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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 affected 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, particularly through social networks and gender-disaggregated participatory group approaches.

Keywords: 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 et al., 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 et al., 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

[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.

prophylactic control options for 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 et al., 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 intraspecific competitors (Mutamiswa et al., 2021). *B. dorsalis* has been reported to reduce yields by between 30 and 90% (Vayssières et al., 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., 2024; 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 et al., 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 & 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 & Norton, 2019; Rahman, 2022; Wangithi et al., 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 et al., 2019; Khan et al., 2021; Punzano et al., 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 the current 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 & 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 may be 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 paper is organised as follows: In Section 3, we discuss the research

[2] Throughout this paper, 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 et al., 2021).

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 8,176.7 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 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.

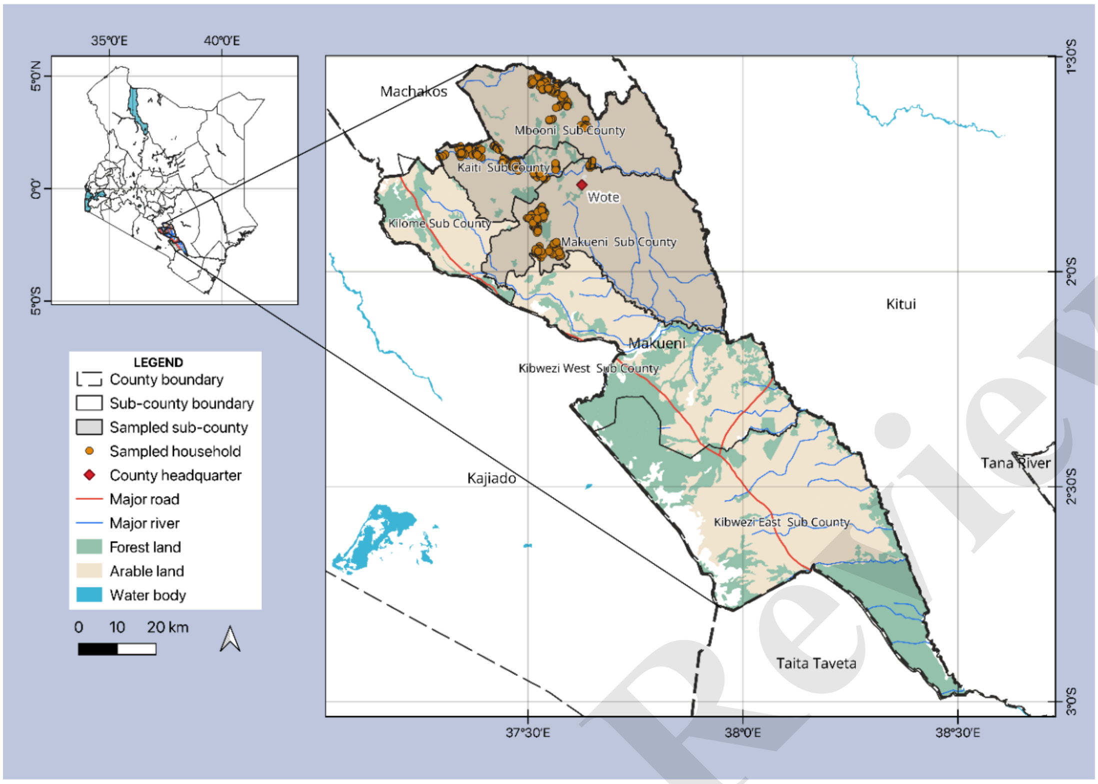

Figure 1: Map of the study sites in Makueni County, Kenya

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

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

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, 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 2 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 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, which 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 et al., 1944). Risks in pest management are associated with yield loss and management costs due to pest damage, as well as health and market uncertainties. Due to loss aversion, the uncertainty associated with innovations such as APM makes them less appealing to smallholder farmers than conventional alternatives (Alwang et al., 2019). Shifting to APM can be risky, particularly when there are limited or no insurance safety nets in place, as is often the case in SSA. Choices under such scenarios involve varying degrees of risk and are often linked to multifaceted outcomes. Consequently, decisions to adopt innovations are primarily based on expectations (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 $C = \{c_{i1}, c_{i2}, \cdots, c_{IN}\}$ and let the set of all available alternatives be represented by another set $A = \{a_{\text{APM}}, a_{\text{conventional}}, \cdots, a_{IN}\}$. Then, adoption is associated with a probability distribution of consequences such that:

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

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

where p_i and q_i represent the probabilities of obtaining result c_i when APM or other alternative methods are adopted, respectively. The von Neumann–Morgenstern utility function $u(\cdot)$ is defined as $u{:}C \longrightarrow \mathbb{R}$ such that:

$$\mathbb{E}[U(a)] = \sum_{c \in C} a(c)\, u(c) \quad \forall a_{\text{APM}}, a_{\text{conventional}}, \cdots \in A \tag{3}$$

$$\mathbb{E}[U(a_{\text{APM}})] = \sum_{c \in C} p_i\, u(c_i) \text{ and } \mathbb{E}[U(a_{\text{conventional}})] = \sum_{c \in C} q_i\, u(c_i)$$

The expected utility function $\mathbb{E}[U(\cdot)]$ takes the form $\mathbb{E}[U]{:}a \longrightarrow \mathbb{R}$, 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:

$$a_{\text{APM}} \succ a_{\text{conventional}} \Leftrightarrow \mathbb{E}[U(a_{\text{APM}})] - \mathbb{E}[U(a_{\text{conventional}})] > 0 \tag{4}$$

Since the adoption decision is dichotomous, modelling is typically performed using discrete choice models such as a probit or logit.

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 et al. (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. 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 & Demont, 2007) and the 'knowledge

[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.

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 fractional response model (TP-FRM) developed by Ramalho and 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:

$$(a_i|\boldsymbol{z}_i,\omega_i = 1) = \begin{cases} 1, & \text{if} \quad a_i^* \in (0,1], \\ 0, & \text{otherwise if} \quad a_i^* = 0, \end{cases} \tag{5}$$

where a_i^* is the latent adoption, ω_i is a binary variable indicating APM awareness (1 = aware), and $\boldsymbol{z}_i$ 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:

$$Pr(a_i = 1|\boldsymbol{z}_i,\omega_i = 1) = Pr(a_i^* \in (0,1]|\boldsymbol{z}_i,\omega_i = 1) = \Phi(\boldsymbol{\vartheta}\boldsymbol{z}_i) \tag{6}$$

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

Using the delta method, the average marginal effects (AMEs) for continuous and

[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.

discrete covariates are estimated, respectively, as (Papke & Wooldridge, 2008):

$$\frac{\partial \mathbb{E}(a_i|\boldsymbol{z},\omega_i=1)}{\partial x_j} = \boldsymbol{\vartheta}_j\Phi(\boldsymbol{\vartheta z}) \equiv \boldsymbol{\vartheta}_j\mathbb{E}[\Phi(\boldsymbol{\vartheta z})] \equiv \hat{\vartheta}_j\left[N^{-1}\sum_{i=1}^{N}\Phi\big(\hat{\boldsymbol{\vartheta}}z_i\big)\right] \tag{7}$$

$$\Phi\big(\boldsymbol{\vartheta}z_{(1)}\big)-\Phi\big(\boldsymbol{\vartheta}z_{(0)}\big) \equiv N^{-1}\sum_{i=1}^{N}\Phi\big(\hat{\boldsymbol{\vartheta}}z_{(1)}\big)-\Phi\big(\hat{\boldsymbol{\vartheta}}z_{(0)}\big) \tag{8}$$

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, $\mathbb{E}(y_i|\boldsymbol{x}_i, a_i^*,\omega_i)$ is estimated as a generalised linear model (GLM) with a direct nonlinear transformation of the linear index function as:

$$\mathbb{E}(y_i|\boldsymbol{x}_i, a_i^* \in (0,1],\omega_i = 1) = \mathrm{G}(\boldsymbol{\varphi x}) \tag{9}$$

where $\mathbb{E}(\cdot)$ is the expectations operator, $\boldsymbol{x}_i$ is the $1 \times K$ set of regressors, $\boldsymbol{\varphi}$ is the $K \times 1$ vector of parameters of interest, and $\mathrm{G}(\cdot)$ 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:

$$\ell(\boldsymbol{\varphi};y_i;\boldsymbol{x}) = \underset{\boldsymbol{\varphi}}{\operatorname{argmax}}\sum_{i=1}^{N}[y_i\cdot\log(\Phi(\boldsymbol{\varphi x})) + (1-y_i)\log(1-\Phi(\boldsymbol{\varphi x}))] \tag{10}$$

The QMLE yields consistent $\boldsymbol{\varphi}$s provided that Eqs. (6) and (9) are not misspecified (Papke & 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:

$$\mathbb{E}(y_i|\boldsymbol{x}_i,a_i^* \in (0,1],\omega_i = 1\,)\cdot Pr(a_i^* \in (0,1]|\boldsymbol{z}_i) = G(\boldsymbol{\varphi x})\cdot\Phi(\boldsymbol{\vartheta z}) \tag{11}$$

Given Eq. (9), we are interested in the marginal effects of $\boldsymbol{x}_i$ 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:

$$\frac{\partial \mathbb{E}(y_i|\boldsymbol{x}_i, a_i^* \in (0,1], \omega_i = 1)}{\partial \boldsymbol{x}_j} \Phi(\boldsymbol{\vartheta z}) + \frac{\partial Pr(a_i^* \in (0,1]|\boldsymbol{z}_i, \omega_i = 1)}{\partial \boldsymbol{x}_j} G(\boldsymbol{\varphi x}) \quad (12)$$

We also harvested the unconditional marginal effects (UCMEs) obtained as the marginal effect of $\boldsymbol{x}_i$ for the total expected value of y_i for the whole sample at the mean intensity:

$$\mathbb{E}(y_i|\boldsymbol{x}_i) \cdot Pr(a_i^* \in (0,1]|\boldsymbol{z}_i) = G(\boldsymbol{\varphi x}) \cdot \Phi(\boldsymbol{\vartheta z}) \quad (13)$$

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

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 Silva, 2009). Second, the estimates obtained from the QMLE are always consistent since the conditional expectation is directly approximated based on the regressors (Papke & Wooldridge, 1996). 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 & 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 et al., 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; Rahman, 2022; Wangithi et al., 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 five 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”. 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 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 et al., 2023), and access to training on pest management (Alwang et al., 2019; Gautam et al., 2017; Kirui et al., 2023; Korir et al., 2015; Tambo et al., 2023; Wangithi et al., 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).

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

Table 1: Characteristics of APM adopters and nonadopters

Variable	**Description**	**Pooled**	**Adopters** (a)	**Non-adopters** (b)	**Test of statistical difference** (a – b)	
		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).

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.

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 the current study. Source: Survey Data (2023).

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.

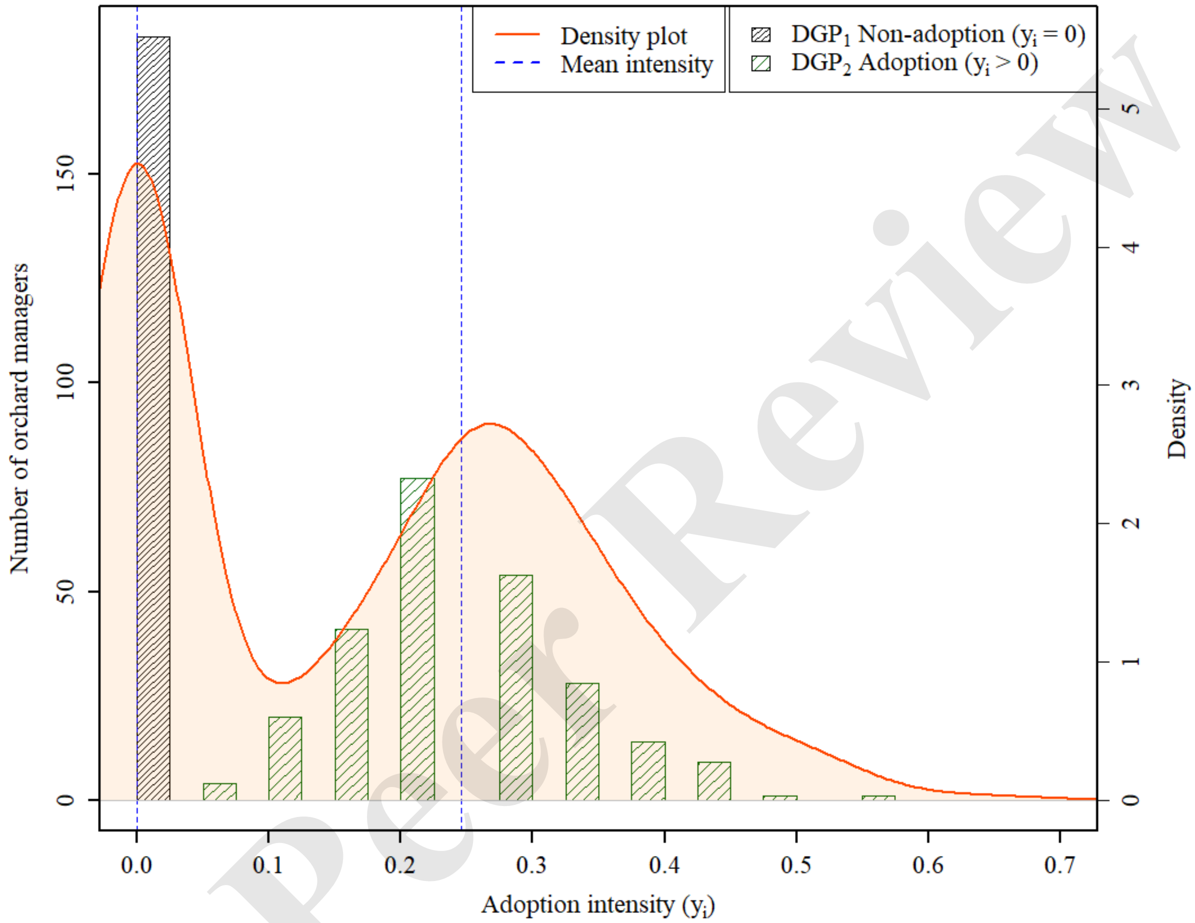

Figure 2: Intensity of adoption of agro-ecological pest management options

Source: Survey data (2023).

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 et al. (2011) and Ramalho et al. (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 & 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.

Table 3: Model diagnostics for the TP-FRM

Test	**Version**	**Part I**: *Probit*	**Part II**: *Fractional probit*
		Statistic (*p* value)	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* values. Abbreviations: LM, Lagrangian multiplier; RESET, regression equation specification error test; LR, likelihood ratio; VIF, variance inflation factor. Source: Survey Data (2023)

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.

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			

Note: *, **, and *** denote statistical significance at the 10, 5, and 1% levels, respectively. Abbreviations: 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).

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 those Midingoyi et al. (2019), Mwungu et al. (2020), Wangithi et al. (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 significant and positive 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 oftenexpensive synthetic pesticides. The relationship between farm size and the adoption of sustainable pest management technologies is inconclusive in the literature. Despotović et al. (2019) found that farm size negatively influenced the intention to adopt IPM. In contrast, Mwungu et al. (2020) and Wangithi et al. (2021) reported a positive relationship between mango orchard area and the adoption of fruit fly IPM in Kenya. Similarly, 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 et al. (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 et al., 2019; Ejelöv et al., 2022).

4.3.3 Drivers of the intensity of APM adoption

Columns 4 to 7 of Table 4 summarise the results from the second part of the TP-FRM 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, tropical livestock unit, 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 et al. (2019) and Wangithi et al. (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 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 et al. (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 et al. (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 toward 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 et al., 2019; Dessart et al., 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 et al. (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 programs 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.

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Disclosure statement

The authors declare no conflicts of interest.

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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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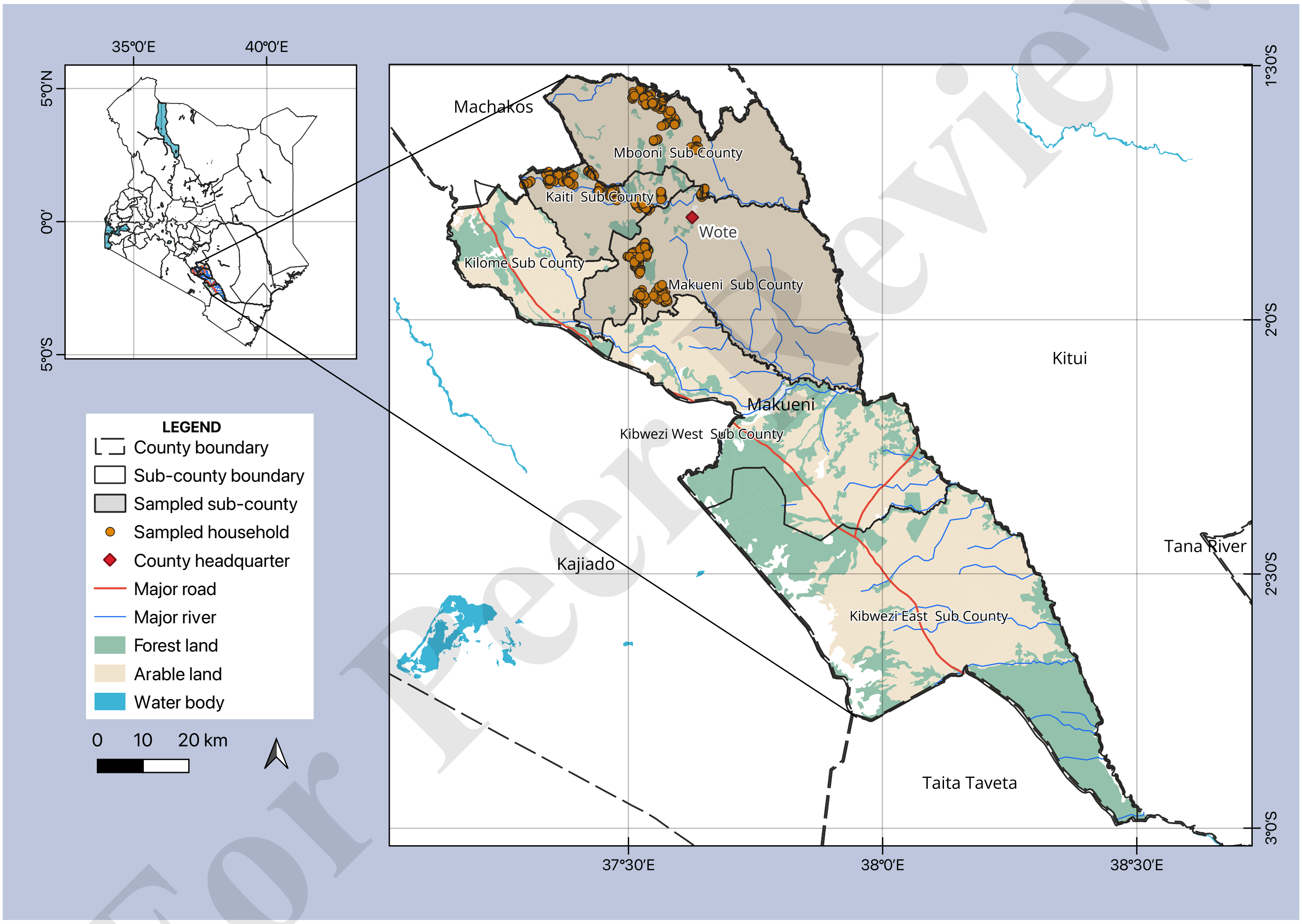
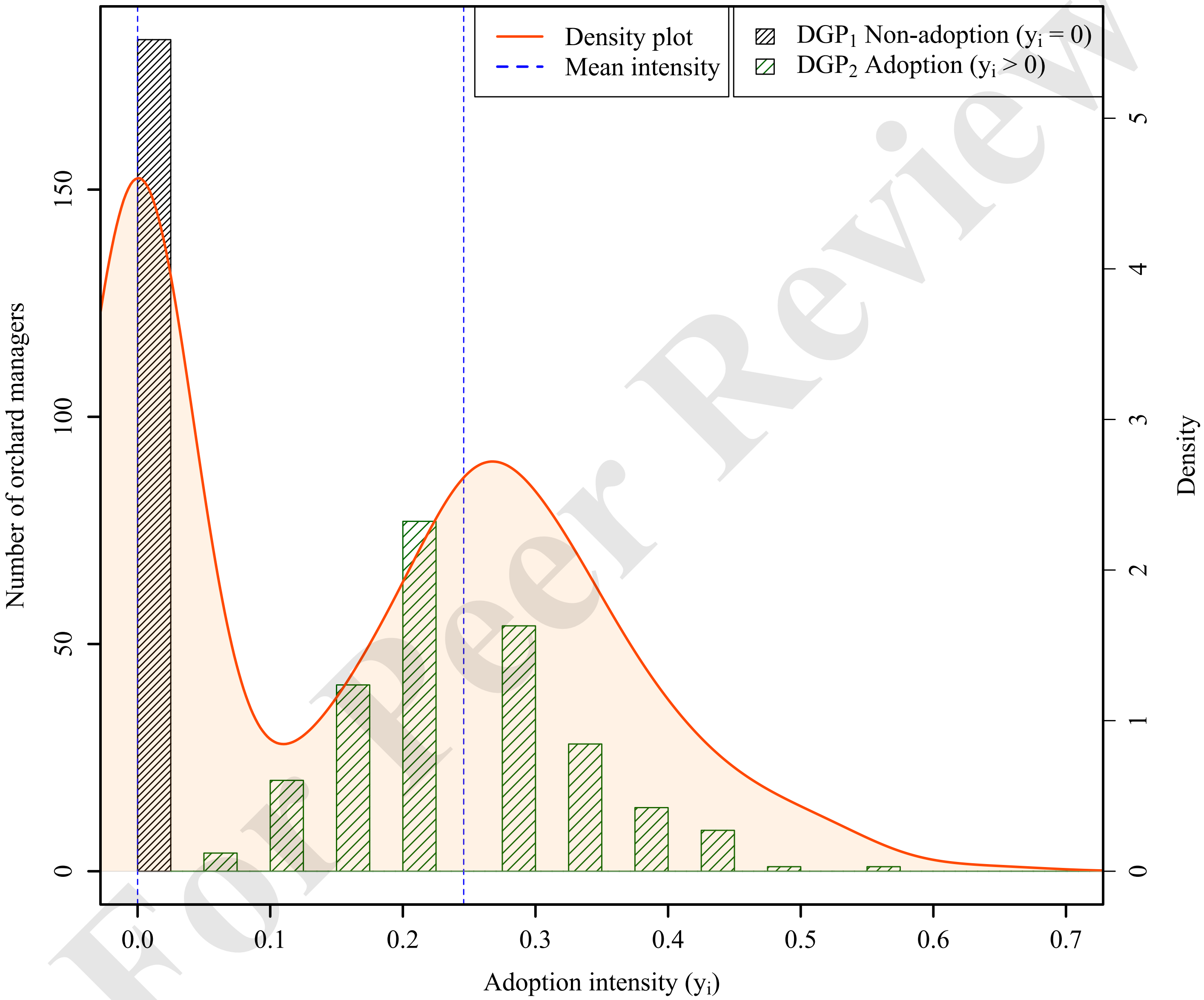

35°0'E
40°0'E
5°0'N
0°0'
5°0'S
LEGEND
County boundary
Sub-county boundary
Sampled sub-county
Sampled household
County headquarter
Major road
Major river
Forest land
Arable land
Water body
0 10 20 km
Machakos
Mbooni Sub County
Kaiti Sub County
Wote
Kilome Sub County
Makueni Sub County
Kitui
Makueni
Kibwezi West Sub County
Kajiado
Tana River
Kibwezi East Sub County
Taita Taveta
1°30'S
2°0'S
2°30'S
3°0'S
37°30'E
38°0'E
38°30'E


Density plot
Mean intensity
DGP1 Non-adoption (yi = 0)
DGP2 Adoption (yi > 0)
Number of orchard managers
0
50
100
150
Density
0
1
2
3
4
5
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Adoption intensity (yi)

Response to reviewer's comments

Journal name: International Journal of Pest Management

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

Manuscript ID: TTPM-2024-0100

Dear Editor,

We are very grateful to the editor and reviewers for their insightful comments and suggestions, which we have incorporated in the revised manuscript. The specific revisions are highlighted in green colour within the manuscript and summarised in the tables below.

Table 1: Comments and suggestions from Reviewer 1

Comment/suggestion	Authors' response
Section of paper: Overall	
The study novelty and knowledge gap are not clear.	We have added a section on 'past related studies' on page 5 to page 8, line 101 to line 173 that identifies the knowledge gaps that our study contributes to fill.
Section of paper: Conclusions and policy implications	
The part of recommendation policy is so local. Authors should mention international suggestions.	We appreciate this observation. The policy recommendations have been revised to make them more generalisable and global.
Also, they should mention research limitations.	We have revised the paragraph on page 34 and 35, line 709 to line 718 that outlines the limitations of the study, and now reads: '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.'

Table 2: Comments and suggestions from Reviewer 2

Comment/suggestion	Authors' response
Section of paper: Methodology	
1. Sample description: need a more detailed description of the sample, including the year of the survey, the sample size, the effective response rate, etc.	We have revised the 'Sampling technique and data collection' subsection to accommodate these aspects. The following statements have been added to provide more details on page 10 and 11, line 212 to line 216, and line 217 to line 221: '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, 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.' 'We encountered 2 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 conditioning all analyses on positive awareness as discussed in Section 3.4.1. Data were collected between August and September 2023…' Since the survey involved face-to-face interviews, the effective response rate was 100%. We have, however, omitted this information from the text since it is directly implied.
2. Variables chosen: First, why do authors choose the six reactive APM practices as in line 186? Table 2 presents 19 APM practices. What makes the authors drop 13 of them and choose the six?	A paragraph has been added to clarify this on page 12 and 13, line 265 to line 272. 'This study defined reactive APM options as practices that could be applied as stand-alone 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…' We also provide two reasons why we believe our classification strategy is best suited for APM on page 13, line 272 to line 280. First, that a good classification should account for the technology's holism and, therefore, cannot be restricted to a single practice. Second, that APM, unlike IPM, advocates for the utilisation of

	indigenous and locally-available inputs; therefore, farmers using such practices are considered adopters: ‘Although previous studies on adoption of fruit fly IPM, including Otieno et al. (2023) and Wangithi et al. (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. 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.’
Second, lines 376 and 383 suggest that more trees increase the adoption of APM and larger size decreases the adoption of APM. In this case, the density of trees should be considered as a dependent variable in the regression.	We have created and included ‘tree density’ as a covariate in our analyses. However, due to positive skewness, the variable has been log-transformed. See Table 1 and 4. Consequently, we have dropped two variables, namely ‘number of mature trees’ and ‘orchard size,’ as both are implicitly embedded in the new variable—the former being positively related to the regressand, and the latter having an inverse relation.
Third, as APM is a skill- and labor-intensive technology, farmers’ household income might be a determinant of their APM adoption practices. Although this study includes the proportion of off-farm income as one dependent variable, it does not fully represent farmers’ financial capability in adopting APM technologies.	Our analysis includes a variable for household size as a proxy for farm labour (see description on page 17 line 357 to line 360). We also included ‘knowledge constraint’ to capture the technical agronomic ‘skill gap’ in the implementation of APM (see page 18 line 402 to line 412). Unfortunately, our data was collected at a time when the country was planning to implement agricultural tax reforms, resulting in most farmers being reluctant to reveal their household income from agricultural streams. Therefore, we relied on off-farm income as a proxy for household income. We have replaced the variable ‘access to off-farm income’ with ‘quantity of income from non-agricultural sources’ (see Table 1 and Table 4). Additionally, we have included tropical livestock units for the same purpose, as most households in the study area often rely on livestock to offset financial constraints (see page 16 and 17, line 354 to line 356).
Last, this study includes the “knowledge constraint” in analyses. However, the definition of knowledge constraint is not clear enough. Does it represent	We use ‘knowledge constraint’ to refer to mango farmers’ insufficient agronomic skill set to properly implement APM. Following Meijer et al. (2015), we included another question to encompass ‘what it [the practice(s)] can achieve.’ We have added

the experience of farmers in mango production or mango farmers' knowledge of pest management? If the latter, how does the study quantify it?	the following statements to describe the variable and how it was measured on page 18 line 402 to line 412: '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).'
What is the difference between "knowledge constraint" and "quality of awareness"?	We defined the 'quality of awareness' on page 18, line 399 to line 401 as: '…the proportion of the APM practices an orchard manager has ever heard of, and thus somehow synonymous with the level of awareness …' Thus, while 'knowledge constraint' measures the farmers' agronomic knowledge of implementing APM, 'quality of awareness' measures the extent of awareness in terms of the number of APM components the farmer has been exposed to, regardless of whether or not they have the knowledge of their implementation. The two variables had a weak pairwise correlation of -0.067 (well below the critical threshold of 0.30) and were free from multicollinearity, as indicated by their VIF values of 1.22 and 1.13, respectively, against the critical value of 10. These results validate their independence in our models.
Besides, are "training" and "knowledge constraint" correlated, as training would increase farmers' knowledge?	We conducted a series of correlation tests to examine the relationships between all the regressors used in our models. Findings from the pairwise correlation tests indicate that most regressors exhibit weak correlations, remaining well within the acceptable threshold of below 30%. The correlation between 'training on pest management' and 'knowledge constraints' is weak at -17.4%, suggesting no significant collinearity problems between these variables. Additionally, there was no multicollinearity observed among our regressors. We have included the following statement in the manuscript on page 22, line 467 to line 469 for clarity:

	'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).' Thus, while training in pest management might contribute to enhancing agronomic knowledge of the implementation of eco-friendly pest management practices, the relationship is not strong enough to invalidate their independence within our analytical framework.
Section of paper: Results and discussion	
3. Results explanation: In Table 4, line 25 indicates that higher perceived ease of use increases the adoption of APM but decreases the intensity of adoption. How does this happen?	We acknowledge that our initial computation of the latent constructs, based on the linear aggregation of respondents' scores on perceptual and attitudinal constructs followed by a binary categorisation as either positive or negative, was biased as it did not account for the variance of the latent variables explained by each observed item. To address this, we subjected the observed items to a Principal Component Analysis (PCA). A detailed explanation is provided on page 18, line 381 to line 389 which reads: '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 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.' Interestingly, re-analysis based on these component scores from PCA reveals that perceived ease of use significantly increases the probability of adoption but does not significantly increase the intensity of adoption, although it is positively related. See results in Table 4. Consequently, we have omitted the previous discussion on this due to the lack of statistical significance.
Line 26 in Table 4 indicates the same problem. Why do farmers adopt APM when they believe that chemical pesticides could effectively suppress fruit flies? I can understand that a higher	Similar to 'perceived ease of use' re-analysis based on PCA-subjected items revealed a negative albeit insignificant association between adoption and 'perceived pesticide effectiveness.' See results in Table 4. Consequently, we have omitted the previous discussion on this topic due to the lack of statistical significance.

perception of pesticide effectiveness decreases the intensity of APM adoption.	
Section of paper: References	
4. Reference: The reference lists of this study do not include enough literature on the mango industry, which questions the contributions of this study.	We have expanded our literature review to include more recent relevant publications on mango: 1. M. Kibira, H Affognon, B Njehia, B. Muriithi, S Mohamed, and S. Ekesi, "Economic evaluation of integrated management of fruit fly in mango production in Embu county, Kenya," African Journal of Agricultural and Resource Economics, vol. 10, pp. 343–353, 4 2015. [Online]. Available: https://www.researchgate.net/publication/285577702. 2. B. W. Muriithi, G. M. Diiro, H. Affognon, and S. Ekesi, "Economic impact of integrated pest management strategies for the suppression of mango-infesting fruit fly species in Africa," in Springer International Publishing, Jan. 2016, pp. 755–770, isbn:9783319432267. doi: 10.1007/978-3-319-43226-7_33. 3. B. W. Muriithi et al., "Impact assessment of integrated pest management (ipm) strategy for suppression of mango-infesting fruit flies in Kenya," Crop Protection, vol. 81, pp. 20–29, Mar. 2016, issn: 02612194. doi:10.1016/j.cropro.2015.11.014. 4. P. N. Nyang'au, B. W. Muriithi, J. M. Nzuma, P. Irungu, H. M. Gichungi, and G. Diiro, "Impact of integrated fruit fly management strategy on food security among smallholder mango farmers in Kenya," African Journal of Food, Agriculture, Nutrition and Development, vol. 20, pp. 15 431–15 454, 2 2020, issn: 16845374. doi:10.18697/AJFAND.90.18455. 5. H. Gichungi, B. Muriithi, P. Irungu, G. Diiro, and J. Busienei, "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," European Journal of Development Research, vol. 33, pp. 407–426, 3 Jun. 2021, issn: 17439728. doi:10.1057/s41287-020-00282-z. 6. K. Onyango, P. Bolo, A. Ndiwa, R. Wanyama, and C. G. K. Chege, A rapid agroecological mango value chain analysis in Kenya Makueni agroecological living landscape (all), Dec. 2023. [Online]. Available: https://www.cgiar.org/initiative/agroecology/. 7. K. Mulungu et al., "One size does not fit all: Heterogeneous economic impact of integrated pest management practices

	for mango fruit flies in Kenya—a machine learning approach," Journal of Agricultural Economics, vol. 75, pp. 261–279, 1 Feb. 2024, issn: 14779552. doi: 10.1111/1477-9552.12550. 8. B. Muriithi et al., "Gendered barriers and opportunities for scaling integrated pest management practices along the mango value chain in Kenya," Journal of Integrated Pest Management, vol. 15, 1 2024, issn: 21557470. doi:10.1093/jipm/pmad034. We have also added this statement to emphasise the importance of eco-friendly fruit fly control in mango industry based on the findings of these additional studies on page 4 and 5, line 82 to line 87 that reads: '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., 2024; 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).'

Table 3: Comments and suggestions from Reviewer 3

Comment/suggestion	Authors' response
Section of paper: Overall	
The research topic is very interesting, the methodology is scientific and the data is more adequate.	Noted with appreciation.
Section of paper: Introduction	
Firstly, the formulation of two hypotheses lacks a theoretical and practical basis, so please analyze them in detail from a theoretical and literature perspective in order to arrive at reasonable hypothesis.	We have revised the two hypotheses on page 18 line 176 to line 181: '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.'
Section of paper: Methodology	

Secondly, How is the minimum sample size calculated in equation (1), give the calculation procedure.	We have added the following line to clarify how we arrived at our minimum sample size on page 10 line 212 to line 216: '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, 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 × 395 = 434) orchard managers to address potential issues related to incomplete questionnaires and outliers.'
Thirdly, Please give details on how the variables are assigned values, and the categorization of the variables is a bit problematic, e.g. non-farm income should be a continuous variable, not a categorical variable.	We have added detailed description of how we measured the variables included in the study on page 16 to page 19 line 347 to line 418. We are grateful for this suggestion. We have now included 'off-farm income' as a continuous variable, being the amount of income from non-agricultural streams. However, due to positive skewness and presence of zero values, we transformed the variable using an inverse hyperbolic sine. See Table 1 and 4.
Forthly, Please describe in detail how the intensity of APM adoption is measured.	We have clearly described how intensity of adoption of APM was measured on page 13 line 280 to line 282. '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…'
Section of paper: Literature review	
Fifthly, lacking of literature review.	We have added a section on 'past related studies' on page 5 to page 8, line 101 to line 173 that identifies the knowledge gaps that our study contributes to fill.

Table 4: Comments and suggestions from Reviewer 4

Comment/suggestion	Authors' response
Section of paper: Overall	
The paper is well written and presents robust analysis of the issue being studied.	Noted with appreciation.
My only concern is why the authors thought of evaluating adoption	Information constraints have been cited as a demotivating factor in the continued use of eco-friendly practices due to their characteristic

under information constraints. It is obvious and also from the literature reviewed that people would adopt what they know.	knowledge-intensiveness. We have included a footnote on page 8 to clarify this: 'Throughout this paper, 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 et al., 2021).' All our analyses were conditioned on positive awareness so as to control for non-exposure and lack of awareness - see page 13 and 14 line 283 to line 289 that reads as: '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 & Demont, 2007) and the 'knowledge deficit problem' (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.'
Section of paper: Keywords	
Invasive alien pests should be included as key word	Done.
Section of paper: Introduction	
why information constraints? would we expect adoption if people dont know the practice/technology?	Information constraints have been cited as a demotivating factor in the continued use of eco-friendly practices due to their characteristic knowledge-intensiveness. We have included a footnote on page 8 to clarify this: 'Throughout this paper, 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 et al., 2021).’ We also clarify that all our analyses were conditioned on positive awareness so as to control for non-exposure and lack of awareness in page 13 and 14 line 283 to line 289 that reads as: ‘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 & Demont, 2007) and the ‘knowledge deficit problem’ (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.’
Section of paper: Methodology	
Besides, it is not clear how knowledge constraint was really measured. Table 4, indicates knowledge constraint, which I think would make more sense since people may have access to information but not necessarily sufficient knowledge to implement the learned techniques. I would suggest the authors re-look at this concept and harmonise across the paper.	We are grateful for this observation. Indeed, we use the phrase ‘knowledge constraint,’ to refer to mango farmers’ insufficient agronomic skill set to implement APM. Additionally, following Meijer et al. (2015), we included another question to encompass ‘what it [knowledge] can achieve.’ We have added the following statements to describe the variable and how it was measured in page 18 line 402 to line 412 which read as: ‘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).’

	We have harmonised this aspect throughout the paper.
DGPs [write in full at first mention]	Done.
is awareness considering formal and informal awareness? farmers do share information through their networks.	We have clarified this on page 18 line 391 to line 396 that reads: '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?" '
information or knowledge? cf description in Table 1.	Knowledge is a type of information that has been assimilated and understood, allowing it to be applied in practical contexts. Thus, both awareness and knowledge constraints are subsets of information constraints. We have added footnote on page 8 to clarify what we refer to as 'information constraints.'
Section of paper: Results	
[Table 1] so the person could have received training but has limited expertise? you describe it here as knowledge constraint, so its not information constraint, since they could have been trained or received information from other sources.	Noted with appreciation.
[Table 4] how was quality of awareness computed?	We defined the 'quality of awareness' on page 18 line 399 to line 401 as the: '…the proportion of the APM practices an orchard manager has ever heard of, and thus somehow synonymous with the level of awareness …'
Section of paper: Conclusions and policy implications	
56.7% this would not really be low.	The statement has been revised and now reads on page 33 line 675 to line 677 as: '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.'

	We have harmonised this throughout the document as well.
would this not be obvious? how do you adopt what you dont know ho?	We are grateful for this observation. The sentence has been revised on page 33 line 677 to line 679 as: 'This limited uptake can be attributed to the high agronomic knowledge constraints in the implementation of APM technology, particularly prevalent among non-adopters (83%).' We have also added a footnote on page 8 that clarifies this: '…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 et al., 2021).'

Table 5: Comments and suggestions from Reviewer 5

Comment/suggestion	Authors' response
Section of paper: Overall	
First of all i would like to congratulate for the very interesting topic and the work well done.	Noted with appreciation.
The manuscript is well organized and the methodology is clear and replicable. However, According to my evaluation the manuscript is well structured, the methodology is replicable.	Noted with appreciation.
Section of paper: Methodology	
However, it should be great if authors include measurement model and structural model information for reliability	A detailed description and justification of the items used in PCA procedure has been added on page 18 line 381 to line 389: 'To reduce dimensionality and identify uncorrelated linear factors explaining maximal variance in the latent constructs, these statements

of latent variables employed in the study.	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 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.'