and a Bernoulli specification of the quasi-maximum likelihood estimator (QMLE) whose logarithm is specified as:

$$l(\varphi; y_i; x) = arg \max_{\varphi} \sum_{i=1}^{N} \left[y_i \cdot log\left(\Phi(\boldsymbol{\varphi x})\right) + (1 - y_i) log\left(1 - \Phi(\boldsymbol{\varphi x})\right)\right] \quad (14)$$

Consequently, Equation (13) becomes a fractional probit regression. The QMLE yields consistent φs provided that Equations (10) and (13) are not misspecified (Papke and Wooldridge 1996). The conditional adoption intensity can be expressed as the product of the expectations from the TP-FRM's first and second components, following the principles of decomposition of a joint probability distribution function into marginal and conditional distributions as:

$$\mathbb{E}\left(y_i | x_i, a_i^* \in (0,1], \omega_i = 1\right) \cdot Pr\left(a_i^* \in (0,1] | z_i\right) = G(\boldsymbol{\varphi x}) \cdot \Phi(\boldsymbol{\vartheta z}) \quad (15)$$

Given Equation (13), we are interested in the marginal effects of x_i on the expected value of adoption intensity among adopters, weighted by the probability of adoption given that an orchard manager is aware of APM practices. These effects are henceforth referred to as conditional marginal effects (CMEs) and are estimated as:

$$\frac{\partial \mathbb{E}\left(y_i | x_i, a_i^* \in (0,1], \omega_i = 1\right)}{\partial x_j} \Phi(\boldsymbol{\vartheta z}) + \frac{\partial Pr\left(a_i^* \in (0,1] | z_i, \omega_i = 1\right)}{\partial x_j} G(\boldsymbol{\varphi x}) \quad (16)$$

We also harvested the unconditional marginal effects (UCMEs) as the marginal effect of x_i for the total expected value of y_i for the whole sample, assuming universal exposure, at the mean intensity:

$$\mathbb{E}\left(y_i | x_i\right) \cdot Pr\left(a_i^* \in (0,1] | z_i\right) = G(\boldsymbol{\varphi x}) \cdot \Phi(\boldsymbol{\vartheta z}) \quad (17)$$

$$\frac{\partial \mathbb{E}\left(y | x\right)}{\partial x_j} = \frac{\partial G(\varphi x)}{\partial x_j} \Phi(\vartheta z) + \frac{\partial \Phi(\vartheta z)}{\partial x_j} G(\varphi x)$$

The TP-FRM model is attractive for several reasons. First, it allows for separate treatment of adoption and intensity decisions, which permits different covariates to have dissimilar effects at the adoption and intensity stages (Ramalho and da Silva 2009). Second, the estimates obtained from the QMLE are always consistent since the conditional expectation is directly approximated based on the regressors. Third, no special transformations are required to handle high probability masses at either extremum of the unit interval. Finally, the model accounts for nonlinearities and yields better-fitted estimates when predicting response values within the [0, 1] limits of the response variable while controlling for non-constant effects of any regressor along its entire range (Papke and Wooldridge 1996).

3.5. Measurement of variables

The study considered three types of intrinsic latent variables, including attitudes, perceptions and information constraints, as well as extrinsic covariates such as institutional and social factors, orchard-specific attributes and resource endowment. Variable selection followed a *priori* expectations based on the relevant empirical literature (Despotović, Rodić, and Caracciolo 2019; Kabir et al. 2022; Midingoyi et al. 2019; Misango et al. 2022; Muriithi et al. 2021; Mwungu et al. 2020; Nyangau et al. 2022; Otieno et al. 2023; Sadique Rahman 2022; Wangithi, Muriithi, and Belmin 2021; Zeweld et al. 2017). In eastern Kenya, livestock serves as a resource base that facilitates household and farm decision-making. Therefore, we included household tropical livestock units (TLUs) as a proxy for wealth status. We also included off-farm income, defined as the amount of household income from non-agricultural streams, for the same purpose. Since APM is labour-intensive, we utilised household size as a proxy for household labour endowment. It is well known that household size and farm labour availability have a positive relationship in SSA. We controlled for plot-level attributes by including the number of trees under production per acre of orchard. The perception of fruit fly severity was measured based on orchard managers' rating of the level of damage caused by the pest in the previous season relative to normal seasons.

There is growing discontent in mango production in the study area attributable to low prices coupled with high pest management costs, which might deter APM adoption and its extent. Consequently, we assessed the attitude towards orchard prospects by examining whether a farmer intends to remain in the mango production business in 5 years or beyond, whether the enterprise is financially beneficial, and whether challenges in production are manageable. We also evaluated farmers' attitudes towards preserving biodiversity in the orchard to promote the presence of natural enemies of fruit flies based on their personal experience and feedback from other farmers, and hence their willingness to maintain or increase the biodiversity of plants in their orchards.

We also assessed orchard managers' perception of the benefits of the APM technology in terms of reducing yield loss, pest management costs and health risks, compared to the conventional application of insecticides. Similarly, we assessed the perception of the ease of learning and understanding, accessing APM inputs and implementing the APM technology. Perceived pesticide effectiveness was measured as a rating of the effectiveness of pesticides in suppressing fruit flies, quick action and the subsequent impact on the yields in comparison to APM. All latent attitudinal and perceptual constructs were measured using several items and were graded on five-point Likert scale items anchored from "1 = strongly disagree" to "5 = strongly agree" (see Table S1 of the supplementary document). To reduce dimensionality and identify uncorrelated linear factors explaining maximal variance in the latent constructs, these statements were subjected to principal component analysis (PCA). We validated the use of PCA through the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, where a score of at least greater than 0.5 is acceptable (Kaiser 1974). Our KMO scores ranged between 0.598 and 0.815. Bartlett's test for sphericity was statistically significant ($Prob > \chi^2 = 0.000$) for all analyses. We retained only the items whose factor loadings were above the threshold of 0.5 in the composition of the perceptual and attitudinal indices. In addition, only components with eigenvalues of at least unity were used in the computation of the scores.

To account for the effects of information constraints, we considered the quality of awareness and agronomic knowledge constraints. At the fundamental level, we use the term "information" to refer to awareness of the existence of an innovation, regardless of whether obtained from formal or informal sources. In this study, this corresponds to the awareness of the existence of APM technology either as a package or through its constituent practices, determined by at least a positive response to a series of questions such as: "Have you ever heard of the use of [… APM practice…] for mango fruit fly management?" It has been observed that farmers do not adopt eco-friendly fruit fly management practices as a package, but rather components that they perceive as affordable and easy to use (Muriithi et al. 2016a). We hypothesised that the quality of awareness (measured as the proportion of the APM practices an orchard manager has ever heard of, and thus somehow synonymous with the level of awareness) influences the extent of APM uptake.

The second type of information considered in this study pertains to the orchard manager's self-reported (i) ability (agronomic knowledge) to effectively implement the APM innovation (i.e. "how it works"), as well as (ii) having information on the potential economic, environmental and social benefits and/or costs associated with its adoption and intensity decisions (i.e. "what it can achieve") (Meijer et al. 2015). While the former was measured as a Likert scale item anchored at "1 = strongly disagree" to "5 = strongly agree", the later was measured as the number of correct responses with scores ranging from "0 = no correct response" to "5 = five or more correct responses". The item scores were linearly aggregated into a composite score. Farmers scoring half or more were considered knowledgeable (knowledge constraint = 0) while those scoring below half were deemed to suffer from knowledge constraints (knowledge constraint = 1).

To control for information transfer pathways, we included several variables from relevant literature, including the number of adopting neighbours (Midingoyi et al. 2019), cocreation with fellow farmers (Murage et al. 2015; Pretty et al. 2018), group membership (Alhassan, Boateng, and Danso-Abbeam 2023) and access to training on pest management (Alwang, Norton, and Larochelle 2019; Gautam et al. 2017; Kirui et al. 2023; Korir et al. 2015; Tambo et al. 2023; Wangithi, Muriithi, and Belmin 2021).

4. Results and discussion

4.1. Characteristics of the surveyed households

Table 1 presents the summary statistics of the surveyed households. To determine the mean differences between adopters and non-adopters, we utilised both two-sample *t* tests and Pearson chi-square tests. The results indicate that the orchard management role was male-dominated at 71%, conforming to the patriarchal nature of the community in the study area. A typical farmer belonged to the middle-aged category (54 years), and only 12% of the orchard managers were youths (18–35 years). Eighty percent of the interviewed orchard managers were household heads, which supported our preference for the orchard manager as the unit of analysis. The average household consisted of 5 people, which aligns with the county average of 4 (County Government of Makueni 2022).

Majority of the households (95%) owned livestock, with an average TLU of 3. This is expected given the privatised, fragmented and limited land holdings in the study area. On average, an orchard manager cultivated an approximately 50 mature trees per acre, adopters having a significantly higher density than non-adopters. The average orchard size was 1.34 acres. Thus, most of the orchard managers were smallholders. Ninety percent of the cultivars grown were grafted hybrids, which are more preferred by the pest compared to traditional

Table 1. Characteristics of APM adopters and nonadopters

		Pooled	**Adopters** (a)	**Non-adopters** (b)	**Test of statistical difference** (a − b)	
Variable	Description	Mean (SD)	Mean (SD)	Mean (SD)	Diff.	*t*-test
Continuous variables						
Age	Age of the orchard manager (years)	53.586 (14.620)	53.707 (14.649)	53.421 (14.619)	0.286	0.201
Household size	Number of household members (count)	5.134 (2.562)	5.265 (2.733)	4.956 (2.303)	0.309	1.239
Neighbours	Number of adopting neighbours (count)	8.162 (11.291)	10.129 (13.135)	5.486 (7.372)	4.620	4.308***
Tree density	Number of mature trees per acre (trees acre^{-1})	50.122 (47.929)	54.862 (54.949)	43.671 (35.398)	11.191	2.494**
Off-farm income	Annual household income from non-agricultural streams ('000 KES year^{-1})	166.220 (281.005)	192.857 (324.875)	129.975 (202.205)	62.881	2.471**
TLU	Tropical livestock units (index)	3.068 (3.188)	3.369 (3.608)	2.659 (2.458)	0.710	2.298**
Quality of awareness	Proportion of APM practices the orchard manager has ever heard of to the total practices (proportion)	0.385 (0.175)	0.403 (0.174)	0.361 (0.174)	0.042	2.494**
Biodiversity	Attitude towards orchard biodiversity (index)	−0.001 (1.374)	0.115 (1.294)	−0.156 (1.465)	0.270	1.990**
Prospects	Attitude towards orchard prospects (index)	−0.001 (1.300)	0.090 (1.291)	−0.122 (1.300)	0.212	1.682*
Perceived benefit	Perception on the benefits of APM to suppress fruit fly (index)	−0.001 (1.678)	0.382 (1.483)	−0.520 (1.790)	0.902	5.557***
Perceived ease of use	Perception on the ease of use of APM (index)	0.001 (1.550)	0.378 (1.588)	−0.500 (1.346)	0.868	6.134***
Pesticide effectiveness	Perception on the ability of synthetic pesticides to control fruit fly (index)	0.001 (1.524)	−0.020 (1.541)	0.028 (1.505)	−0.048	−0.323
Categorical variables		***Proportions*** (%)				***χ^2 test***
Gender	Orchard manager is a male (dummy: 1 = male)	70.6	73.5	66.7	6.8	2.369
Fruit fly severity	Fruit fly severity is rated as severe (dummy: 1 = severe)	56.9	55.8	58.5	−2.6	0.301
Co-creation	Participated in co-creation activities (dummy: 1 = yes)	44.7	48.6	39.3	9.3	3.651*
Group membership	A member of a farmer group (dummy: 1 = yes)	38.0	45.8	27.3	18.5	15.264***
Training on pest management	Accessed training on pest management (dummy: 1 = yes)	25.9	32.1	17.5	14.6	11.775***
Knowledge constraint	Limited agronomic expertise on the implementation of APM (dummy: 1 = yes)	39.8	8.4	82.5	−74.1	335.637***
N		432	249	183		

Note: *, **, and *** denote statistical significance at the 10, 5, and 1% levels, respectively. Values in parentheses are standard deviations. The TLU conversion factors utilised were as follows: cattle (0.70), calf (0.25), donkey (0.50), sheep (0.10), goat (0.08), pig (0.20), rabbit (0.01), and poultry (0.01) (FAO, 1993). Source: Survey Data (2023).

Table 2. Adoption of APM technology components for fruit fly management.

Category	Component	APM practice	% of adopters (n = 432)
Reactive options	Biological control and bio-derived products	Male annihilation	50.2
		Smoking herbs and dung	14.4
		Spraying botanical pesticides (concoctions)	4.2
		Spot spray of food baits	1.6
		Soil inoculation with bio-pesticides	0.5
		Spraying ash/baking powder and tobacco	0.5
		Release of ovivorous ants and parasitoid wasps*	–
Preventive options	Orchard sanitation	Feeding infested fruits to livestock	45.6
		Deep burying infested fruits	35.2
		Composting infested fruits	17.1
		Burning infested fruits	6.9
		Solarisation with special "solar" bags	3.2
		Use of an augmentorium	0.2
	Habitat management	Regular scouting and monitoring	53.5
		Proper management of alternate hosts	50.2
		Inter-tree raking	43.3
		Intercropping with non-host crops	13.4
		Early harvesting	13.0
		Trap cropping with passion fruits	2.1

*Biological pest control through natural enemies is often associated with ecological processes on larger scales than at the orchard-level. Additionally, this practice is self-spreading and is implemented at no cost to the farmer (Korir et al. 2015). Therefore, we did not consider it in this study.
Source: Survey Data (2023).

varieties. Knowledge constraints were notably prevalent among non-adopters, 83% of whom faced this challenge.

4.2. Adoption and intensity of the APM

Table 2 provides an overview of the uptake of the 18 APM practices considered in this study. Almost all respondents (98%) utilised synthetic insecticides to control fruit fly. However, only 56.7% of the farmers adopted APM. On average, a farmer was aware of 2 out of the 6 reactive APM practices, which could be the reason behind the limited uptake of the technology. Only 3 (16.7%) of the practices were adopted by more than half of the respondents. Most of the respondents (85%) confirmed access to protective gear, 83% of whom utilised them when applying pesticides. About 68% of the orchard managers reported always reading pesticide labels before use, while 41% were unaware of adulterated, banned, counterfeit or unregistered products.

The APM options are synergistic and complementary – the adoption of additional practices synergises pest suppression efforts. We observed low intensities of adoption (Figure 2), with only 0.5% of the orchard managers using more than half of the practices concurrently. While the most intensive adopter incorporated approximately 56% of the practices, the average adopter utilised only 25% of the options.

4.3. Empirical results

4.3.1. Model selection

Table 3 outlines the model diagnostics for the TP-FRM. The robust goodness-of-functional-form (GGOFF) test proposed by Ramalho, Ramalho, and Murteira (2011) and Ramalho, Ramalho, and Murteira (2014) failed to reject our probit link specification. Similarly, the robust Ramsey (1969) regression-equation-specification-error test (RESET) confirmed the absence of omitted variable bias. Since our censoring mechanism yields genuine zeros for non-adopters, no exclusion restrictions were necessary for model identification. No multicollinearity was observed in the data, as indicated by the mean variance inflation factor (VIF) test coefficient of 1.2 (against the critical value of 10). Regression models on semi-continuous variables with finite boundary observations always exhibit non-constant error variance (Papke and Wooldridge 1996). Therefore, we did not need to test for heteroskedasticity, and the QMLE inherently handles this problem. Overall, the covariates employed in this study explained the 39.4% of the variation in both adoption and intensity decisions. All analyses were performed in R and Stata version 18 StataCorp, College Station, TX.

4.3.2. Determinants of adoption of APM practices

The results of the first part of the TP-FRM governing the adoption decision are presented in Table 4 Columns 2 and 3. Our probit results suggested that, conditional on positive awareness, APM adoption was positively influenced by the orchard manager's affiliation to social groups, access to training on pest management, the density of mango trees in the orchard, perceived ease of use and the perceived benefit of APM. Other factors that influenced adoption, albeit at the 10% level of significance, included the orchard manager's gender and the number of neighbours already practicing the technology within the orchard's vicinity.

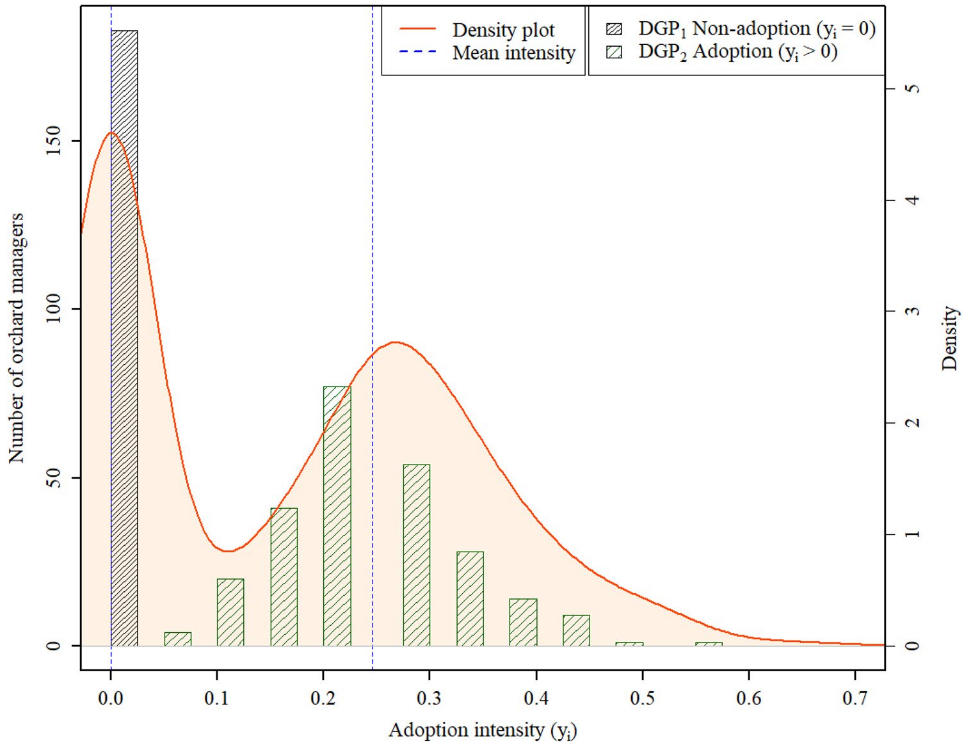

Figure 2. Intensity of adoption of agro-ecological pest management options.
Source: Survey Data (2023).

Table 3. Model diagnostics for the TP-FRM.

Test	Version	Part I: *Probit* Statistic (*p* value)	Part II: *Fractional probit* Statistic (*p* value)
Robust RESET	LM	3.964 (0.138)	4.426 (0.109)
Goodness of functional form			
	LM	4.469 (0.107)	4.252 (0.119)
	Wald	4.260 (0.119)	4.252 (0.119)
	LR	3.546 (0.170)	–
Mean VIF		1.20	
N		423	249

Note: Values in parentheses are *p* value.
LM: Lagrangian multiplier; RESET: regression equation specification error test; LR: likelihood ratio; VIF: variance inflation factor
Source: Survey Data (2023)

Affiliation with a social group increased the likelihood of APM adoption by 11.6%. Membership in groups facilitates access to inputs and product markets and enhances information transfer through social learning. Although similar conclusions have been reached by some studies (for example, Kabir et al. 2022; Midingoyi et al. 2019; Otieno et al. 2023), others such as Mwungu et al. (2020), reported a negative association between fruit fly IPM adoption and membership in agricultural groups. This unexpected finding could be associated with the reverse effects of large social groups, such as free-riding, which are not uncommon in these settings. Although group dynamics can significantly influence the efficacy of collective action by facilitating resource access and information sharing, it can also diminish individual accountability. Extension officers and other information dissemination personnel should therefore understand the specific contexts and characteristics of social groups when designing effective group-based interventions for promoting agricultural innovations like APM.

The relationship between information-seeking behaviour and adoption is well-documented as positive. Our findings align with these expectations, indicating a 11.3% increase in the likelihood of adoption among trained farmers. Extant studies on fruit fly IPM, such as Midingoyi et al. (2019), Mwungu et al. (2020), Wangithi, Muriithi, and Belmin (2021), Otieno et al. (2023) and Muriithi et al. (2024), have demonstrated similar effects. Training indirectly influences adoption by creating awareness, shaping attitudes and perceptions and reducing knowledge deficits, culminating in the observed positive effect on adoption. Therefore, access to training can enhance farmers' technical skills, increase their confidence in adopting new technologies and strengthen their social networks, thereby promoting the adoption of innovative practices such as APM.

Our findings suggest that a unit increase in the density of mature mango trees increases the probability of APM adoption by 10.7 percentage points. This implies a positive relationship between the number of producing mango trees and the uptake of

APM practices, and an inverse association between orchard size and APM adoption. These findings align with the results of Korir et al. (2015) and Mwungu et al. (2020), who reported a positive significant influence of the number of mature trees on IPM adoption. Producers with a large number of trees are more likely to be commercialised, prioritising cost-effective practices that alleviate overdependence on often-expensive synthetic pesticides. The relationship between farm size and the adoption of sustainable pest management technologies is inconclusive in the literature. Despotović, Rodić, and Caracciolo (2019) found that farm size negatively influenced the intention to adopt IPM. In contrast, Mwungu et al. (2020) and Wangithi, Muriithi, and Belmin (2021) reported a positive relationship between mango orchard area and the adoption of fruit fly IPM in Kenya. Similarly, Sadique Rahman (2022) reported a positive association between land size and IPM adoption by vegetable farmers in Bangladesh. Farmers with larger farms are usually more oriented towards commercialised production and may be less likely to adopt alternative technologies due to the perceived risks of yield loss associated with new technologies.

Perceived ease of use of APM technology was positively associated with the likelihood of its adoption. One of the barriers to technology uptake is the relative complexity of its implementation. Thus, orchard managers who perceive a technology as difficult to implement are likely to shun it. A study by Zeweld et al. (2017) arrived at similar conclusions, observing a positive effect of perceived ease of operation on the decision to adopt sustainable practices such as minimum tillage. Therefore, agricultural innovations should be user-friendly and easily implementable to encourage their uptake. Providing adequate targeted training and continuous support can further mitigate perceived complexity and encourage wider adoption of sustainable innovations.

It is well established that producers are more likely to adopt technologies when they are associated with economic benefits. Our results corroborate these expectations, demonstrating that farmers who perceived APM technology as advantageous for suppressing fruit flies, reducing management costs and mitigating health risks were more likely to adopt it. This finding aligns with the results of Kabir et al. (2022), who identified a positive association between perceived benefits and the adoption of IPM, a subset of APM. Similarly, Zeweld et al. (2017) reported a positive relationship between perceived usefulness and farmers' intention to adopt sustainable practices. Thus, providing targeted information and education about the multifaceted advantages of APM could further incentivise adoption and contribute to more sustainable agricultural practices.

Being a male orchard manager was associated with a 10.5% increase in the likelihood of adopting APM. In many patriarchal SSA communities, male privilege offers greater access to and control over household resources, such as livestock, which facilitate household and farm financial decisions. In line with these findings, Muriithi et al. (2021) reported that males were more willing to pay for fruit fly IPM. This finding is also consistent with the results of Wangithi, Muriithi, and Belmin (2021) and Otieno et al. (2023), who reported that male farmers were more likely to be continued users of fruit fly IPM. It is therefore important that socio-cultural dynamics of targeted communities be considered when promoting agricultural innovations.

The number of adopting neighbours positively influenced APM adoption. These findings corroborate the results of Midingoyi et al. (2019), who found that knowledge of more neighbours who were adopters within the farmer's vicinity increased the probability of uptake of fruit fly IPM. Similarly, Bakker et al. (2021) reported that descriptive norms associated with neighbourhood connections positively influence farmers' intentions to reduce pesticide usage and opt for sustainable alternatives. It has been observed that if the participation of nearby farmers reaches a substantial threshold, non-adopters might perceive this cue as the descriptive norm or may want to adopt it for social comparison purposes (Dessart, Barreiro-Hurlé, and Van Bavel 2019; Ejelöv et al. 2022).

4.3.3. Drivers of the intensity of APM adoption

Columns 4–7 of Table 4 summarise the results from the second part of the TP-FRM (fractional probit) for drivers of intensity of adoption. Both the CMEs and UCMEs were consistent across all covariates, except that the former predicted relatively small effects with slightly more precise standard errors. However, since we were interested in the effects of the covariates after controlling for awareness, we focus the ensuing discussion on the CMEs. The results suggested that the quality of awareness, knowledge constraints, knowledge co-creation with fellow farmers, gender, TLU, attitude towards orchard prospects and number of adopting neighbours had significant positive effects on the intensity of adoption. Group membership and off-farm income were positively associated with the extent of APM adoption, although they did not significantly impact the decision. On the other hand, perceived pesticide effectiveness, and age significantly reduced the intensity of adoption.

As hypothesised, the quality of awareness had a significant positive effect on the intensity of adoption. For every percentage increase in the quality of awareness, the extent of adoption increased by 10%. Increased exposure to APM practices offers orchard managers the flexibility to choose from a wider range of complementary practices. Thus, farmers are likely to adopt more practices as they become exposed to more technology components. Similarly, Tambo et al. (2023) reported that recipients of information from mass media campaigns were more inclined to adopt multiple non-chemical fall armyworm control strategies in Rwanda and Uganda. We also observed that orchard managers with limited expertise in APM implementation were likely to adopt the technology 4.8% less intensively than those without this constraint. This aligns with expectations since APM technology is knowledge-intensive. Despotović, Rodić, and Caracciolo (2019) and Wangithi, Muriithi, and Belmin (2021) also arrived at similar conclusions. Poor expertise increases the uncertainty associated with the intensive adoption of APM, reinforcing confidence in conventional methods. The promotion of intensive uptake of eco-friendly practices should prioritise awareness creation and the development of agronomic expertise, facilitated through targeted training and effective information dissemination.

Participation in knowledge co-creation and co-production activities with fellow farmers increased the extent of APM adoption by 3.2%. Information-sharing activities among farmers enhance the awareness and expertise necessary for the intensive adoption of the APM strategy. A similar pattern was observed by Schreinemachers et al. (2017), who noted that pesticide usage decreased when farmers consulted fellow friends or neighbours. In contrast, Murage et al. (2015) found that the rates of IPM adoption decreased when farmers received first information on the technology from an early

Table 4. Maximum likelihood estimates of the TP-FRM for the adoption and intensity decisions.

Variables	Part I: *Adoption* (Probit)		Part II: *Intensity of adoption* (Fractional probit)			
	AME	Robust Std. Err.	CME	Robust Std. Err.	UCME	Robust Std. Err.
Demographic factors						
Age (years)	0.000	0.002	−0.001**	0.000	−0.001**	0.000
Gender (1 = male)	0.085*	0.047	0.029***	0.011	0.027***	0.010
Resource endowment						
Household size (count)	0.006	0.009	−0.001	0.002	−0.001	0.001
Off-farm income (KES year^{-1})†	−0.003	0.006	0.002*	0.011	0.002*	0.010
TLU (index)†	0.023	0.026	0.014**	0.006	0.013**	0.005
Attitudes						
Biodiversity (index)			0.006	0.004	0.006	0.004
Prospects (index)	−0.026	0.016	0.008**	0.003	0.008**	0.003
Perceptions						
Perceived benefit (index)	0.037**	0.015	−0.005	0.004	−0.005	0.004
Perceived ease of use (index)	0.049***	0.015	0.004	0.004	0.004	0.004
Pesticide effectiveness (index)	−0.001	0.016	−0.010***	0.003	−0.009***	0.003
Orchard-specific factors						
Fruit fly severity (1 = severe)	−0.048	0.046	−0.013	0.010	−0.012	0.009
Log(Tree density (tree acre^{-1}))	0.107***	0.031	0.003	0.006	0.002	0.006
Institutional and social factors						
Neighbours (count)	0.006*	0.003	0.001***	0.000	0.001***	0.000
Co-creation (1 = yes)	0.070	0.046	0.032***	0.010	0.030***	0.009
Group membership (1 = yes)	0.116**	0.048	0.020*	0.011	0.018*	0.010
Training on pest management (1 = yes)	0.113**	0.055	0.009	0.011	0.008	0.011
Information constraints						
Quality of awareness (proportion)	0.085	0.138	0.100***	0.028	0.089***	0.026
Knowledge constraint (1 = yes)			−0.048***	0.018	−0.045***	0.016
Constant	−1.942***	0.663	−1.000***	0.120		
Goodness of fit statistics						
Log pseudo-likelihood	−244.169		−94.189	–	–	–
Deviance	488.338		7.197	–	–	–
Pearson	422.902		7.095	–	–	–
R^2 type measure	0.189		0.304	–	–	–
Overall R^2 type measure	0.394			–	–	–
AIC	1.235		0.909	–	–	–
BIC	−1966.895		−1261.817	–	–	–
N	423		249		432	

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
AME: average marginal effect; AIC: Akaike information criterion; BIC: Bayesian information criterion; CME: conditional marginal effect; UCME: unconditional marginal effect
†This variable was transformed using an inverse hyperbolic sine to reduce positive skewness and mitigate potential heteroskedasticity while avoiding the loss of observations with zero values.
Source: Survey Data (2023).

adopter. However, their finding was relative to when farmers received information from extension officers, who are expected to have more comprehensive and reliable information than early adopters. To adapt to changing agro-ecosystems due to climate change, it is essential to foster farmer-to-farmer connections supported by strong social capital. This approach leads to cumulative and synergistic benefits from social learning and boosts the confidence to innovate (Pretty et al. 2018).

Being a male orchard manager was associated with a 2.9% increase in APM adoption intensity, suggesting that females are less likely to adopt the technology intensively as males. This disparity could be attributed to potential challenges faced by female orchard managers, such as heavier household workloads and limited access to essential services such as extension and credit, which may result in time, information and liquidity constraints. In most patriarchal SSA communities, male privilege offers greater access to and control over jointly-owned household resources, such as livestock and income emanating from production activities (Gichungi et al. 2021; Muriithi et al. 2024), facilitating household and farm financial decisions. In line with these findings, Muriithi et al. (2021) reported that males were more willing to pay for fruit fly IPM. This observation is also consistent with the results of Wangithi, Muriithi, and Belmin (2021) and Otieno et al. (2023), who found that male farmers were more likely to be continued users of the fruit fly IPM. Moreover, Murage et al. (2015) established a positive correlation between gender and the intensity of adoption of climate-smart push-pull technology in Kenya, while Misango et al. (2022) revealed that males committed more land to push-pull technology in Rwanda.

Households with higher livestock numbers, measured in TLUs, were positively associated with intensive APM adoption. A study by Anang, Amesimeku, and Fearon (2021) also revealed that the intensity of crop protection adoption and soil fertility management practices increased with herd size among soybean farmers in Ghana. Similarly, Misango et al. (2022) reported a positive relationship between TLU and the intensity of use of push–pull technology in Rwanda. The transition to APM requires financial investment, and among most smallholder households in SSA, livestock provide a resource base that can be utilised to offset household liquidity constraints, providing financial access to the technology. This result is also in agreement with the observed positive association between the extent of APM adoption and the amount of income the household accessed from non-farm streams.

Our findings also revealed a positive association between the attitude towards orchard prospects and the intensity of adoption, suggesting that orchard managers who were more likely to quit mango production were likely to adopt fewer APM components. Uncertainties regarding farm prospects may lead to reduced adoption levels, particularly when the technology offers more relative advantages in the long run, as is the case for APM technology. This implies that confidence in the future of the mango production business could lead to long-term commitment and a positive outlook on orchard prospects, which in turn can promote the uptake of eco-friendly practices.

The extent of APM adoption increased with a higher number of adopting neighbours. Neighbourhood effects can alleviate common barriers to the intensive adoption of eco-friendly practices, such as poor awareness and expertise and inadequate resources, by harnessing social capital. Moreover, within-group social dynamics such as peer effects and reputation can also improve the rate of uptake of innovations such as APM. Neighbouring farms exert peer pressure among farmers due to the perceived need for social comparison within the locality. It has been observed that if the participation of nearby farmers reaches a substantial threshold, non-adopters might perceive this cue as the descriptive norm or may want to adopt it for social comparison purposes (Despotović, Rodić, and Caracciolo 2019; Dessart, Barreiro-Hurlé, and Van Bavel 2019; Ejelöv et al. 2022). Intensive adoption by reputable neighbouring farms may also serve as a cue that encourages others to adopt it more intensively. A similar effect is observed with affiliation with groups, although the association is insignificant at the 5% level. Membership in a group can alleviate common barriers to intensive adoption of eco-friendly practices, such as poor awareness and expertise and inadequate resources, by harnessing social capital. Similar findings have been reported by Misango et al. (2022) and Alhassan, Boateng, and Danso-Abbeam (2023).

Perception of the effectiveness of inorganic pesticides in suppressing fruit flies was inversely related with the intensity of APM adoption. These findings are consistent with the results of Schreinemachers et al. (2017), who reported that farmers who believed in the effectiveness and indispensability of synthetic pesticides increased their use despite being aware of their health impacts. Orchard managers who perceive synthetic pesticides as effective at suppressing fruit flies are likely to adopt APM technology less intensively due to greater reliance on synthetic pesticides, diminishing the finite resources that can be allocated to APM. This preference for synthetic insecticides presents a form of technological lock-in, where the perceived immediate benefits of inorganic pesticide use overshadow the long-term advantages of adopting more sustainable practices such as APM.

Older farmers were inclined to adopt fewer APM practices than their younger counterparts. This finding aligns with those of Kabir and Rainis (2015), who observed that older farmers in Bangladesh adopted IPM vegetable farming less intensively than younger farmers. Similarly, Nyangau et al. (2022) reported a lower willingness to pay for bio-pesticides among older farmers in Uganda, while Kabir et al. (2022) noted that older producers had a lower willingness to adopt botanical pesticides. The labour-intensive nature of APM makes younger, more energetic farmers more likely to adopt it intensively. Moreover, older farmers may be more attached to traditional practices and may be reluctant to deviate from methods that have worked for them in the past. This generational gap in the intensive continued use of APM practices confirms the need for targeted interventions that address the specific needs and constraints of farmers of various age categories.

5. Conclusions and policy implications

Mango production and marketing in Kenya are impeded by *B. dorsalis* invasion, which has led farmers to heavily depend on synthetic pesticides. Since the trade-offs between pesticide usage and socio-environmental risks are inextricable, eco-friendly control methods such as APM have been encouraged. This study assessed the drivers of the transition towards the APM for mango fruit fly suppression among smallholders. The results suggest a high dependence on synthetic pesticides (98%) and moderate APM adoption rates (56.7%), with the average adopter utilising only 25% of the practices concurrently. This limited uptake can be attributed to the high agronomic knowledge constraints in the implementation of APM technology, particularly prevalent among non-adopters (83%). The findings from the two-part fractional regression model indicate that both the decisions to adopt and the extent of adoption of APM were primarily motivated by socio-psychological attributes of the decision maker. While orchard managers' perceptions of technology attributes and institutional and social factors primarily influenced both the adoption decision and intensity decisions, information constraints, resource endowment, gender and inter-generational factors significantly affected only the intensity decision.

We recommend that policymakers consider incentives that appeal to farmers' intrinsic motivations when designing agro-ecological policies and interventions. Awareness campaigns, farmer training and opportunities for co-creation of knowledge should be increased, with a specific focus on gender-disaggregated participatory group approaches such as farmer field schools, participatory field trials and co-design workshops. Both training and knowledge co-creation activities should aim to increase awareness of the relative advantages of APM technology by providing a non-complex understanding of its principles and hands-on implementation through "observation- and discovery-based" learning. Additive and synergistic effects between various practices should be emphasised at the outset of such interventions. Older orchard managers and women should be considered the primary beneficiaries of these activities. Training programmes and extension services tailored to older farmers could potentially mitigate their reluctance and promote wider adoption of sustainable pest management strategies. Inclusive and targeted interventions for addressing gender-based disparities and promoting equitable access to agricultural innovations are required to encourage their uptake. Support mechanisms such as the provision of subsidised inputs that address the resource constraints associated with the intensive adoption of sustainable practices are required to encourage their intensive uptake.

Interventions should capitalise on building local social networks, promoting interpersonal knowledge transfer, strengthening social capital and harnessing farmers' innovative capacities. Enhancing knowledge exchange activities among farmers while ensuring access to expert advice should be prioritised to ensure effective uptake of agricultural innovations. Leveraging social learning and fostering community-based approaches could enhance the widespread adoption of sustainable pest management practices.

This study is not without limitations. First, despite the numerous benefits of employing the TP-FRM, the framework is unable to measure the distinct, and occasionally contradictory, effects that each explanatory variable exerts on the two consecutive adoption decisions undertaken by farmers. This limitation arises due to the framework's inherent structure, which does not accommodate the simultaneous analysis of multiple influences with potentially opposing impacts. Second, we utilised cross-sectional data, which precluded the application of dynamic selection-on-observable estimators and limited our ability to capture the temporal dynamics of key drivers of sustainable technology uptake that evolve over time. Future longitudinal studies could address this by considering the dynamic effects of time-variant adopter attributes, such as behavioural factors, along the transition pathway.

Notes

1. This is a situation in which extensive use of pesticides results in pest resistance, compelling farmers to apply larger quantities and often more toxic pesticides to manage pest populations.
2. Throughout this article, we use the phrase "information constraint" to broadly refer to the lack of exposure to a technology (i.e. non-exposure biases (see Diagne and Demont 2007) and knowledge deficit problems (see Khan et al. 2021)), poor awareness and/or knowledge constraints in its implementation. We observed that farmers, particularly those in social groups, adopted some components of APM, particularly the male annihilation technique, for various reasons, including peer pressure or the fear of being perceived as "lagging behind" even if they did not fully understand how the APM technology works or how to properly implement it. Information constraints have been cited as a significant demotivating factor in the sustained use of sustainable fruit fly management practices (Muriithi et al. 2024), also ultimately leading to their dis-adoption (Wangithi, Muriithi, and Belmin 2021).
3. Although the effectiveness of the APM strategy heavily relies on the integrated use of multiple complementary and synergistic practices, we observed that, at the outset, farmers often adopted at least one primary (reactive) component of the technology before gradually incorporating additional preventive measures. In the few instances where farmers utilised synergistic options without including a reactive component, they indicated that their primary focus was not on fruit fly management but rather on other aspects of orchard management.
4. This phenomenon suggests that DMUs may fail to adopt an innovation due to information constraints, even though they are likely to adopt it if they are informed. Therefore, failing to account for this aspect potentially results in the underestimation of the population adoption rate.

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Data availability statement

The data utilised in this study are available from the corresponding author upon reasonable request.

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