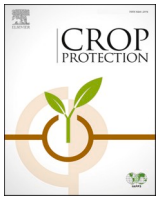
Crop Protection 202 (2026) 107500



Contents lists available at ScienceDirect

Crop Protection

journal homepage: www.elsevier.com/locate/cropro



Adoption and dis-adoption of push-pull technology in East Africa: Evidence from survival analysis and machine learning

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ARTICLE INFO

Keywords:
Agricultural innovation
Discrete-time proportional hazard model
Duration analysis
Extreme gradient boosting
Technology adoption
Social interaction

ABSTRACT

This study examines the timing to adoption and dis-adoption, as well as the key drivers influencing these transitions, for Push-Pull Technology (PPT) in East Africa using household-level panel data from extensive surveys conducted in Ethiopia, Kenya, Rwanda, Uganda, and Tanzania. Using discrete-time proportional hazard models, we estimate the hazard functions for PPT adoption and dis-adoption and complement this with machine learning–based survival analysis through Extreme Gradient Boosting (XGBoost) to evaluate and enhance predictive performance. Both approaches consistently identify peer networks measured by the number of known PPT adopters, frequent extension contact, and farmer group membership as the most influential drivers of adoption and long-term retention. Farmers' positive perceptions of PPT's pest-control effectiveness (against stemborer, Striga, and fall armyworm) significantly accelerate uptake and reduce exit risk. Access to diverse information sources also speeds adoption, while participation in PPT training programs and repeated training sessions are essential for sustaining use over time. These findings suggest that complementary to ongoing efforts to improve input access, enhancing farmers' perceptions through targeted education, visible adopter clusters, and evidence-based demonstrations, together with embedded extension services, repeated interactive training, and country-tailored strategies, offer a roadmap for accelerating uptake and securing the sustained use of PPT across East Africa.

1. Introduction

Cereals like maize (*Zea mays* L.) and sorghum (*Sorghum bicolor* L. Moench) are crucial for food security and nutrition in Sub-Saharan Africa (SSA). Maize is the primary cereal, contributing two-fifths of the total output, with over 80 % used as food. Sorghum follows in importance, with Africa producing about 42 % of the world's supply (Cheruiyot et al., 2021). However, the productivity of these crops is severely hindered by stressors such as striga weeds (*Striga hermonthica* Del. Benth. and *Striga asiatica* (L.) Kuntze), stemborer (*Chilo partellus* Swinhoe and *Busseola fusca* Fuller), and fall armyworms (*Spodoptera frugiperda* J.E. Smith), exacerbated by unpredictable weather and poor soil fertility. These stressors lead to significantly reduced yields, affecting food production and contributing to high levels of food insecurity and poverty (Murage et al., 2015a; Chepchirchir et al., 2018; Muriithi et al., 2018). To address these challenges, the Push-Pull Technology (PPT) was introduced in the 1990s by the International Centre of Insect Physiology and Ecology *(icipe)* and partners as an effective integrated pest management strategy controlling these three constraints (Khan et al., 2008a, 2008b; Amudavi et al., 2009).

PPT involves intercropping desmodium (e.g., *Desmodium uncinatum* or *Desmodium intortum (Mill. Urb.*) between rows of the cereals (maize and sorghum). This practice repels pests using airborne semiochemicals, while the root exudates suppress striga weed through suicidal germination (Hooper et al., 2015). Additionally, the plot is surrounded by a border crop, either Napier grass (*Pennisetum purpureum Schumach*) or *Brachiaria spp*., which attracts pests away from the main crop, acting as a dead-end trap that prevents complete larval development

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https://doi.org/10.1016/j.cropro.2025.107500
Received 8 March 2025; Received in revised form 23 November 2025; Accepted 27 November 2025
Available online 28 November 2025
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(Chidawanyika et al., 2014; Khan et al., 2009). This technology has shown remarkable benefits, such as doubling or tripling cereal yields and enhancing soil health. Extensive research has proven that PPT is more profitable compared to traditional monocropping methods, offering a sustainable solution to pest management in the region (Khan et al., 2008a, 2008c).

Despite its benefits and extensive promotion, the adoption of PPT remains slow. Currently, approximately 350,298 smallholder farmers across 18 countries in Africa have embraced the technology (icipe, 2024). This figure remains relatively low compared to the population of smallholder farmers whose livelihoods have suffered adverse impacts from stemborer pests, striga weed, and fall armyworms (Niassy et al., 2020). In response to the question of low adoption, the adoption literature is filled with studies examining the determinants of PPT adoption. These studies consistently highlight the significant impact of socioeconomic factors in the adoption of the technology. Key factors include farmers' demographic characteristics, ownership of assets such as land and livestock, dissemination pathways, access to inputs and extension services, social interaction through group membership, among others (Murage et al., 2011, 2015a, 2015b, 2019; Muriithi et al., 2018; Niassy et al., 2020; Gwada et al., 2019; Misango et al., 2022).

Except for the study by Murage et al. (2011), previous research has largely overlooked the significance of the timing of the adoption event and the impact of various explanatory variables on this timing. This oversight fails to capture critical policy insights related to the timing and speed of technology adoption (Khataza et al., 2018). Moreover, scholars have emphasized that adoption is an iterative and evolving process rather than a fixed or binary state, arguing that empirical studies of adoption in agriculture should consider adoption as dynamic (de Oca Munguia et al., 2021; Defrancesco et al., 2018; Ofori et al., 2020). For instance, Pannell et al. (Pannell et al., 2006) categorized the adoption process into six stages: awareness, non-trial evaluation, trial evaluation, adoption, review and modification, and non-adoption or dis-adoption. Building on this, de Oca Munguia et al. (de Oca Munguia et al., 2021) emphasize that technologies are often used flexibly, continuously evolving to suit individual contexts within a dynamic process of adaptation and change, during which they may also be dis-adopted at any time. To account for these dynamics in adoption, duration models are particularly useful as they allow the full consideration of the effects of time and the dynamics of background factors on the adoption of a technology (Defrancesco et al., 2018; Ofori et al., 2020; Gatto et al., 2019).

Building on Murage et al. (Murage et al., 2011), who applied a parametric Weibull model using cross-sectional data from western Kenya to assess dissemination pathways, our study makes several distinct contributions to the literature on technology adoption and sustainable pest management in sub-Saharan Africa.

First, we use a panel dataset spanning two survey waves (2021 and 2023) from five East African countries (Kenya, Uganda, Tanzania, Rwanda, and Ethiopia) collected under the H2020 UPSCALE project (https://upscale-h2020.eu/about-us/). Unlike Murage et al. (Murage et al., 2011)'s single-location, cross-sectional design, our panel allows us to control for unobserved household heterogeneity (Murage et al., 2019) and capture temporal dynamics in adoption and dis-adoption behavior across socio-culturally diverse contexts (Alem et al., 2014). This broader geographic and temporal scope significantly improves the generalizability of findings for scaling PPT across East Africa.

Second, while Murage et al. (Murage et al., 2011) utilized a Weibull parametric duration model, we adopt a discrete-time proportional hazard model tailored to the discrete nature of our time-to-event variable. This approach reduces misspecification risk from continuous-time assumptions and bias from unobserved heterogeneity thereby producing more robust estimates than the continuous-time Weibull specification (Alem et al., 2014; Kassie, 2015). By pairing this with panel data, our results are not only more reliable for PPT but also transferable to other agricultural technologies facing similar adoption dynamics in SSA. In the literature, authors such as Alem et al. (Alem et al., 2014) and Otieno et al. (Otieno et al., 2023) have utilized the discrete-time proportional hazard model to examine the determinants of adoption and dis-adoption of electric cookstoves in Ethiopia and integrated pest management practices in Kenya, respectively.

Third, we introduce machine learning based survival analysis to the study of agricultural technology adoption. Using Extreme Gradient Boosting (XGBoost), a state-of-the-art algorithm, we compare traditional hazard modeling with a nonparametric, high-dimensional approach that can detect non-linear relationships and complex feature interactions (Lee et al., 2024). To our knowledge, this is the first application of XGBoost or similar ML-based survival methods to PPT and rare in agricultural adoption broadly, demonstrating their potential to improve predictive performance and uncover nuanced drivers overlooked by parametric models. However, they (machine learning techniques) have been extensively utilized in the medical field to predict a range of health outcomes, demonstrating their versatility and effectiveness in various applications (Lee et al., 2024; Moncada-Torres et al., 2021). This study, therefore, makes a novel contribution to the agricultural adoption literature by filling this gap.

Fourth, while many studies note that farmers' perceptions influence adoption, we go further by quantifying the relative importance of perceived pest-control effectiveness (for stemborer, Striga weed, and fall armyworm) and farmers' social networks with existing adopters within both hazard and machine learning frameworks. Previous PPT studies including Murage et al. (Murage et al., 2011) did not evaluate these factors' predictive strength across multiple countries or compare their influence on both adoption and dis-adoption. By doing so, we show that perceived effectiveness and peer networks consistently rank among the strongest drivers, a finding that refines existing theory e.g., the diffusion of innovations theory by Rogers (1983) and the Technology Acceptance Model (TAM) by Davis (1989), thereby providing guidance for designing peer-led demonstrations and dissemination strategies. According to existing theory, farmers are more likely to adopt a technology they find effective, integrating it rapidly into their practices, while perceiving it as ineffective leads to resistance and slower adoption (Sharifzadeh et al., 2017; Dong et al., 2022; Doanh et al., 2022). Additionally, the extent of a farmer's social network with other adopters of new technology facilitates knowledge exchange and provides essential support and motivation during the adoption process (Rogers, 1983; Takahashi et al., 2019). Leveraging the collective knowledge, experience, and insights of fellow farmers enhances understanding of the opportunities and challenges of the new technology (Rogers, 1983). Additionally, observing successful implementation by peers serves as inspiration and motivation, boosting confidence among hesitant or skeptical farmers. This, in turn, fosters a collective attitude shift, promoting more widespread adoption of new technologies. Studies such as those by Bjørkhaug and Blekesaune (2013), Wollni and Andersson (2014), Läpple et al. (Läpple et al., 2017), Haensch et al. (Haensch et al., 2019), Gu (2024), and Chen et al. (Chen et al., 2024a) underscore the pivotal role peers play in influencing adoption decisions.

Lastly, we extend beyond the scope of adoption to explore a novel model for dis-adoption, a dimension largely absent from prior PPT research. By doing so, we address the broader question of what factors underpin the sustained use of PPT by households across East Africa. We analyze the impact of training variables, such as whether a farmer received PPT training, the frequency of training sessions, and the modes of training, alongside other variables crucial for the sustained use of agricultural technologies. Comprehensive and targeted training programs equip farmers with the knowledge and skills necessary to effectively adopt and maintain new technologies, fostering continuous learning and improvement (Takahashi et al., 2019; Mgendi et al., 2022; Liu et al., 2022). Very few agricultural adoption studies have modeled dis-adoption timing, exceptions include Läpple (2010), Alem et al. (Alem et al., 2014), and Otieno et al. (Otieno et al., 2023), making our analysis one of the first to reveal the predictors of sustained use of PPT at

scale.

Collectively, these contributions advance the field by broadening geographic and temporal scope (panel based survey data from five countries), improving methodological rigor (discrete-time hazard framework), introducing innovative analytical tools (ML survival analysis), refining theoretical understanding of peer effects and perceptions, and highlighting the underexplored challenge of sustaining adoption, all of which enhance the relevance of PPT research for scaling sustainable pest management technologies across diverse African farming systems.

In this study, we specifically focus on two distinct models: Model 1, the adoption/entry model, evaluates the speed of adoption by considering the timeframe from when the farmer first learned about PPT to when they began using the technology. Model 2, the dis-adoption/exit model, assesses the speed of dis-adoption by measuring the duration from the start date, when the farmer first adopted PPT, to the end date, when they ceased using the technology. Through this comprehensive approach, we aim to shed light on the dynamics influencing the long-term utilization of PPT in the region.

2. Materials and methods

2.1. Data collection and the study area

This study utilizes household-level survey data collected at baseline and mid-line of the UPSCALE project in Ethiopia, Kenya, Rwanda, Tanzania, and Uganda. These areas include Kisumu, Vihiga, Siaya, and Homabay counties in Kenya, North Shewa, Oromia Special zone, and South Wollo in Amhara in Ethiopia, Butiama, Bunda, Tarime, and Rorya districts in Mara region in Tanzania, Nyagihanga Sector in Gatsibo district in Rwanda, and Iganga, Kamuli, and Namutumba districts in Uganda (Fig. 1). However, households in Ethiopia were not followed up during the midline survey due to the civil unrest in the study regions. These specific regions were chosen due to previous PPT dissemination efforts and the significant impact of striga weed, stemborer, and fall armyworms (FAW) on cereal production in these regions.

Extension officers and country project partners were instrumental in obtaining a census of cereal growers, both PPT and non-PPT, from which respondents were randomly selected for the survey. The baseline survey data was collected in 2021 from both PPT and non-PPT farmers at the beginning of the project. The midline survey data was collected from August to October of 2023 by tracking the same farmers who were interviewed at baseline. Except for Ethiopia where the midline survey was not conducted, farmers who couldn't be traced at midline were replaced. Both surveys were conducted using enumerators who were familiar with the local languages using a closed-ended questionnaire programmed in the Open Data Kit (ODK). The questionnaire was co-designed by the UPSCALE consortium partners, with leadership from the socio-economics team at the Kenya Agricultural and Livestock Research Organization (KALRO) and ICIPE.

2.2. Econometric approach

2.2.1. Discrete-time proportional hazard model

The primary objective of the duration analysis employed in this study is to determine the likelihood of a farmer's decision to adopt or dis-adopt PPT at any given time t, assuming that the farmer has not yet chosen to do so. This analytical approach focuses on the variable of interest, which is the duration of time from a specific event to another event (Läpple, 2010). We employ a discrete-time proportional hazard model to examine the transition of households between adoption and dis-adoption. Specifically, we focus on the analysis of adoption spells and the estimation of entry into adoption and exit from adoption

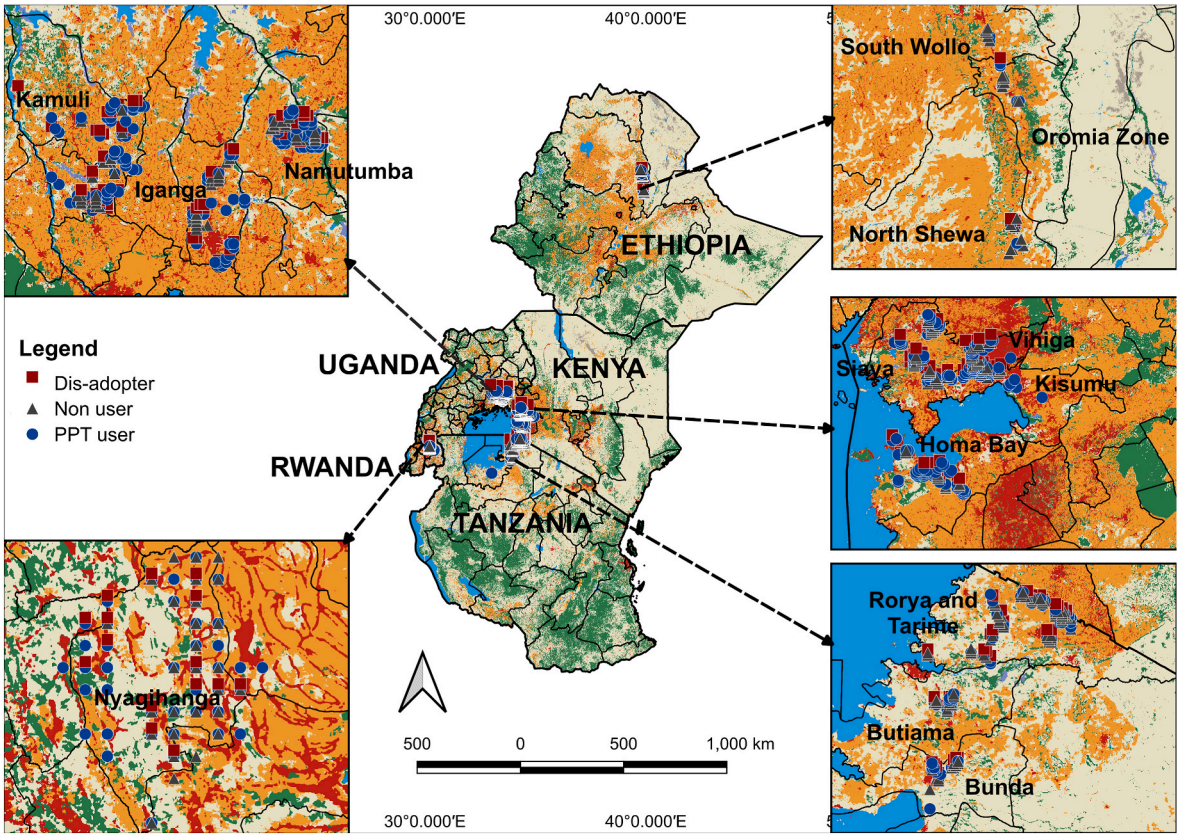


Fig. 1. Study regions and sampled households across Ethiopia, Kenya, Rwanda, Uganda, and Tanzania. This figure shows the geographic distribution of the study sites and the surveyed households in each country included in this study's analysis. The maps are based on 2023 land use or land cover data downloaded from https://livingatlas.arcgis.com/landcover/.

hazards. The entry model, which denotes the speed of adoption, was measured in terms of the period between the time when the farmer became aware of PPT and the year the farmer adopted the technology on the farm for adopters. The exit model, which denotes the speed of dis-adoption was measured in terms of the date when the farmer adopted PPT, and the end of a spell was the date when the farmer dropped out of using the technology for dis-adopters. Non-adopters in the entry model and continuing users in the exit model were right censored at the survey time.

If we consider 1 to represent households that have completed spells of non-adoption and transitioned into adoption, while 0 indicates those still in a non-adoption spell during the survey time, the proportion of completed non-adoption spells signifies the hazard rate for that period. This hazard rate mirrors the likelihood of exiting from non-adoption and correlates with the survivor rate, indicating the proportion of households in non-adoption at that time (Alem et al., 2014). Following Alem et al. (Alem et al., 2014), a discrete-time hazard rate h_{it} can be specified as:

$$h_{it} = prob(T_i = t | T_i \geq t;\ X_{it}) \tag{1}$$

Where X_{it} denotes a set of explanatory variables, which may vary with time or remain constant over time, and T_i stands for a discrete random variable indicating the time when a non-adoption spell ends. Consequently, the probability of ending a non-adoption spell at T_i = t can be expressed as:

$$prob(T_i = t) = h_{it} * \prod_{k=1}^{t-1}(1 - h_{ik}) = \left[\frac{h_{it}}{1 - h_{it}} * \prod_{k=1}^{t}(1 - h_{ik})\right] \tag{2}$$

While the probability of ending a non-adoption spell at $T_i >$ t can be expressed as:

$$prob(T_i > t) = \prod_{k=1}^{t}(1 - h_{ik}) \tag{3}$$

Consider individuals indexed by i = 1,…,N, who each transition into a state of non-adoption at time t = 0. It is assumed that the hazard rate function for individual i at time t > 0 follows a proportional hazards form given by Equation (4) (Alem et al., 2014; Jenkins, 1997).

$$h_{it} = h_0(t).exp(X'_{it}\beta) \tag{4}$$

Where $h_0(t)$ represents the baseline hazard function, which may take a parametric or non-parametric form and is presumed to be identical across all households, exp(.) denotes the exponential function, X'_{it} denotes a set of explanatory variables summarizing observed differences between individuals at t, while β stands for the parameters to be estimated. To address unobserved household heterogeneity, a multiplicative gamma-distributed random error term v is introduced (Alem et al., 2014; Jenkins, 1997). This term is assumed to be uncorrelated with any of the X variables and is integrated into the proportional hazard model presented in Equation (4) as:

$$h_{it} = h_0(t).v_i.exp(X'_{it}\beta) = h_0(t).\exp\left[X'_{it}\beta + log(v_i)\right] \tag{5}$$

where v_i is a gamma-distributed random variate with unit mean and variance $\sigma^2 \equiv \nu$ and the discrete-time hazard function corresponding to Equation (5) is expressed as in Equation (6), where γ_j is the parameter of the baseline hazard.

$$h_j(X_{ij}) = 1 - \exp\left\{-exp\left[X'_{ij}\beta\right] + \gamma_j + log(v_i)\right\} \tag{6}$$

The discrete-time proportional hazard model was fitted using the "pgmhaz8" command in STATA by Jenkins (1997). This command utilizes maximum likelihood estimation to compute two discrete-time proportional hazards regression models. One of these models integrates a gamma mixture distribution to address unobserved individual heterogeneity, also referred to as 'frailty,' as presented in Equation (5). Refer to Jenkins (1997) for a comprehensive derivation of both models.

2.2.2. Extreme Gradient Boosting (XGBoost)

XGBoost's high computational efficiency and excellent performance have made it extremely popular in the machine-learning community (Moncada-Torres et al., 2021; Faska et al., 2023). We chose XGBoost over approaches like the Random Survival Forest (RSF) due to its ability to sequentially build an ensemble of decision trees, each correcting the errors of the previous ones, which uncovers subtle patterns and enhances predictive accuracy even with small datasets (Moncada-Torres et al., 2021; Chakraborty and Tsokos, 2023; Borrmann, 2022). This ensemble method provides a robust model by aggregating many trees, addressing the weaknesses of a single tree (Moncada-Torres et al., 2021; Carmona et al., 2019). XGBoost includes robust feature selection and regularization mechanisms, such as L1 (Lasso) and L2 (Ridge) regularization, to prevent overfitting and produce parsimonious models that generalize well to new data (Faska et al., 2023). It effectively handles missing values through sparsity-aware algorithms and is recognized for its speed, efficiency, and scalability, making it suitable for large or high-dimensional datasets (Moncada-Torres et al., 2021; Carmona et al., 2019; Teke, 2022; Chen et al., 2024b).

XGBoost's optimized implementation supports parallel and distributed computing, enabling extensive parameter searches and efficient data handling. Its wide range of hyperparameters allows for fine-tuning to capture underlying patterns more effectively (Moncada-Torres et al., 2021; Climent et al., 2019). The boosting process iteratively improves the model by focusing on difficult-to-predict instances, enhancing accuracy and robustness. XGBoost accommodates various predictor types, including categorical variables, and supports cross-validation, capturing complex, non-linear relationships among variables (Moncada-Torres et al., 2021; Faska et al., 2023). Moreover, its flexibility, speed, and superior performance have contributed to its exceptional success in Kaggle competitions (Faska et al., 2023; Teke, 2022). This algorithm has been widely applied across various fields, including predicting the survival of pancreatic cancer patients (Chakraborty and Tsokos, 2023), forecasting failures in the banking sector (Carmona et al., 2019; Climent et al., 2019), image segmentation (Faska et al., 2023), classification of levels of geometry of building elements (Borrmann, 2022), streamflow modeling (Sahour et al., 2021), and predicting landslide susceptibility mapping (Teke, 2022).

Fig. 2 provides a detailed representation of the XGBoost workflow, illustrating each step in the process. This figure breaks down the workflow into its constituent parts, showing how data is processed and transformed at various stages, how the sequential ensemble of weak learners is built, and how the model iteratively improves its predictions.

XGBoost's workflow begins by calculating the initial loss and then sequentially adding trees to the model, each designed to reduce the loss through gradient descent. This involves parameterizing each tree and adjusting these parameters to minimize the loss while existing trees in the model remain unchanged. Trees are added until a specified number is reached, the loss reaches an acceptable level, or no further improvement is observed (Moncada-Torres et al., 2021; Faska et al., 2023; Carmona et al., 2019). The final output of XGBoost is the weighted sum of the predictions made by all individual trees (Moncada-Torres et al., 2021; Faska et al., 2023; Carmona et al., 2019). This optimization can be represented mathematically as shown in Equation (7) (Borrmann, 2022; Teke, 2022; Sheridan et al., 2016).

$$\widehat{y}_i = \phi(x_i) = \sum_{k=1}^{k} f_k(x_i), f_k \in F \tag{7}$$

Where $\widehat{y}_i$ is the target variable to be predicted, f_k represents an individual decision tree, F is the set of all possible regression trees, x_i denotes the independent variables, and K represents the total number of additive functions. F can be calculated following Equation (8) (Teke, 2022).

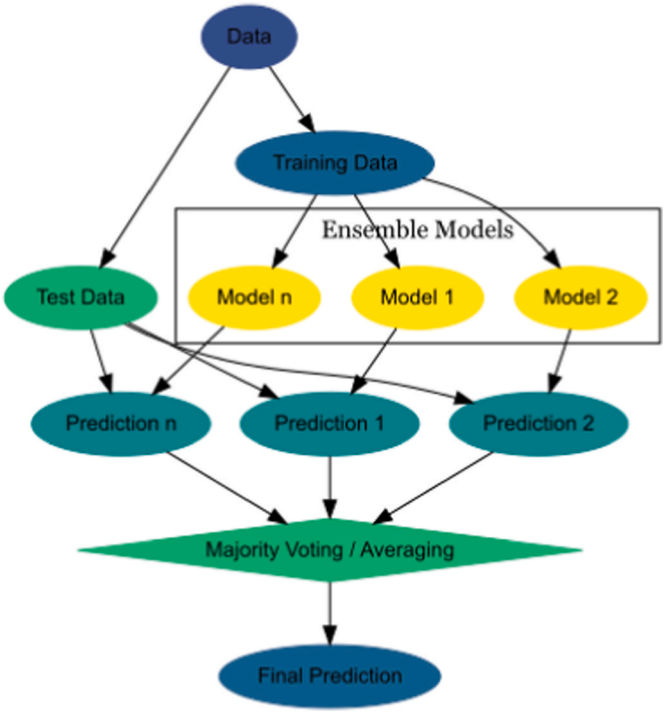


Fig. 2. Overview of the XGBoost survival analysis workflow.

$$F = \{f(x) = w_q(x)\}\,(q : R^m \to T, w \in R^T) \tag{8}$$

Here, q is the structure of an individual tree and T indicates the number of leaves in the individual tree. Besides, the function f_k corresponds to the leaf weights w and the individual tree structure q. In the XGBoost algorithm, the goal is to minimize Equation (9) below (Faska et al., 2023; Borrmann, 2022; Sahour et al., 2021)

$$\mathscr{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \tag{9}$$

Where $\mathscr{L}$ is a loss function that quantifies the error between measured and estimated values. In the equation above, l is a differentiable convex loss function that measures the difference between the prediction $\hat{y}_i$ and the target y_i and Ω is a penalty value representing the complexity of the model by considering the number and score of leaves. Where,

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda\|\omega\|^2 \tag{10}$$

The second term penalizes the complexity of the model in terms of the number of leaves in the tree T and the vector of scores on leaves ω. It helps to smooth the final learned weights to avoid overfitting (Sheridan et al., 2016).

Fine-tuning parameters is essential for enhancing the model's performance because it controls the model's complexity and has a significant impact on its predictive performance. Important parameters include the maximum number of boosting iterations or rounds, the maximum depth or size of each tree, and the learning rate, which influences each tree's contribution to the overall model (Moncada-Torres et al., 2021; Climent et al., 2019). In this study, we used 10-fold cross-validation for parameter tuning. The learning rate varied from 0.001 to 1 for all models, the maximum depth of each tree varied between 2 and 20, and the number of boosting rounds varied from 100 to 1000. The dataset was randomly split into two parts: 80 % for training and the remaining 20 % for testing.

We assessed each model's performance using Harrell's and Uno's concordance indices (C-index), which evaluate the proportion of pairs in which the individual with a higher predicted survival rate outlives the other (Lee et al., 2024). These indices measure the rank correlation between the model's predicted risk scores and the observed times in the test dataset (Moncada-Torres et al., 2021). The C-index ranges from 0 to 1, with 0.5 indicating random predictions and 1 signifying perfect model discrimination (Lee et al., 2024).

The models were fitted in R (R Core Team, 2024) version 4.4.0 using the "xgboost" (Chen et al., 2024b), "survival" (Therneau, 2024), "survminer" (Kassambara et al., 2021), "caret" (Kuhn, 2008), "survAUC", "Hmisc", and "SHAPforxgboost" (Liu and Just, 2023) packages.

2.3. Data and description of variables

The data utilized in this study is derived from the UPSCALE project's baseline and midline surveys conducted in 2021 and 2023, respectively. The baseline survey encompassed a total of 1556 households, whereas the midline survey covered 1237 households, resulting in a combined sample size of 2793 households for both surveys. During the midline survey, efforts were made to track the same households that were originally surveyed during the baseline survey. Out of the initial 1556 households, 1045 were successfully traced, and the remaining households were replaced. In our analysis of adoption, we utilize the unbalanced panel dataset, encompassing all 2793 households. However, when examining dis-adoption determinants, we utilize solely the midline survey data, which includes 1237 households. This is due to the absence of the "time to dis-adoption" variable in the baseline survey.

We investigate the determinants of adoption/dis-adoption under six categories: household characteristics, perceived effectiveness of PPT against striga weed, stemborer, and fall armyworms, social interaction, information sources for adoption models, modes of training for dis-adoption models, and country variables. These variables were selected based on three complementary theoretical perspectives that together explain both the adoption and the sustained use (dis-adoption) of agricultural technologies.

2.3.1. Diffusion of innovations theory (DoI)

Rogers (1983) posits that the rate of adoption of new technologies depends on their perceived attributes particularly relative advantage, observability, and compatibility, type of innovation decision, communication channels, nature of the social system, and extent of the agents' promotion efforts. In our context, farmers' perceived effectiveness of PPT against stemborer, Striga weed, and fall armyworm represents perceived relative advantage. Knowing other PPT adopters and group membership captures social influence and observability, while information sources and training modes represent dissemination pathways affecting compatibility and trialability.

2.3.2. Technology Acceptance Model (TAM)

TAM (Davis, 1989) emphasizes perceived usefulness and ease of use as primary determinants of technology adoption. We operationalize perceived usefulness as pest-control effectiveness and ease of use through variables such as extension contact, training frequency, and hands-on experiential learning, which reduce implementation complexity.

2.3.3. Social network theory and learning-by-doing

Social network theory (Granovetter, 1983) highlights that peer exchange, farmer-to-farmer learning, and visible adopter clusters accelerate diffusion and reduce abandonment risk. Farmers' contacts with extension agents, organized farmer networks, and professional advisory services represent formal knowledge channels that complement peer learning. Learning-by-doing (Arrow, 1962) suggests that repeated training and interactive modes (field days, demonstrations) reinforce knowledge and skills, increasing the likelihood of sustained use. By integrating these perspectives, we expect that perceived pest-control benefits, strong peer networks, frequent and high-quality extension contact, and repeated, hands-on training will significantly accelerate

PPT adoption and reduce dis-adoption.

Detailed variables under each category are presented in Table 1 and further discussed in the results section. Several of these variables have been examined in previous studies on PPT adoption, including works by Murage et al. (Murage et al., 2015a),Muriithi et al. (Muriithi et al., 2018),Niassy et al. (Niassy et al., 2020),Murage et al. (Murage et al., 2015b),Gwada et al. (Gwada et al., 2019),Misango et al. (Misango et al., 2022),Murage et al. (Murage et al., 2011),Waiswa et al. (Waiswa et al., 2025).

In the dis-adoption models, our objective is to analyze the factors influencing the sustained or long-term use of PPT by households. Consequently, rather than focusing on the initial information sources, we examined variables such as whether the farmer received PPT training post-adoption, the number of training sessions attended, and the different training modes. These variables are intended to assess the impact of continuous engagement with farmers on their long-term use of PPT.

Table 1 presents the variables used in this study, illustrating variations in the values for adopters and non-adopters of PPT in the two surveys. We utilized Chi-square tests to analyze categorical variables and Mann-Whitney U tests to evaluate continuous variables, facilitating a comparison between the two groups. The data reveals notable and statistically significant differences in several key variables between adopter and non-adopter households. Adopter households, in comparison with non-adopter households, tend to be older and have a higher level of education. They also face fewer constraints in accessing extension services, hold stronger perceptions regarding the effectiveness of PPT against the target pests and weeds, exhibit higher rates of group membership, possess greater acquaintance with PPT farmers, maintained more frequent contact with extension services over the previous two years, have heard about PPT through the different pathways, and have undergone more PPT training sessions in the preceding three years through the various training modes.

3. Results

3.1. Time to adoption and dis-adoption

Table 2 presents the distribution of time to adoption and dis-adoption across the five countries. The minimum time to adoption was less than one year, with a maximum of 20 years and an average of 0.7 years. Time to dis-adoption ranged from less than one year to 23 years, with an average of 2.8 years. A one-way ANOVA indicates statistically significant differences across countries for both adoption and dis-adoption durations (F-statistic, $p < 0.01$). Uganda and Rwanda recorded the shortest mean durations for both adoption and dis-adoption, while Kenya and Tanzania exhibited comparatively longer durations.

3.2. Trends in farmers' PPT awareness, adoption, and dis-adoption

Fig. 3 provides a time-based overview of PPT diffusion across countries, showing yearly and cumulative counts of newly aware farmers, new adopters, and dis-adopters. The top row presents the annual counts, whereas the bottom row presents the cumulative number of farmers. This visualization contextualizes adoption dynamics, highlights periods of rapid scaling and decline, and reveals cross-country contrasts that justify including country effects in our models. Moreover, the clustered timing of adoption and dis-adoption events underscores the appropriateness of time-to-event methods and non-linear approaches (e.g., XGBoost) rather than static cross-sectional analyses.

The "Newly Aware Farmers" plot on the top left presents the annual count of farmers becoming aware of PPT, while centrally located in the top row, the "New Adopters" plot represents the yearly count of farmers adopting PPT for the first time. Annual awareness remained low in all countries until the mid-2000s, after which increases occurred at different periods across countries. Kenya and Tanzania showed gradual increases in awareness and adoption beginning around 2006, with peaks in 2018 and 2019 respectively. Uganda, Rwanda, and Ethiopia recorded increases starting around 2014, peaking in 2019.

The "New Dis-adopters" plot on the top right demonstrates the annual number of farmers who discontinued the use of PPT after initial adoption. Annual dis-adoption remained low during the early 2000s but increased from 2014 onward, peaking in 2022 for most countries and in 2020 for Tanzania. Cumulative adoption plots across countries show continued upward movement without reaching an asymptote during the study period.

3.3. Kaplan Meier survivor estimates for PPT adoption and dis-adoption

Figs. 4 and 5 present Kaplan Meier survival estimates for adoption and dis-adoption, respectively, offering an initial, non-parametric view of the timing of farmers' transitions before applying hazard and machine-learning models. Plotting these survival curves serves three purposes: (i) visualizing the overall speed of adoption and abandonment across the sample without imposing functional-form assumptions (Kassie, 2015), (ii) revealing the steep early declines indicating periods of rapid adoption or exit, and (iii) offering a baseline against which to compare the results of the discrete-time hazard and XGBoost models. Including these plots ensures transparency about the underlying event-time distributions and supports the justification for using time-to-event methods. For adoption (Fig. 4), the survival function showed the steepest decline within the first three years after awareness, after which the curve flattened.

Fig. 5 illustrates the relationship between the proportion of adopters and the duration of dis-adoption. In this context, the term 'dis-adoption spell' refers to the period that elapses between the initial adoption of PPT and its subsequent dis-adoption. Conforming to the prior pattern observed in adoption duration, the survival function declined most rapidly during the first three years following initial adoption and showed slower declines thereafter. The stepwise pattern indicates time-dependent variation in exit risk.

3.4. Results from the discrete-time proportional hazard model

To examine the impact of the different variables on the hazards of entry into and exit from PPT adoption across East Africa, we use discrete-time hazard models and estimate hazard functions for entry into and exit from PPT adoption for each country and the pooled set containing data from the five countries. As stated earlier, we present our results under six distinct categories: household characteristics, perceived effectiveness of PPT against target pests and weeds, social interaction, information sources, modes of training, and country variables (Table 3). To address sparse data issues and improve model stability, closely related information sources and training modes presented in Table 1 were grouped into broader categories. Hands-on experiential learning combined trials, demonstrations, field days, and farmer field schools. Professional advisory sources grouped interactions with icipe staff, government extension agents, NGOs, universities, and mass media outlets (TV, radio, social media, YouTube). Organized farmer networks combined farmer cooperatives and groups.

For training modes, hands-on experiential training included field days, demonstration plots, and on-farm training; structured group learning was represented by farmer field schools; classroom training captured participation in classroom sessions often conducted as seminars. We report effects as hazard ratios ($HR = \exp(\beta)$) from discrete-time proportional hazard models; for count variables, HRs are interpreted per one-unit increase. A hazard ratio (HR) greater than 1 indicates that the variable accelerates the adoption or dis-adoption process, whereas an HR less than 1 signifies that the variable is associated with a slower or delayed adoption or dis-adoption process (Murage et al., 2011). As expected, most of the significant variables display effects on the hazard of exit that are the opposite of their effects on the hazard of entry (Läpple,

Table 1
Description and summary statistics of the variables used in the adoption and dis-adoption models. The table defines all variables included in the hazard and machine-learning models, including measurement units, category, mean and standard deviation values across countries, as well as the significancy of variables based on Chi-square and Mann-Whitney U tests between farmers practicing PPT and those not practicing the technology.

Variable	Description	Category	Pooled Sample		Non-adopters		Adopters		
			Mean	SD	Mean	SD	Mean	SD	P-value
Time to adoption	Number of years from the date of first hearing to the date of adoption	Discrete	0.69	1.86			1.76	2.01	
Time to dis-adoption	Number of years from the date of adoption to the date of dis-adoption	Discrete	2.81	3.56	3.81	3.56			
Household characteristics									
Gender	Gender of the household head	Binary, 1 = Male, 0 = Female	0.82	0.38	0.83	0.37	0.81	0.40	0.096
Age	Age of the household head	Continuous, years	51.34	12.86	50.70	13.33	52.33	12.04	0.001
Years of education	Education of the household head	Continuous, years	6.49	3.95	6.34	3.94	6.71	3.95	0.070
Household size	Number of household members	Continuous, number	6.46	2.92	6.45	2.92	6.47	2.92	0.799
Main occupation agriculture	Main occupation of the household head	Binary, 1 = Agriculture, 0 Otherwise	0.86	0.35	0.85	0.36	0.87	0.34	0.102
Tropical Livestock Units	Tropical Livestock Units	Continuous	1.84	3.30	1.77	3.16	1.94	3.50	0.119
Availability of off-farm income	Household participates in off-farm income generating activity	Binary, 1 = Yes, 0 = No	0.61	0.49	0.61	0.49	0.59	0.49	0.282
Credit constraint	Household needed credit and didn't receive	Binary, 1 = Yes, 0 = No	0.16	0.37	0.16	0.36	0.17	0.38	0.334
Extension constraint	Household needed extension and didn't receive	Binary, 1 = Yes, 0 = No	0.42	0.49	0.49	0.50	0.31	0.46	0.000
Land size	Total land owned by the household	Continuous, hectares	1.30	4.86	1.20	5.11	1.45	4.45	0.923
Perceived Effectiveness on:									
Stemborer	Perceived effectiveness against stemborer	Binary, 1 = Very effective, 0 otherwise	0.17	0.38	0.04	0.19	0.39	0.49	0.000
Striga weed	Perceived effectiveness of PPT against striga weed	Binary, 1 = Very effective, 0 otherwise	0.16	0.37	0.05	0.21	0.34	0.47	0.000
Fall armyworms	Perceived effectiveness of PPT against fall armyworms	Binary, 1 = Very effective, 0 otherwise	0.14	0.34	0.03	0.16	0.31	0.46	0.000
Social interaction									
Group membership	Household head is a member of a farmer group	Binary, 1 = Yes, 0 = No	0.79	0.41	0.73	0.45	0.88	0.33	0.000
Number of PPT farmers	Number of PPT farmers known by the farmer	Continuous, number	4.75	8.04	1.92	4.88	9.11	9.81	0.000
Contacts with extension	Contacts a farmer had with extension agents in the past 24 months, before the survey	Continuous, days	0.90	3.93	0.37	1.52	1.73	5.87	0.000
Information sources									
Icipe staff	Farmer first heard about PPT through icipe staff	Binary, 1 = Yes, 0 = No	0.30	0.46	0.33	0.47	0.29	0.45	0.000
Trials, demos, and field days	Farmer first heard about PPT through Trials, demos, and field days	Binary, 1 = Yes, 0 = No	0.29	0.46	0.26	0.44	0.32	0.47	0.000
Government extension	Farmer first heard about PPT through Government extension	Binary, 1 = Yes, 0 = No	0.06	0.24	0.06	0.23	0.07	0.25	0.000
Farmer cooperatives or group	Farmer first heard about PPT through Farmer cooperatives or group	Binary, 1 = Yes, 0 = No	0.03	0.18	0.03	0.17	0.03	0.18	0.002
Farmer Field School	Farmer first heard about PPT through Farmer Field School	Binary, 1 = Yes, 0 = No	0.01	0.09	0.01	0.08	0.01	0.09	0.058
Fellow farmers	Farmer first heard about PPT through fellow farmers (reference category)	Binary, 1 = Yes, 0 = No	0.11	0.32	0.16	0.37	0.07	0.26	0.235
NGO	Farmer first heard about PPT through NGO	Binary, 1 = Yes, 0 = No	0.17	0.37	0.14	0.35	0.19	0.39	0.000
Media	Farmer first heard about PPT through media (TV, radio, social media, YouTube)	Binary, 1 = Yes, 0 = No	0.00	0.07	0.01	0.08	0.00	0.06	0.756
Universities	Farmer first heard about PPT through Universities	Binary, 1 = Yes, 0 = No	0.01	0.11	0.01	0.10	0.02	0.12	0.006
Received PPT training	Farmer received training on PPT in the past 3 years, before the survey	Binary, 1 = Yes, 0 = No	0.39	0.49	0.12	0.32	0.81	0.39	0.000
Number of PPT training	Number of PPT training attended in the last 3 years, before the survey	Continuous, number	1.47	4.30	0.29	1.09	3.28	6.31	0.000
Modes of training									
Field days	Training was conducted through field days	Binary, 1 = Yes, 0 = No	0.28	0.45	0.16	0.37	0.31	0.46	0.000
Farmer Field Schools	Training was conducted through Farmer Field Schools	Binary, 1 = Yes, 0 = No	0.33	0.47	0.26	0.44	0.34	0.47	0.000
Demonstration plots	Training was conducted through demonstration plots	Binary, 1 = Yes, 0 = No	0.39	0.49	0.33	0.47	0.40	0.49	0.000
Seminar by extension staff	Training was conducted in the form of training seminars by extension staff	Binary, 1 = Yes, 0 = No	0.30	0.46	0.32	0.47	0.29	0.46	0.000
On-farm training	Training was conducted on-farm directly	Binary, 1 = Yes, 0 = No	0.28	0.45	0.32	0.47	0.27	0.44	0.000
Country variables									
Kenya	Variable for farmers in Kenya (reference category)	Binary, 1 = Yes, 0 = No	0.22	0.41	0.20	0.40	0.25	0.43	0.002
Uganda	Variable for farmers in Uganda	Binary, 1 = Yes, 0 = No	0.22	0.41	0.26	0.44	0.16	0.36	0.000
Tanzania	Variable for farmers in Tanzania	Binary, 1 = Yes, 0 = No	0.22	0.41	0.25	0.43	0.17	0.38	0.000
Rwanda	Variable for farmers in Rwanda	Binary, 1 = Yes, 0 = No	0.23	0.42	0.16	0.37	0.34	0.47	0.000
Ethiopia	Variable for farmers in Ethiopia	Binary, 1 = Yes, 0 = No	0.11	0.31	0.13	0.33	0.08	0.28	0.000

Note: Within the group of adopters, a notable portion of farmers embraced PPT in the year they first heard about it. Similarly, within the group of dis-adopters, a considerable number of farmers discontinued the technology in the same year they initially implemented it. To prevent these farmers from being excluded due to zero time (years) between hearing and adoption or between adoption and dis-adoption, a constant value of 1 was added to both the adoption time (for the entry model) and dis-adoption time (for the exit model) during analysis.

Table 2
Duration from awareness to adoption and from adoption to dis-adoption of PPT across five countries. "Time to adoption" refers to the number of years between a farmer first learning about PPT and their initial use of the technology, while "time to dis-adoption" refers to the duration between a farmer's first use of PPT and the point at which they discontinue its use.

	Time to adoption (years)					Time to dis-adoption (years)				
	N	Min.	Max.	Mean	Std. Dev.	N	Min.	Max.	Mean	Std. Dev.
Kenya	333	<1	18	0.98	2.50	38	<1	23	5.61	5.94
Uganda	334	<1	18	0.51	1.54	93	<1	6	1.70	1.25
Tanzania	292	<1	20	0.78	2.24	55	<1	18	3.45	3.71
Rwanda	437	<1	9	0.55	0.87	29	<1	4	1.48	1.09
Ethiopia	102	<1	12	0.74	2.12					
Overall	1498	<1	20	0.69	1.86	215	<1	23	2.81	3.56
F-statistic	3.69***(4)					15.35***(3)				

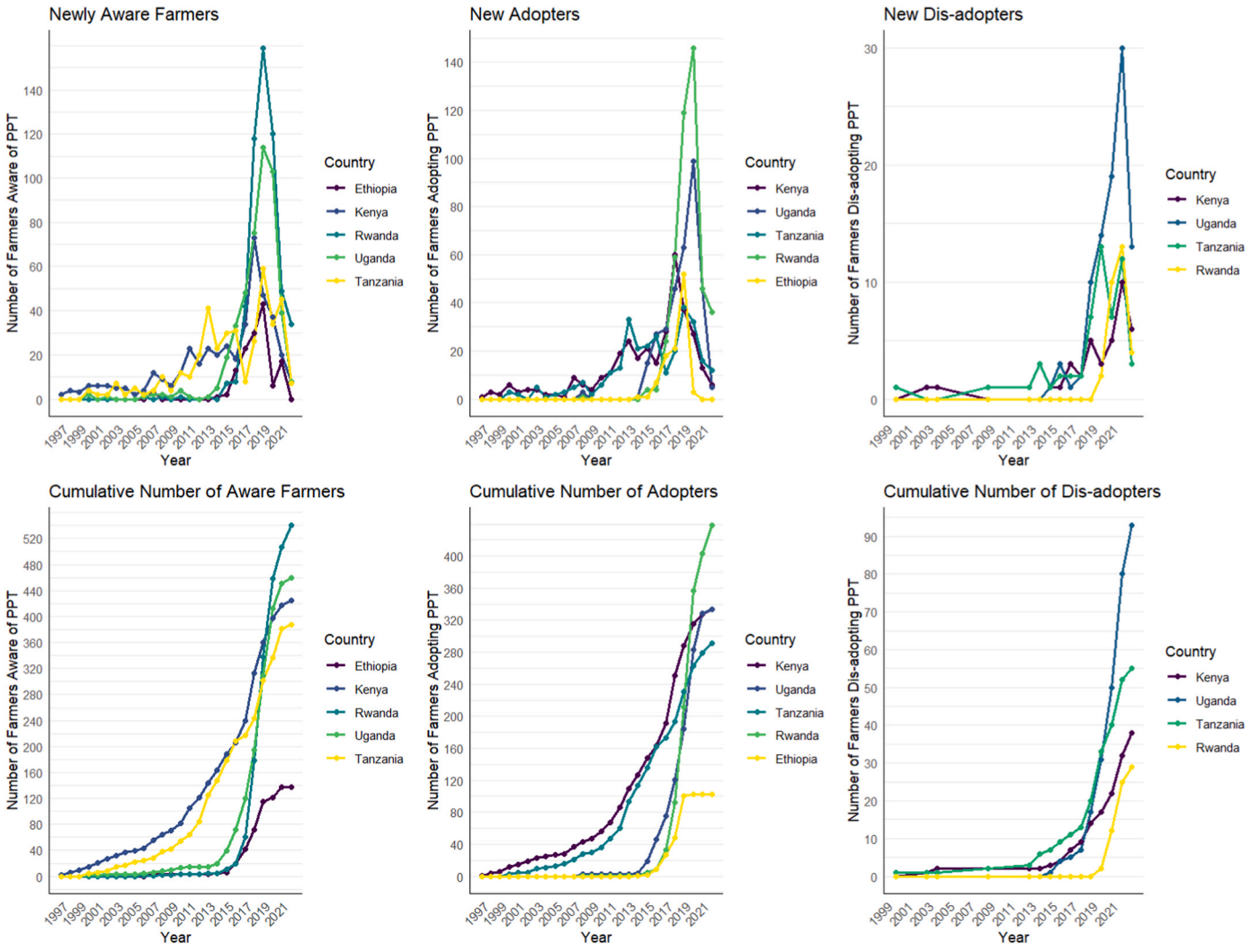


Fig. 3. Annual and cumulative trends in farmers' awareness, adoption, and dis-adoption of PPT by country (1997–2023). This figure presents both yearly counts and cumulative totals, illustrating the diffusion and discontinuation patterns of PPT across time in each country.

2010).

3.4.1. Household characteristics

The results presented in Table 3 reveal some notable country-specific effects of household characteristics on the transition from non-adoption to adoption of PPT or from adoption to dis-adoption. Gender has a delaying effect on the transition from non-adoption to adoption in Rwanda (HR = 0.62, $p < 0.05$) and Ethiopia (HR = 0.30, $p < 0.01$), with male farmers being about 38 % and 70 % less likely to adopt early than their counterparts, respectively. Age effects are modest: Ethiopia's adoption HR = 1.03 ($p < 0.05$) suggests each additional year increases adoption speed by about 3 %, while elsewhere age is neutral. For dis-adoption, Uganda's HR = 1.02 ($p < 0.10$) indicates slightly higher exit risk among older farmers.

Household size plays a significant role in expediting adoption in Ethiopia and delaying the transition from adoption to dis-adoption in Rwanda with larger households in Ethiopia adopting faster (HR = 1.16, $p < 0.05 \approx 16$ % faster per additional member). Rwanda's HR = 0.75 (p

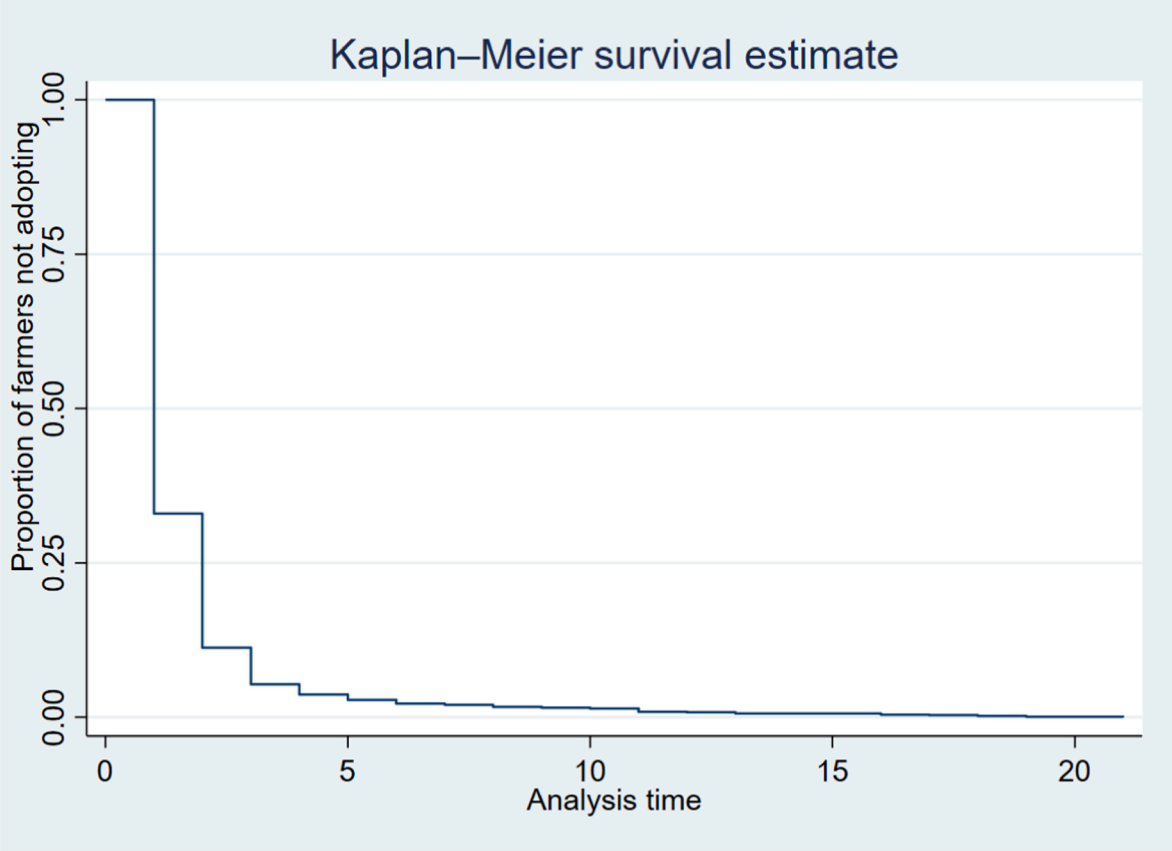


Fig. 4. Kaplan–Meier survival estimates for time to adoption of PPT. The curve displays the probability of farmers remaining non-adopters over time after first learning about PPT, providing a non-parametric baseline for adoption dynamics.

< 0.05) in the dis-adoption model corresponds to a 25 % lower exit hazard per additional household member. The availability of off-farm income accelerates the adoption of PPT in Ethiopia (HR = 2.12, $p < 0.01$). Credit constraints delay PPT adoption in Rwanda (HR = 0.56 ($p < 0.01$), suggesting that credit-constrained farmers adopt 44 % more slowly. Extension constraints delay PPT adoption in Ethiopia (HR = 0.31, $p < 0.01 \approx 69$ % slower adoption) and Rwanda (HR = 0.76, $p < 0.10 \approx 24$ % slower adoption).

3.4.2. *Farmers' perceived effectiveness of PPT*

Farmers' perception of the effectiveness of PPT against striga weed, stemborer, and fall armyworms have strong and significant expediting effects on the transition from non-adoption to adoption of PPT and delaying effects on the transition from adoption to dis-adoption of PPT. In Uganda (HR = 2.78, $p < 0.01$), Tanzania (HR = 2.49, $p < 0.05$), and the pooled sample (HR = 2.97, $p < 0.01$), farmers highly perceiving PPT as effective against stemborers were roughly 2.5–3 times more likely to adopt early compared with those with lower perceptions. Perceived Striga suppression strongly accelerates adoption in Rwanda (HR = 2.33, $p < 0.10$), Uganda (HR = 1.74, $p < 0.01$), Tanzania (HR = 3.83, $p < 0.01$), Kenya (HR = 5.88, $p < 0.01$), and the pooled sample (HR = 2.22, $p < 0.01$). These estimates imply that farmers who trust PPT to control Striga are 2–6 times more likely to adopt promptly. For dis-adoption, perceived Striga effectiveness significantly lowers exit risk in the pooled sample (HR = 0.64, $p < 0.10$). Perceived FAW control also influences adoption and sustained use. Significant effects appear in Uganda (HR = 1.77, $p < 0.10$), Kenya (HR = 2.40, $p < 0.10$), and the pooled sample (HR = 1.90, $p < 0.01$), meaning farmers confident in PPT's FAW control were about 1.8–2.4 times more likely to adopt quickly. For dis-adoption, perceptions substantially reduce exit hazards: Kenya (HR = 0.22, $p < 0.10$) and the pooled sample (HR = 0.49, $p < 0.05$) indicate 50–78 % lower exit risk for farmers perceiving effective FAW control.

3.4.3. *Social interaction*

Social networks function as informal financial resources and learning platforms, enabling farmers to understand and evaluate technologies, overcome implementation challenges, and maximize benefits (Andersson, 2014; Chen et al., 2024a). The transition to adoption and dis-adoption of PPT is significantly influenced by the three social interaction variables: group membership, farmer's social network with other PPT adopters denoted by the number of PPT farmers known by the farmer, and contacts with extension services.

Belonging to a farmer group or cooperative significantly accelerates adoption, particularly in Rwanda (HR = 1.49, $p < 0.05$) and Tanzania (HR = 1.94, $p < 0.01$). These values imply group members adopt 49–94 % faster than non-members.

The number of PPT farmers known by a farmer is statistically significant in both the adoption and dis-adoption models across all countries studied. Each additional known PPT farmer increases the hazard of adoption, Ethiopia (HR = 1.10, $p < 0.01$), Rwanda (HR = 1.09, $p < 0.01$), Uganda (HR = 1.04, $p < 0.01$), Tanzania (HR = 1.02, $p < 0.01$), Kenya (HR = 1.38, $p < 0.01$), and pooled sample (HR = 1.03, $p < 0.01$). For dis-adoption, peer exposure reduces exit risk: pooled HR = 0.89 ($p < 0.01$) indicates an 11 % lower hazard per additional known adopter, with similar reductions in Rwanda (HR = 0.87, $p < 0.05$), Uganda (HR = 0.86, $p < 0.01$), Tanzania (HR = 0.92, $p < 0.05$), and Kenya (HR = 0.88, $p < 0.10$).

The positive effect of contacts with extension on adoption in Rwanda, Uganda, and Kenya and its negative effect on dis-adoption in Uganda and Tanzania, underscores the role of formal information channels in facilitating PPT uptake and sustained use. Significant hazard

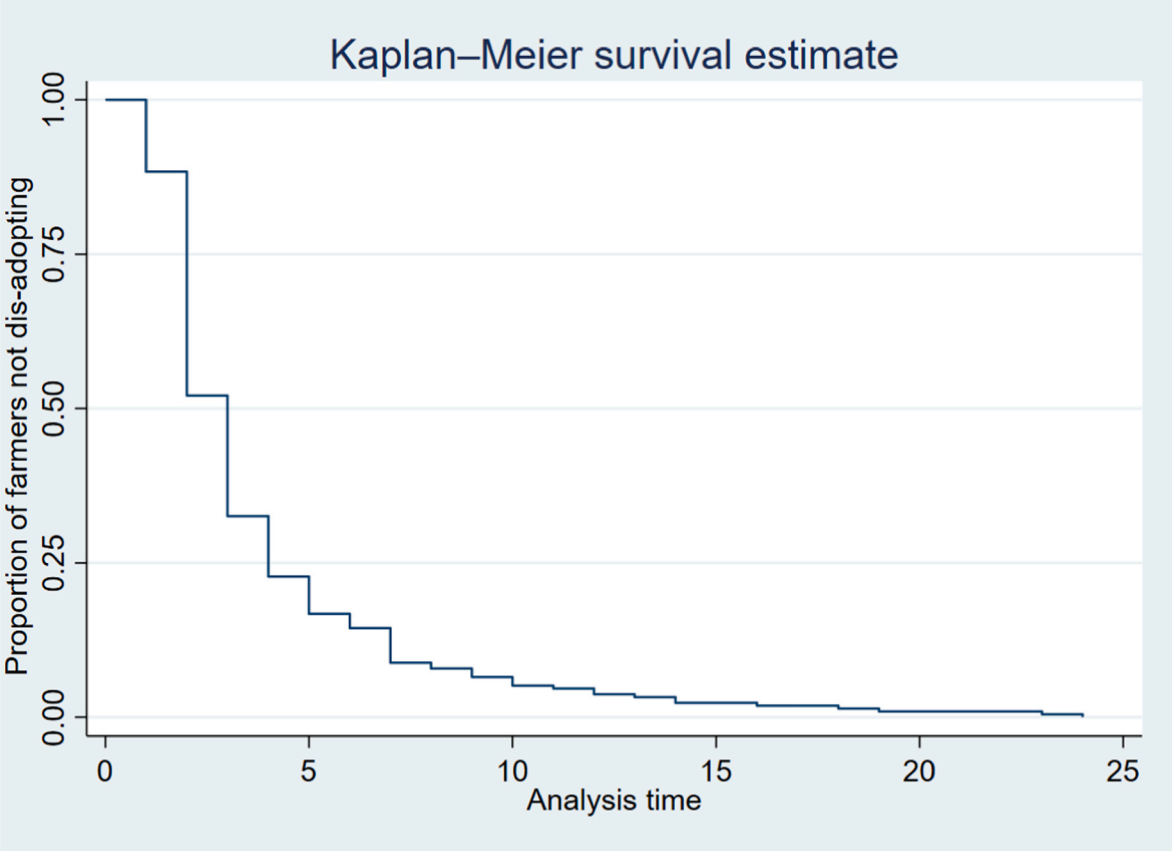


Fig. 5. Kaplan–Meier survival estimates for time to dis-adoption of PPT. The curve represents the probability that farmers continue using PPT over time after adopting it, highlighting periods of rapid discontinuation.

ratios are observed in Rwanda (HR = 1.09, $p < 0.05$), Uganda (HR = 1.10, $p < 0.10$), Kenya (HR = 1.09, $p < 0.05$), and the pooled sample (HR = 1.06, $p < 0.01$). Extension access likewise reduces dis-adoption: pooled HR = 0.91 ($p < 0.05$), Uganda (HR = 0.80, $p < 0.05$), and Tanzania (HR = 0.88, $p < 0.10$) show lower exit hazards for farmers with more contact.

3.4.4. Information sources

Farmers obtaining information through hands-on experiential learning (trials/demonstrations/field days or farmer field schools) adopted PPT faster than those relying on fellow farmers alone. Hazards were 8.46–16.14 times higher across Rwanda (HR = 8.46, $p < 0.01$), Uganda (HR = 11.86, $p < 0.01$), Tanzania (HR = 8.44, $p < 0.01$), Kenya (HR = 16.14, $p < 0.01$), and the pooled sample (HR = 11.16, $p < 0.01$). Professional advisory channels (icipe staff, government extension, universities or NGOs) were even stronger in some contexts e.g., Tanzania (HR = 14.67, $p < 0.01$), pooled sample (HR = 12.20, $p < 0.01$), Rwanda (HR = 10.16, $p < 0.01$), Uganda (HR = 9.97, $p < 0.01$), and Kenya (HR = 8.35, $p < 0.01$) indicating that expert guidance accelerates adoption over tenfold. Organized farmer networks (farmer cooperatives or groups) also boosted adoption substantially relative to fellow farmers: Tanzania (HR = 18.42, $p < 0.01$), Kenya (HR = 7.25, $p < 0.01$), Uganda (HR = 4.3, $p < 0.05$), Rwanda (HR = 3.74, $p < 0.01$), and pooled sample (HR = 5.67, $p < 0.01$).

3.4.5. PPT training

This study's results further reveal that merely having received PPT training did not significantly reduce dis-adoption hazards, but training intensity (number of trainings attended) clearly mattered: pooled HR = 0.80 ($p < 0.01$) indicates a 20 % lower exit risk per additional training session. This effect is strongest in Tanzania (HR = 0.39, $p < 0.10$) and Kenya (HR = 0.59, $p < 0.05$). By contrast, the modes of training employed had insignificant effects on the transition to dis-adoption.

3.4.6. Country dummies

The coefficients on country dummies show spatial disparities in the adoption and dis-adoption of PPT. Relative to Kenya, farmers in Tanzania adopt significantly more slowly (HR = 0.72, $p < 0.05$), meaning a 28 % lower hazard of adoption. Similarly, Ethiopia shows a slower adoption rate (HR = 0.69, $p < 0.05$). In contrast, Rwanda adopts slightly faster (HR = 1.29, $p < 0.05$), implying a 29 % higher hazard of adoption relative to Kenya. Uganda is not significantly different (HR = 0.99), suggesting adoption rates there are broadly comparable to Kenya. In the dis-adoption model, Uganda (HR = 2.51, $p < 0.01$) and Tanzania (HR = 1.94, $p < 0.01$) show substantially higher exit hazards, 2.5- and 1.9-times greater risk of dis-adoption compared to Kenya. Rwanda demonstrates greater stability (HR = 0.57, $p < 0.10$), implying a 43 % lower risk of exiting, while Ethiopia's effect is not estimated in the dis-adoption model.

3.5. XGBoost survival analysis results

Figs. 7 and 8 present the feature importance plots for the adoption and dis-adoption models. We evaluated each model's predictive performance on the holdout test set using Uno's C and Harrell's C-index, which both measure concordance between predicted and observed outcomes. These are presented in Fig. 6. For the adoption models, values were consistently high across both metrics: Ethiopia (Uno's C = 0.927, Harrell's C = 0.928), Kenya (0.850, 0.851), Tanzania (0.849, 0.849), pooled sample (0.837, 0.837), Uganda (0.768, 0.769), and Rwanda (0.760, 0.760). These results indicate excellent discriminatory power overall, with Ethiopia's model approaching near-perfect prediction. For

Table 3
Estimated effects of household, perceptual, social, informational, training, and country factors on PPT adoption and dis-adoption hazards. Values represent hazard ratios, expressed as exp(b), from discrete-time proportional hazard models. A hazard ratio >1 indicates a variable increases the likelihood of adoption (or dis-adoption), while a value < 1 indicates a reduced likelihood.

	Adoption (Entry)						Dis-adoption (Exit)				
	Ethiopia	Rwanda	Uganda	Tanzania	Kenya	Pooled Sample	Rwanda	Uganda	Tanzania	Kenya	Pooled Sample
	exp(b)	exp(b)	exp(b)	exp(b)	exp(b)	exp(b)	exp(b)	exp(b)	exp(b)	exp(b)	exp(b)
Household characteristics											
Gender	0.30**	0.62**	1.18	0.75	1.48	0.92	2.25	1.29	0.46	0.72	1.00
Age	1.03**	1.00	1.01	1.01	1.00	1.00	1.01	1.02*	1.01	0.98	1.01
Years of education	1.05	1.00	1.01	1.04	0.96	1.01	0.98	1.05	1.03	0.97	1.03
Household size	1.16**	1.02	1.02	0.98	1.03	1.00	0.75**	1.01	0.99	0.89	0.97
Main occupation agriculture		1.29	1.11	0.96	0.61*	0.96		0.70	0.94	0.88	0.92
Tropical Livestock Units	0.99	1.09	0.94	1.00	1.05	1.00	1.02	1.04	0.98	0.99	0.98
Availability of off-farm income	2.12***	0.93	0.84	1.25	0.99	1.03	0.61	0.66	1.15	1.50	0.93
Credit constraint	1.44	0.56***	0.90	1.23	1.50	0.99	1.26	0.89	0.65	0.48	0.79
Extension Constraint	0.31***	0.76*	1.16	1.13	1.34	1.00	1.74	0.86	0.65	1.81	1.05
Land size (ha)	0.58*	1.01	0.98	1.10	0.95	1.00	0.88	0.90	1.10	1.08	0.98
Perceived Effectiveness on:											
Stemborer			2.78***	2.49**	1.57	2.97***		0.71	0.74	1.20	0.95
Striga weed		2.33*	1.74***	3.83***	5.88***	2.22***	2.05	0.58	0.54	0.52	0.64*
Fall armyworms			1.77*	1.10	2.40*	1.90***		0.68	0.76	0.22*	0.49**
Social interaction											
Group membership	1.95	1.49**	1.25	1.94***	1.09	1.38***		0.87	1.01	1.02	0.97
Number of PPT farmers	1.10***	1.09***	1.04***	1.02***	1.38***	1.03***	0.87**	0.86***	0.92**	0.88*	0.89***
Contacts with extension	1.27	1.09**	1.10*	1.03	1.09**	1.06***	0.81	0.80**	0.88*	1.02	0.91**
Information sources											
Fellow farmers (reference)											
Hands-on experiential		8.46***	11.86***	8.44***	16.14***	11.16***					
Professional advisory		10.16***	9.97***	14.67***	8.35***	12.20***					
Organized farmer network		3.74***	4.30**	18.42***	7.25***	5.67***					
Received PPT training							0.90	0.95	1.49	0.49	1.04
Number of PPT training							0.94	0.88	0.39*	0.59**	0.80***
Modes of training											
Hands-on experiential							0.52	1.09	1.13	5.08	1.03
Farmer field schools							1.41	1.71	0.61	0.90	0.89
Seminar by extension staff							1.63	1.29	1.18	5.32	1.10
Country variables											
Uganda						0.99					2.51***
Tanzania						0.72**					1.94***
Rwanda						1.29**					0.57*
Ethiopia						0.69**					
Constant	0.05***	0.10***	0.04***	0.02***	0.04***	0.06***	0.85	1.17	2.71	9.08	0.91
Log-likelihood	−126.78	−217.76	−232.04	−199.58	−120.56	−916.35	−69.35	−84.47	−58.97	−63.14	−304.31
N	308	648	613	616	608	2793	245	175	134	177	731

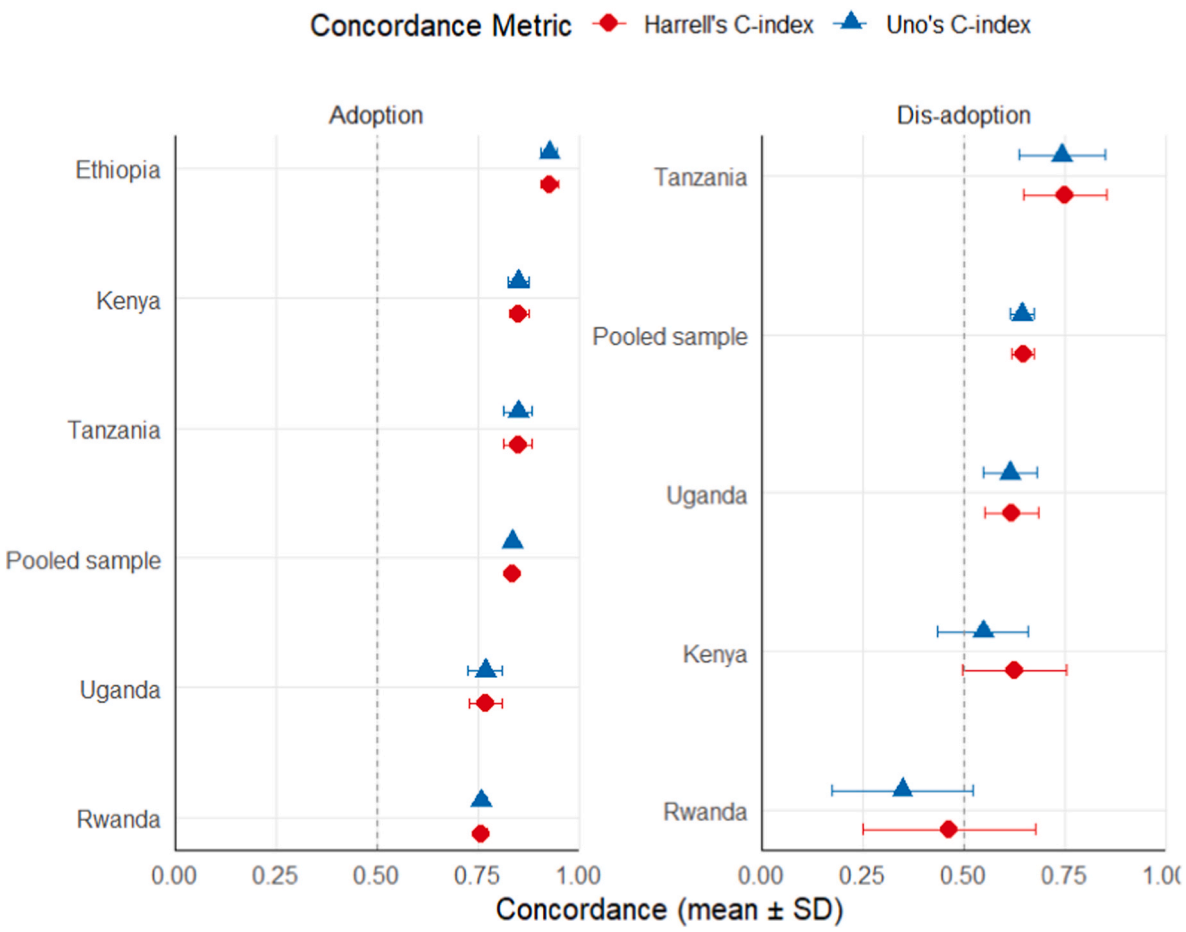


Fig. 6. Comparison of two concordance metrics Harrell's C-index (red) and Uno's C-index (blue) for evaluating adoption and dis-adoption prediction models. Bars show mean ± SD across countries, with higher values indicating better discriminative ability.

the dis-adoption models, predictive ability was lower but showed some variation: Tanzania (Uno's C = 0.743, Harrell's C = 0.752) showed the strongest performance, followed by the pooled sample (0.644, 0.647), Uganda (0.614, 0.617), Kenya (0.547, 0.625), and Rwanda (0.347, 0.463). The relatively low concordance for Rwanda suggests limited predictive capability, potentially due to smaller sample size or unobserved factors affecting dis-adoption dynamics.

Because a C-index of 0.5 reflects random prediction and 1.0 represents perfect discrimination (Lee et al., 2024; Moncada-Torres et al., 2021), these results show that adoption models especially for Ethiopia, Kenya, and Tanzania demonstrate strong predictive power, while the pooled and Ugandan models performed reasonably well. In contrast, the dis-adoption models exhibit moderate to weak performance. This could partly be attributed to the smaller sample sizes available for dis-adoption compared to adoption, which may limit the models' ability to capture all relevant variation.

The feature importance plots in Fig. 7 highlight the most influential factors driving PPT adoption across countries. Across all countries, knowing other PPT adopters consistently dominates, with perceived effectiveness against stemborer and Striga weed also ranking highly, land size in Ethiopia and professional advisory services in Uganda add context-specific influence. Overall, these results underscore the central role of peer networks and farmers' perceptions of PPT's pest-control effectiveness particularly against stemborer and Striga weed as consistent and powerful drivers of adoption across all countries.

Fig. 8 shows the key predictors of PPT retention. In the pooled sample, receiving PPT training is most influential, followed by knowing other adopters, training frequency, and perceived effectiveness against Striga weed. Similarly, across countries, retention is primarily driven by knowing other PPT adopters and receiving PPT training, with perceptions of Striga and stemborer control (Kenya, Uganda, Tanzania) and land ownership in Rwanda providing additional influence. These findings indicate that social interaction variables particularly knowing other adopters combined with training and positive perceptions of pest control effectiveness are central to maintaining long-term PPT use.

4. Discussion

This section discusses the study results under two sections i.e., timing to adoption and dis-adoption and drivers of these transitions.

4.1. Timing to adoption and dis-adoption

The adoption patterns observed across countries indicate that many farmers take up PPT shortly after becoming aware of it, with some adopting within the same year they first learn about the practice. This is consistent with the steep initial decline in the adoption survival curve, reflecting rapid uptake during the first three years following awareness. The cumulative adoption plots display a classic S-shaped trajectory aligned with Rogers' Diffusion of Innovations theory (Rogers, 1983). Early flat segments correspond to innovators and early adopters, mid-curve steepening represents the early majority, and tapering slopes show the transition to the late majority. The absence of an asymptote in all countries indicates that PPT diffusion remains incomplete, echoing earlier findings from western Kenya where adoption had not plateaued (Murage et al., 2011). This suggests that PPT is still in a growth phase across East Africa, with considerable room for further scaling. The sharp decline in adoption rates after 2019 corresponds with COVID-19

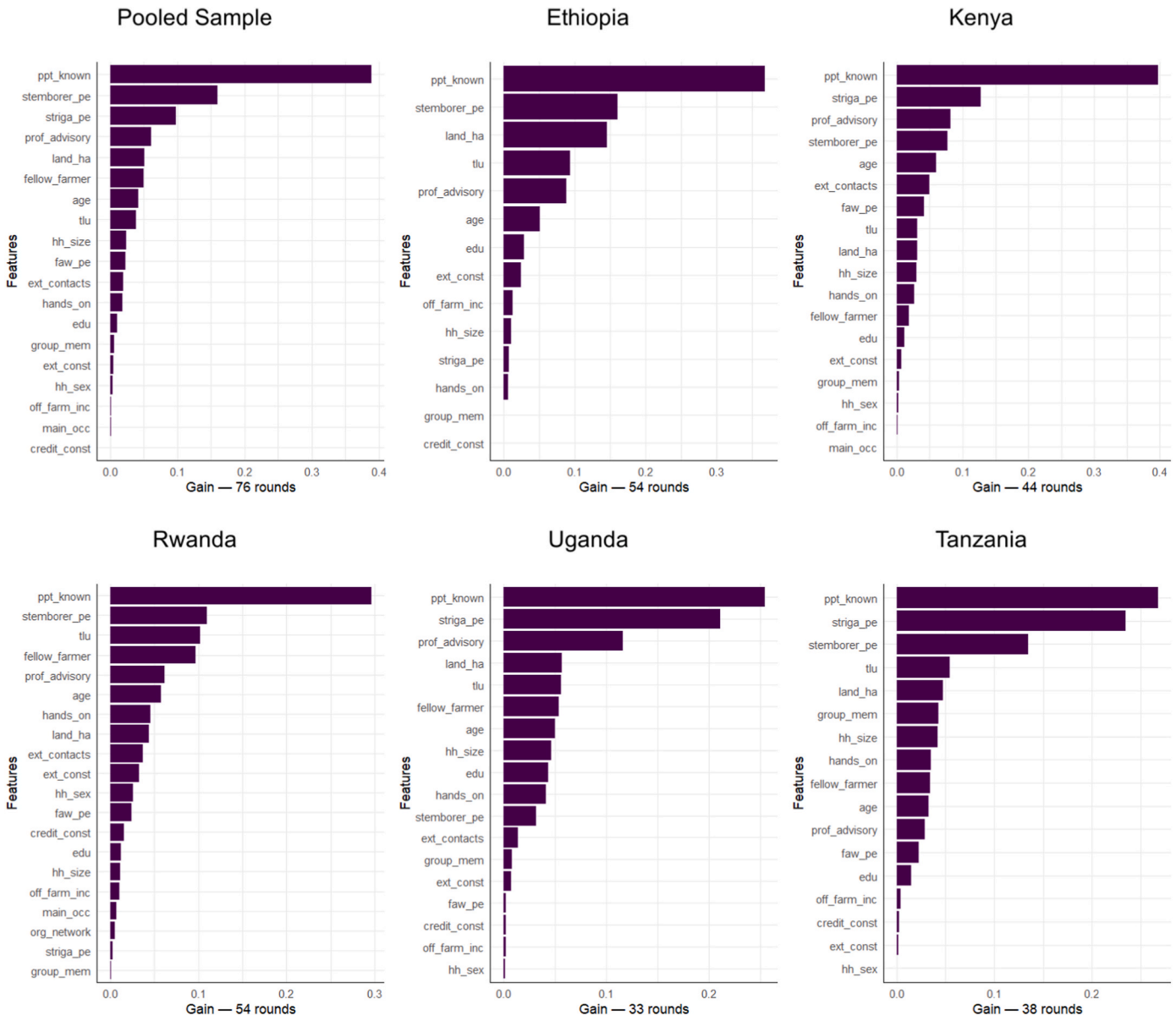


Fig. 7. XGBoost feature importance rankings for predictors of PPT adoption timing, by country. Bars indicate the relative contribution of each variable to predicting when farmers adopt PPT, based on survival-oriented gradient boosting models.

Note: Variable abbreviations are defined as follows: "ppt_known" number of PPT adopters a farmer knows, "stemborer_pe" perceived effectiveness of PPT against stemborer, "striga_pe" perceived effectiveness of PPT against Striga weed, "faw_pe" perceived effectiveness of PPT against fall armyworm, "prof_advisory" access to professional advisory services or information channels, "fellow_farmer" information received from fellow farmers, "group_mem" membership in a farmer group or cooperative, "ext_contacts" number of contacts with extension agents, "hands_on" participation in hands-on experiential learning or demonstrations, "edu" years of formal education of the household head, "age" age of the household head, "hh_size" household size, "hh_sex" gender of the household head, "main_occ" main occupation of the household head (agriculture vs. non-agriculture), "off_farm_inc" availability of off-farm income, "credit_const" credit constraint (difficulty accessing credit), "ext_const" extension constraint (limited access to extension services), "org_network" organized farmer network as information channels, "tlu" Tropical Livestock Units, "land_ha" land size in hectares.

disruptions, which limited extension access and impeded the delivery of essential inputs such as desmodium and Brachiaria seeds.

Dis-adoption dynamics closely mirror these patterns. The early segment of the dis-adoption survival curve shows a steep decline within the first three years after initial adoption, indicating that some farmers quickly abandon PPT shortly after adopting it. The surge in dis-adoption incidents after 2019 further aligns with pandemic-related constraints, which affected access to training, inputs, and follow-up support, factors also reported as drivers of non-adoption. The non-uniform decline in the dis-adoption survival curve suggests that exit hazards vary over time. Farmers face the highest risk of discontinuation in the early years, but the hazard decreases thereafter, stabilizing around the tenth year to reveal a core group of committed long-term adopters.

Collectively, these patterns confirm that PPT diffusion remains ongoing but not saturated, and that adoption and dis-adoption are dynamic, path-dependent processes shaped by evolving information access, institutional constraints, and farmers' early experiences with the technology (de Oca Munguia et al., 2021; Defrancesco et al., 2018; Ofori et al., 2020). The rapid uptake among some farmers, coupled with early abandonment among others, underscores the importance of sustained training, reliable input supply, and continuous extension engagement to support long-term utilization of PPT.

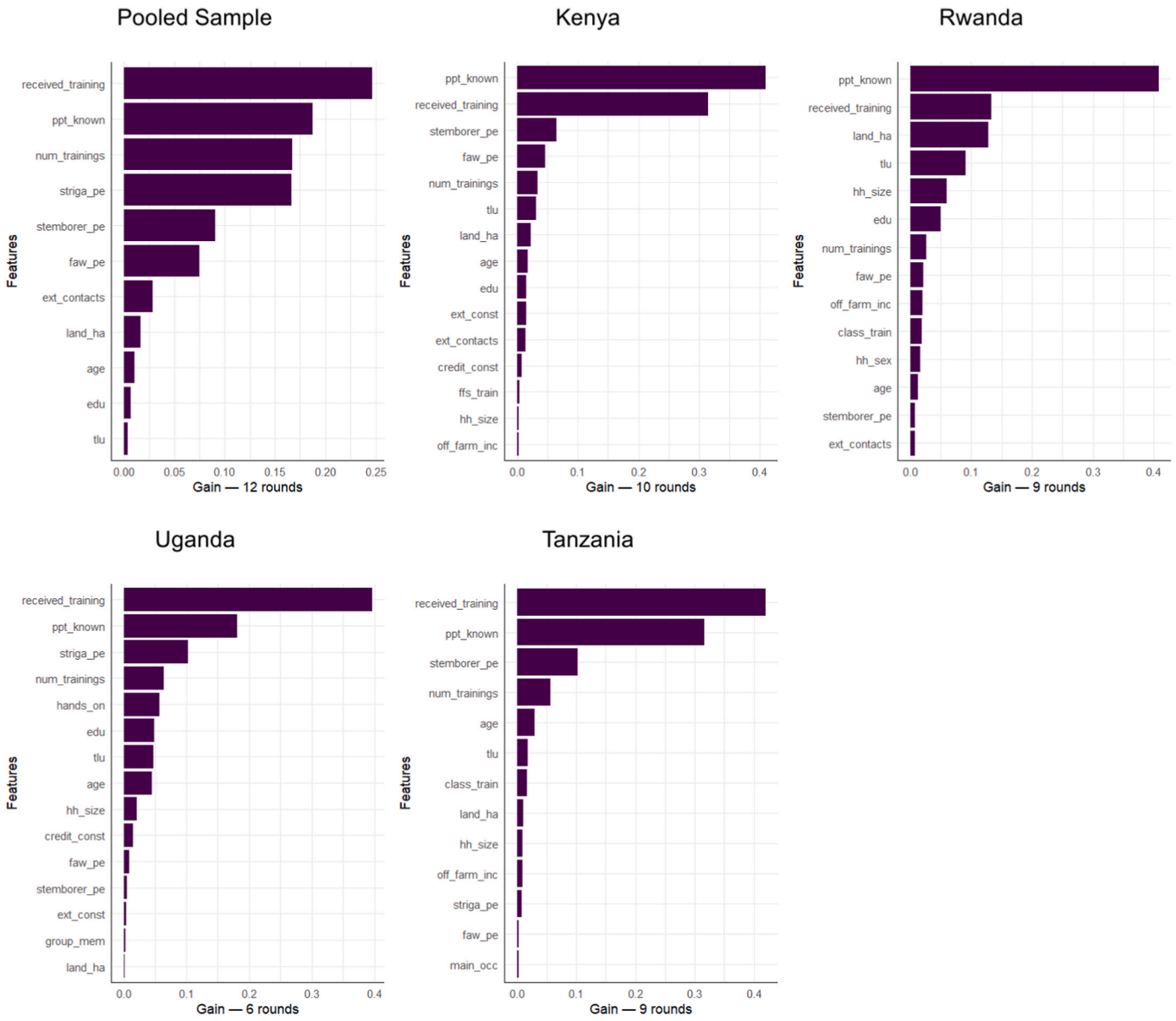


Fig. 8. XGBoost feature importance rankings for predictors of PPT dis-adoption timing, by country. Bars show the relative importance of variables driving when farmers stop using PPT, highlighting factors influencing long-term retention.

Note: Additional variable abbreviations appearing only in the dis-adoption models are defined as follows: "received_training" whether the farmer received PPT training, "num_trainings" total number of PPT training sessions attended, "class_train" participation in classroom-based training sessions, and "ffs_train" participation in farmer field school–type training.

4.2. Drivers of adoption and dis-adoption timing

The influence of household characteristics on PPT uptake and continuity reveals how gender roles, labor dynamics, and economic capacity shape farmers' decision-making processes. The comparatively faster uptake among women is consistent with earlier evidence from Murage et al. (Murage et al., 2019), who found that female farmers often respond more positively to PPT's perceived agronomic and livelihood benefits than men. Household size functions as both an enabler and a constraint. Although larger families can better meet PPT's initial labor demands for establishment and maintenance (Muriithi et al., 2018; Diiro et al., 2021), they may also experience resource pressures that can limit initial uptake, as observed by Niassy et al. (Niassy et al., 2020) in Rwanda. The role of economic capacity reflected in the influence of off-farm income and credit access underscores the importance of liquidity and risk-buffering mechanisms in supporting adoption, particularly for a technology requiring upfront labor and input investments. Finally, the negative effects of extension constraints reinforce the critical role of accessible and consistent technical support in managing a knowledge-intensive system such as PPT, where limited advisory services can deter both initial adoption and sustained use.

Perceived effectiveness emerges as a central driver of both the uptake and continued use of PPT, reinforcing long-standing evidence that farmers' evaluations of pest- and weed-control performance strongly shape technology adoption decisions. When farmers observe or believe that PPT effectively suppresses stemborer, Striga, or fall armyworm, they are more willing to invest the labor and management effort required for establishment and long-term maintenance. This pattern aligns with Rogers' Diffusion of Innovations theory (Rogers, 1983) and the Technology Acceptance Model (Davis, 1989), which both emphasize the importance of perceived benefits in driving adoption decisions. Similar relationships have been reported across diverse agricultural

technologies, where positive performance perceptions reduce uncertainty and facilitate early adoption (Sharifzadeh et al., 2017; Dong et al., 2022; Doanh et al., 2022; Liu et al., 2022). In the context of PPT, strong perceived benefits also help farmers persist despite labor demands, management challenges, or input constraints, consistent with findings by Misango et al. (Misango et al., 2022) and Waiswa et al. (Waiswa et al., 2025). These results underscore the importance of building and sustaining positive perceptions through evidence-based demonstrations, clear communication of pest-management outcomes, and structured farmer learning platforms to support both initial uptake and long-term retention.

Social interaction also plays a central role in shaping both the uptake and sustained use of PPT, reflecting its knowledge-intensive and management-sensitive nature. Farmer groups and cooperatives serve as important platforms for collective learning, trust-building, and problem-solving, consistent with evidence from Misango et al. (Misango et al., 2022), Muriithi et al. (Muriithi et al., 2018), and Niassy et al. (Niassy et al., 2020), and with broader social learning theory. Peer networks, in particular, function as powerful diffusion channels i.e., farmers who observe successful PPT implementation among their neighbors gain confidence in the technology, reduce uncertainty, and benefit from experiential knowledge that complements formal extension, a dynamic long recognized in agricultural innovation diffusion (Takahashi et al., 2019; Gross, 1943). Regular contact with extension services further reinforces these informal mechanisms by providing technical guidance and timely support, thereby strengthening farmers' commitment to PPT and reducing the likelihood of abandonment (Niassy et al., 2020; Gwada et al., 2019). Collectively, these interactions enhance decision-making efficiency, lower learning costs, and create an enabling environment where both adoption and long-term retention of PPT are more likely.

The strong influence of information sources on PPT uptake underscores the importance of credible, structured, and experiential communication channels in shaping farmers' decisions. Formal information pathways particularly hands-on demonstrations, field days, and farmer field schools equip farmers with practical knowledge and direct visual evidence of PPT's performance, thereby reducing uncertainty and enhancing perceived benefits in ways consistent with Rogers (1983)'s diffusion framework. These channels also provide more comprehensive and reliable guidance than informal peer exchange alone, a pattern similarly observed in earlier PPT studies where formal training and extension contact significantly increased adoption intensity and land allocation to PPT (Murage et al., 2011). Professional advisory services from extension agents, icipe staff, NGOs, and universities further strengthen farmers' confidence by offering technical support that complements experiential learning and helps overcome early management challenges (Chen et al., 2024a). Organized farmer networks likewise play an important role by institutionalizing information flow and creating collective learning environments that reinforce adoption decisions.

The influence of PPT training on farmers' long-term engagement highlights the importance of sustained, rather than one-off, capacity-building efforts. The finding that training intensity not mere exposure supports continued use aligns with earlier evidence that repeated technical reinforcement enhances farmers' confidence, skill mastery, and ability to manage complex agroecological practices (Mgendi et al., 2022; Liu et al., 2022). Technologies like PPT require accurate establishment of intercrops, timely management, and multi-season observation of benefits, making consistent follow-up training essential for preventing early abandonment. The limited effect of training mode further suggests that what matters most is not whether training is delivered through field days, farmer field schools, or other modes, but whether farmers receive continuous, hands-on engagement over time. These patterns reinforce the need for training programs that emphasize repetition, field-based learning, and ongoing technical support to build and sustain farmers' capacity to implement PPT effectively.

The spatial disparities in adoption and dis-adoption hazards underscore how national institutional environments, extension capacity, and historical exposure to PPT shape farmers' technology trajectories across East Africa. Differences between Kenya and Tanzania, for example, reflect earlier observations by Murage et al. (Murage et al., 2015b) that Kenya's stronger extension presence, broader experimentation platforms, and more active information-sharing networks created a more enabling environment for PPT uptake. Rwanda's relatively rapid adoption and lower exit risk are consistent with its intensive awareness campaigns, coordinated government-led input support, and strengthened extension services, including land use consolidation and subsidized inputs (Niassy et al., 2020; Hammond et al., 2020). In contrast, the higher exit hazards observed in Uganda and Tanzania likely signal structural challenges such as weaker follow-up support or irregular input supply that hinder sustained use even when initial adoption occurs. These patterns highlight the importance of context-specific institutional support and the need for differentiated diffusion strategies tailored to country conditions.

Finally, the convergence between the discrete-time hazard models and the XGBoost survival analysis provides strong cross-method validation of the core determinants of PPT adoption and retention. The consistently high concordance values for the adoption models demonstrate that machine-learning predictions align closely with the econometric findings, reinforcing the dominant role of peer networks, perceived pest-control effectiveness, and key information channels, patterns similarly emphasized in the feature-importance rankings. Although predictive performance was weaker for dis-adoption, likely reflecting smaller event counts, the machine-learning results still highlighted training frequency, social ties, and perceived pest suppression as central drivers of continued use, mirroring the hazard model outcomes. The agreement across these distinct analytical approaches strengthens confidence in the study's conclusions and aligns with the interpretive standards of survival analysis, where C-index values above 0.7 indicate strong discriminatory ability (Lee et al., 2024; Moncada-Torres et al., 2021). Overall, the cross-method consistency underscores the robustness of the identified behavioral, informational, and social mechanisms shaping PPT uptake and long-term retention.

5. Conclusions and policy recommendations

In this study, we investigate the dynamics of adopting and abandoning push-pull technology (PPT), a sustainable pest management approach targeting stemborer, fall armyworms, and striga weed. Using a panel dataset from household surveys conducted in 2021 and 2023 across Kenya, Uganda, Tanzania, Rwanda, and Ethiopia, we apply discrete-time proportional hazard models and Extreme Gradient Boosting for survival analysis, to estimate hazard functions for PPT adoption and dis-adoption. Key findings reveal that perceived PPT effectiveness, social interaction variables, information sources, training, and country-specific variables significantly influence adoption and dis-adoption decisions, while household level characteristics generally have a lesser impact.

Importantly, this study directly addresses the conceptual and methodological gaps outlined in the introduction. Prior adoption studies have emphasized the need to treat adoption as a dynamic, iterative process rather than a static, binary event, yet empirical evidence on timing and dis-adoption has remained limited. By applying duration-based methods to multi-country panel data, our analysis captures the temporal nature of both adoption and dis-adoption decisions, extending the insights of Murage et al. (Murage et al., 2011) beyond a single-country, cross-sectional design. The integration of XGBoost survival analysis further advances methodological rigor by revealing nonlinearities and complex interactions that traditional models often overlook. Our findings also refine theoretical expectations from Rogers' Diffusion of Innovations (Rogers, 1983) and the Technology Acceptance Model (Davis, 1989) by empirically demonstrating the dominant roles of perceived pest-control effectiveness and peer networks. Finally, by modeling dis-adoption

explicitly, the study contributes rare evidence on the determinants of sustained use, reinforcing the need for long-term support systems if PPT is to remain viable at scale. Drawing on these findings and contributions, we present a set of actionable recommendations designed to accelerate adoption and ensure the sustained use of PPT.

Farmers' social networks with existing PPT adopters were crucial for accelerating uptake and preventing dis-adoption. Therefore, prioritizing farmer-to-farmer exchange by resourcing community groups, supporting lead-farmer "champions", and fostering geographically visible adopter clusters to catalyze word-of-mouth learning and normalize PPT use could be a highly effective policy lever for both accelerating uptake and sustaining long-term use of PPT. Targeting these efforts in areas with sparse adopter networks could maximize impact, as peer learning, local proof, and social reinforcement have the potential to convert initial trials into sustained, long-term adoption.

Farmers' belief in PPT's effectiveness against stemborers, Striga, and fall armyworm emerged as a dominant behavioral driver often doubling or tripling adoption hazards while reducing the risk of dis-adoption. In addition, hands-on experiential information channels proved to be powerful catalysts of adoption across countries. Together, these findings indicate that scaling on-farm demonstrations and strengthening evidence-based extension to make pest-control benefits highly visible could substantially enhance both the uptake and sustained use of PPT.

Regular contact with extension agents was also crucial for accelerating uptake and delaying dis-adoption. Strengthening extension networks and embedding PPT support within routine advisory visits and scheduled follow-ups post initial adoption could therefore be key strategies for sustaining adoption across East Africa. Among information channels, interactive and formal information channels particularly hands-on experiential learning, professional advisory services, and organized farmer networks were the strongest drivers of rapid adoption, outperforming informal peer exchange by an order of magnitude. While attending any training was not enough to prevent dis-adoption, repeated training significantly lowered exit risk. Policies should therefore invest in high-quality, repeated, and interactive training programs and strengthen farmer networks to amplify both uptake speed and long-term retention of PPT. In countries with pronounced gender differences (notably Ethiopia and Rwanda), tailoring outreach to gender differences and engaging local female champions could accelerate adoption and reduce dis-adoption.

The country-level patterns observed in this study highlight significant contextual differences. Rwanda's relatively rapid adoption and lower exit hazard may reflect stronger extension systems or community-based diffusion mechanisms. Uganda's and Tanzania's higher exit hazards suggest structural or institutional challenges such as weaker follow-up support or inconsistent input supply that undermine long term use even after adoption. Tailored policy responses such as strengthening supply chains and extension in Uganda and Tanzania while sustaining Rwanda's enabling environment could be essential to improve regional diffusion and long-term use of PPT.

Collectively, these results highlight a practical roadmap for accelerating PPT scaling and ensuring sustained use across East African farming systems. Policies focused on adopter clustering, embedded extension, evidence-based demonstrations, repeated interactive training, gender-responsive outreach, and country-tailored initiatives can meaningfully enhance both uptake speed and long-term retention of PPT, strengthening sustainable pest management efforts across the region.

CRediT authorship contribution statement

Denis Waiswa: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Beatrice Wambui Muriithi:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Alice Warukira Murage:** Writing – review & editing, Validation, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Dave Mwangi Ireri:** Writing – review & editing, Validation, Investigation, Data curation, Conceptualization. **Fredah Maina:** Writing – review & editing, Validation, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Fahri Yavuz:** Writing – review & editing, Validation, Supervision, Conceptualization.

Funding

The authors gratefully acknowledge the financial support for this research by the European Union (EU) H2020-SFS-2018-2020/H2020-SFS-2019-2, Grant Number 861998.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors gratefully acknowledge the financial support for this research by the European Union (EU) H2020-SFS-2018-2020/H2020-SFS-2019-2, Grant Number 861998. We also acknowledge the country coordinators and partners Maseno University (MU, Kenya), Jomo Kenyatta University of Agriculture and Technology (JKUAT, Kenya), National Agricultural Research Organization (NARO, Uganda), Food for the Hungry International (FHI, Rwanda), Institute for Sustainable Development (ISD, Ethiopia), and Tanzanian Agricultural Research Institute (TARI, Tanzania) for facilitating data collection in the respective countries. ICIPE also acknowledges support from the Swedish International Development Cooperation Agency (Sida); the Swiss Agency for Development and Cooperation (SDC); the Australian Centre for International Agricultural Research (ACIAR); the Norwegian Agency for Development Cooperation (Norad); the German Federal Ministry for Economic Cooperation and Development (BMZ); and the Government of the Republic of Kenya. The views expressed herein do not necessarily reflect the official opinion of the donors.

Data availability

Data will be made available on request.

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