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Factors influencing the adoption and transfer mechanisms for conservation agriculture production systems from early adopters to laggards in Cambodia

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Adoption of conservation agriculture production systems (CAPS) requires changes in knowledge and resources that affect farmers' decision-making on agricultural practices, ultimately impacting production, family income, and food security. The effectiveness of CAPS promotion is influenced by demographic and socioeconomic characteristics, promotion mechanisms, agricultural information sources, and extension methods. This research explored the factors influencing the adoption and transfer mechanisms for CAPS and evaluated their impact from early adopters to laggards in Cambodia. A mixed-methods approach was employed and data were collected through face-to-face and in-depth interviews in Battambang and Preah Vihear provinces. The results indicated that the factors influencing the adoption and transfer included gender, age, field numbers related to farm size (i.e., farmers with more fields tended to have larger farm sizes), and off-farm income, all of which had a positive and significant effect. Early adopters improved productivity [95% confidence interval (CI): 0.87–0.92] and food security (95% CI: 0.86–0.92) by 4% compared to laggard farmers. However, there was no significant impact on family income between both groups. Several mechanisms for promoting CAPS including support, transfer, and adoption, required the engagement of relevant stakeholders such as the government, non-governmental organizations (NGOs), early adopter farmers, and laggard farmers. Farm-to-farmer initiatives were the most effective mechanism for transferring CAPS, followed by demonstration plots, farm or home visits, workshops or discussions, local agriculture fairs, and office calls. Relatives became the fundamental agricultural information sources, followed by mass media, research institutes, NGOs, the government, and personal experiences. The farm-to-farmer approach should be prioritized for CAPS outreach as farmers tend to trust information from their relatives. Future research should assess the sustained adoption of CAPS post-intervention, as outcome values are projected to increase by over 4%, potentially influencing household income.

KEYWORDS

adoption and transfer mechanisms, impact evaluation, agricultural extension methods, agricultural information sources, farmer-to-farmer, decision-making

1 Introduction

Conservation agriculture production systems (CAPS) is a package of practices that include mulching crop residues, minimizing soil disturbance, and intercropping or rotating crops with cover crops (Ward et al., 2018). The benefits of CAPS have increasingly contributed to problem-solving within sustainable agroecosystems (Akter et al., 2021). CAPS was primarily applied to large-scale or commercial farms in the U. S. (Thierfelder et al., 2013). In contrast, Wall (2007) emphasized that in developing countries, CAPS efforts were predominantly aimed at smallholder farmers and their management practices. Adoption of new technologies is valuable for future of smallholder farmers' livelihoods, food security, and ecological and crop productivity (Han and Niles, 2023). The agricultural extension system impacts technology adoption by influencing outcomes such as food security, family income, and crop productivity (Adams and Jumpah, 2021; Norton and Alwang, 2020). Adoption of CAPS by smallholder farmers have been slow, with a focus on factors such as productivity, risk preference, social capital, and farmer knowledge (Ng'ombe et al., 2017). In Cambodia, CAPS started in 2004, whereas this technology began in the U. S. in the 1960s. However, the CAPS adoption rate by Cambodian farmers has remained slow, with only about 0.12% of the total agricultural land area (approximately 6,099,100 ha) utilized for CAPS in 2021 (FAO et al., 2022; Men et al., 2024b).

A variety of information sources are available to support agriculture-related activities, which are essential for the development of small-scale farmers and the sustainability of livelihoods in both rural and urban areas (Adams and Jumpah, 2021; Kolapo et al., 2022; Kolapo and Kolapo, 2023; Mutyasira et al., 2018; Rastegari et al., 2023; Topp et al., 2023). Males are more likely to be impacted by adoption than females and farmers with larger farm sizes have more money and space for investment in a new technology (Sotamenou and Parrot, 2013; Valbuena et al., 2012). Farmers of larger farm sizes are more likely to adopt a new technology than small-scale farmers (Ngaiwi et al., 2023). Age and off-farm income also influence their perception of adoption and transfer (Foguesatto et al., 2020; Mutyasira et al., 2018). Smallholder farmers require knowledge support to make informed decision-making about adopting or rejecting new technologies. Technology information sources are potential key factors in adoption (Chalak et al., 2017). Studies have been limited in considering factors such as education level, marital status, soil fertility, primary crop production, type of main crops, distance to markets, and access to extension services. These factors can influence adoption of technologies including CAPS.

Various information sources are available for agriculture-related activities, upon which small-scale farmer development and people's ability to sustain their livelihoods in rural and urban areas depend (Achichi et al., 2023). Agricultural information sources including relatives (i.e., friends and neighbors), agricultural extension agents, agricultural literacy programs, agricultural product sellers, farmer service providers, non-governmental organizations (NGOs), personal experience, and media play a crucial role in influencing small-scale farmers' decision-making processes regarding adoption and transfer (Fidelugwuowo, 2021; Wale and Mkuna, 2023). Relatives are important information sources influencing adoption and transfer among smallholder farmers (Geleta et al., 2023; Yaseen et al., 2016). The main information sources influencing small farmers' decision-making include the internet, television, extension services, and family members. Farmers identified fellow farmers as their most important and least costly source of information for making decisions (Bjornlund et al., 2019; Drafor, 2016; Nesheim et al., 2017). One could experience the impact of technology adoption through learning from past experiences (Nickens et al., 2023). Agricultural technology transfer efforts aim to achieve adoption, which requires support from agricultural information sources to make extension methods effective.

Agricultural extension methods, including individual or interpersonal, group, and mass media approaches, are among the most effective means of disseminating agricultural technologies, influencing both information sharing and the adoption and transfer of innovations (Melaku et al., 2024; Takahashi et al., 2020; Tegene et al., 2023). Technology adoption and transfer methods include farmer-to-farmer (F2F) methods, demonstrations, farm or home visits, workshops or discussions, local agricultural fairs, and office calls (Chowdhury et al., 2014; Cooreman et al., 2021; Davis et al., 2012; Fisher et al., 2018; Kansanga et al., 2021; Khainga et al., 2021; Mwololo et al., 2019; Singh et al., 2018; Sousa et al., 2020; Thiombiano et al., 2023). F2F is defined as the voluntary delivery of training by farmers who provide technology to other farmers, which helps solve information access, issues and knowledge gaps that could prevent widespread adoption (Fisher et al., 2018). This method has proven valuable for adoption by smallholder farmers. Field days, demonstration plots, and agricultural fairs are effective and intended to persuade farmers to adopt (Sousa et al., 2020).

Technology adoption involves the change of knowledge and resources to improve family outcomes such as productivity, family income, and food security (Kuhl, 2020). Agricultural trials serve as venues for demonstrating and persuading farmers about new technologies (Hermans et al., 2023). The technology transfer process that involves the relationship between providers and users significantly affects adoption (Kuhl, 2020). Effective technology transfer requires understanding the connections between vulnerability, resilience, and adoption. Adoption is significantly linked to increased crop production but not to family income and food security in Mozambique (Nkala et al., 2011). In contrast, Tambo and Mockshell (2018) reported that adopting CAPS significantly enhances total family income in Sub-Saharan Africa, whereas Mideksa et al. (2023) found that adopting CAPS substantially increases food security in Eastern Ethiopia. The relevance of these regions to the present study stems from their comparable agricultural and socio-economic contexts to Cambodia, particularly with respect to smallholder farming systems, vulnerability to climate change, and dependence on subsistence agriculture. Despite these parallels, limited research has examined the factors influencing the impact of CAPS adoption and transfer on crop productivity, family income, and food security, as well as the mechanisms underlying adoption and transfer in the Cambodian context.

In Cambodia, intensifying land degradation and declining soil fertility are becoming more severe, adversely affecting crop productivity, household income, and food security. Although adopting CAPS has the potential to address these issues, the adoption rate among farmers remains slow. Literature indicates a limited focus on training mechanisms to facilitate CAPS adoption. Extension methods have also received limited attention in promoting CAPS from early adopter farmers (EAFs) to laggard farmers (LFs). Filling this knowledge gap could offer valuable information support to stakeholders—including the government, the private sector, NGOs, and farmers—through agricultural extension models and strategies for the adoption of CAPS, ultimately increasing crop production, family income, and food security. This research addresses the following research question (RQ):

> *RQ1:* What factors influence the adoption of CAPS among Cambodian farmers?
>
> *RQ2:* What is the impact of CAPS adoption on household outcomes such as productivity, income, and food security?

This research explored the factors influencing the adoption and transfer mechanisms for CAPS and evaluated their impact in Cambodia. The following section reviews the empirical framework used to assess the current state of CAPS adoption and transfer through the agricultural extension model.

2 Empirical framework

2.1 Literature background and model choice

Adoption is a broad term designed to increase agricultural efficiency (Belay et al., 2023). Agricultural technology adoption refers to the outcome, widely recognized as a key element of sociotechnical change (Kuhl, 2020). Adoption can be identified as changes in farmers' agricultural practices including changes in production costs and crop management (Kuhl, 2020). Adoption theory demonstrates that farmers' source allocation decisions regarding agricultural techniques are subject to adopting agricultural technologies that maximize the projected utility of money and food security (Maina et al., 2020). The literature review identified several key barriers to the adoption of agricultural technologies in developing countries. These include a lack of agricultural credit support, which limits farmers' investment capacity (Balana and Oyeyemi, 2022); limited access to technical knowledge and market information, which hampers informed decision-making; poor rural infrastructure, such as inadequate roads and storage facilities, which restricts input delivery (Magesa et al., 2020) and market access; and an insufficient supply of agricultural inputs, which delays or prevents adoption (Berha, 2022; Ngango and Hong, 2021; Zeweld et al., 2015).

Cambodian farmers employ various strategies to adopt CAPS, with small-scale farmers in this study anticipating benefits such as increased productivity, family income, and food security (Sardar et al., 2021). Farmers embrace new agricultural practices and technology when the expected usefulness or benefits associated with adoption (e.g., CAPS) outweigh those associated with non-adoption (non-CAPS) (Belay et al., 2023; Ngango and Hong, 2021; Nyirahabimana et al., 2021).

2.2 Conceptual framework and variables

The concept of technology adoption and transfer involves three stages: (1) technologies that support adoption, (2) mechanisms for transferring technologies that can meet diverse farmers' needs, and (3) strategies to overcome barriers to adoption (Ngango and Hong, 2021). This perspective aligns with Rogers' (1962) Diffusion of Innovations theory, which remains a cornerstone in adoption studies (Miller, 2015). These are influenced by sustained adoption. The path to resilience includes improving techniques to increase staple crop productivity, introducing high-value crops, and connecting farmers to markets. These measures can improve productivity, enhance food security, and increase family income (Ngango and Hong, 2021).

The dependent variable is binary, where 1 indicates that the farmer has attended CAPS training (EAFs), and 0 indicates otherwise (LFs). CAPS adoption may directly impact the outcome variable, which is an independent variable (i.e., age, gender, marital status, education level, field numbers related to farm size, soil fertility, types of main crops, distance to markets, distance to extension offices, and off-farm income), as shown by estimation. Multicollinearity among the independent variables was assessed using Variance Inflation Factors and tolerance values, which are commonly applied diagnostics in regression analysis. In this study, the majority of the variables did not exhibit multicollinearity.

This method may result in inconsistent estimations since it assumes that exogenous factors have little effect on the uptake of CAPS. LFs can increase agricultural production, family income, and food security by adopting and implementing CAPS. Recent studies have shown that increasing agricultural productivity can increase farmers' wellbeing by increasing household income and ensuring access to food security (Ogunyiola et al., 2022). If farmers decide whether to adopt CAPS, it may affect productivity, family income, and food security.

2.3 Empirical strategy and analytical techniques

2.3.1 Model specification and variable selection

Agricultural technology adoption is a decision-making process in which a unit develops an attitude toward employing an innovative approach and decides whether to accept or reject it (Akter et al., 2021). Farmers either adopt (EAFs) or do not adopt (LFs) CAPS, which is measured by a dichotomous variable: 1 for EAFs and 0 for LFs. This empirical study looks at how CAPS impacts changes in farmers' means of subsistence. This research recorded changes in productivity, family income, and food security as the key livelihood outcome of interest, with a binary decision choice (1 = improved and 0 = otherwise).

The probit or logit model is recommended when the outcome variable is binary or dichotomous (1 or 0) (Breen et al., 2018), whereas the linear regression model has been applied for both binary outcomes (Chatla and Shmueli, 2017) and continuous outcomes (i.e., numerical measurements; Srimaneekarn et al., 2022). Moreover, the probit model is grounded in the multivariate normal distribution, permitting nonzero covariance terms, whereas the logit model is based on the univariate independent extreme value distribution (Hausman and Wise, 1978). The goodness-of-fit test is valuable for the selection of the most adequate model (Andersen, 1973). The model fit test evaluates how effectively the model aligns with the data. Model fit and predictive performance after cross-validation were quantified using Akaike's Information Criterion (*AIC*), Bayesian Information Criterion (*BIC*), and the nonlinear determination coefficient (Pseudo-R^2), which were also used as metrics for model selection (Aertsen et al., 2010; Bozdogan, 1987; Schwamborn et al., 2019; Thomas et al., 2018; Vrieze, 2012). A lower *AIC* or *BIC* value signifies a more favorable model (Vieira et al., 2023; Vrieze, 2012; Wu et al., 2020). In linear regression, the coefficient of determination (R^2) ranges from 0 to 1, with higher values indicating a better model fit; however, it does not apply to binary outcome models such as probit or logit. Instead, the pseudo-R^2 measure is used to assess model fit. Instead, pseudo-R^2 measures are used to evaluate model fit, with values between 0.2 and 0.4 generally considered to indicate a strong fit (McFadden, 1974), while values between 0.1 and 0.3 are generally considered acceptable (Hemmert et al., 2018).

Several types of models with binary choice-dependent variables have been commonly utilized to determine technology adoption including linear probability, logistic (logit, multinomial logit), and normal density functions (D'Souza and Mishra, 2018; Ngango and Hong, 2021; Ward et al., 2018; Wordofa et al., 2021). Probit analysis was conducted in this research because the dependent variable was a dummy variable, which is a popular choice for such analyses (Adams and Jumpah, 2021; Li et al., 2020). The propensity score matching (PSM) framework follows semiparametric estimation techniques to reduce selection bias, as demonstrated by Nkala et al. (2011) and Belay et al. (2023). This technique considers the probability that EAFs and LFs may have systematic differences in traits that make them difficult to compare. D'Agostino (1998) reported that the treatment and control groups were randomly allocated via PSM, suggesting that both groups had an equal probability of being assigned to either the treatment or the control. Farmers often adopt a technology if the benefits outweigh the benefits of not doing so (Equation 1):

$$Adoption\left(D^*\right) = U_{i(EAFs)} - U_{i(LFs)} > 0 \tag{1}$$

where $U_{i(EAFs)}$ is the value of farmer *i* as a result of participation in CAPS training (EAFs), $U_{i(LFs)}$ is a variable of non-CAPS training (FLs), and D^* is a binary variable (1 = EAFs and 0 = LFs). Adoption (*D*), a condensed version of the adoption decision, is the first barrier in Equation 2.

$$Adoption\left(D_i^*\right) = \beta Z_i + \varepsilon_i \ with\ D = 1\ if\ D^* > 0, D_i = 0\ otherwise \tag{2}$$

where Z_i is a matrix of family features; the β parameter needs to be estimated and ε_i is the usual term of error. Theoretically, the expansion of agricultural productivity is anticipated to be significantly affected by CAPS adoption (Ngango and Hong, 2021). Therefore, in evaluating this connection, we presumptively consider the result variable in Equation 3:

$$Y_i = \alpha X_i + \delta D_i + \mu_i \tag{3}$$

To evaluate this connection, the outcome variables (i.e., productivity, family income, and food security) are modeled as linear functions of CAPS adoption (represented by the dummy variable D_i), where X_i denotes the independent variables and μ_i is the error term, as specified in Equation 3. The outcome variables include: (1) productivity, measured as the yield of the main crop in tons per hectare; (2) family income, defined as the total amount of money received by farmers from their main crop production, expressed in U. S. dollars; and (3) food security, which refers to the consistent access of farming families to sufficient, safe, and nutritious food for a healthy and active life. These variables were based on farmers' perceptions of whether each aspect improved as a result of practicing CAPS.

2.3.2 Estimation of propensity score (probit regression model)

A probit regression model was used to explore the factors influencing farmers to adopt or not adopt CAPS. A binary logit or probit model is employed to compare the effects of the intervention between the treatment and control groups and to determine differences in the outcome of interest. In previous studies, the effect of explanatory variables must be taken into account only when the probit model, which is consistent throughout different expected values of the dependent variable, is used and constrains the estimated probabilities to model dichotomous or binary outcome variables in the range of 0 to 1. Equation 4 assumes that *Y* can be described as follows:

$$Y_j = \alpha + \beta_j \sum_{i=1}^{n} Ij + \mu j \tag{4}$$

where Y_j is a dependent variable that is binary to the farmer, who decides a value of 1 if the farmer has attended CAPS training (EAFs), and 0 refers to non-CAPS (LFs). Parameters of the estimate include α and β. The number of variables is *n*, while μj is the error term, and I_j is the explanatory variable.

$$P_i = \alpha_0 + \beta_1 gen + \beta_2 age + \beta_3 mars + \ldots + \beta_{12} offai + \varepsilon_i \tag{5}$$

where in Equation 5:

- P_i is the probability of participating in CAPS training or EAFs
- α_0 is the intercept
- ε_i = Error term
- $\beta_1 \ldots \beta_{12}$ = are the coefficients of explanatory variables
- X_1 = Gender (gen)
- X_2 = Age (age)
- X_3 = Marital status (mars)
- X_4 = Education level (edul)
- X_5 = Field numbers (fien)
- X_6 = Soil fertility (soilf)
- X_7 = Rice is the main crop (ricemc)
- X_8 = Cassava is the main crop (cassavamc)
- X_9 = Maize is the main crop (maizemc)
- X_{10} = Distance to markets (distm)
- X_{11} = Distance to the extension office (disteo)
- X_{12} = Off-farm income (offai)

2.3.3 Matching technique and treatment effect estimation (NNM, KBM, CM)

Propensity score matching (PSM) was employed to evaluate the impact of CAPS adoption between the EAF and LF groups. PSM methods could differ qualitatively from the treatment group in terms of unmeasured variables. Several previous studies have used PSM for adoption or impact evaluation, i.e., Nkala et al. (2011), Nkhoma et al. (2017), and Tambo and Mockshell (2018). This research focused on three dependent variables or outcome variables: productivity, family income, and food security. Age, gender, marital status, field numbers, education level, soil fertility, types of main crops (i.e., rice, cassava, and maize), distance to markets, distance to the extension office, and off-farm income are independent variables or explanatory variables. A probit model is used to estimate PSM for CAPS adoption. Numerous literature reviews show similar match methods of PSM for the adopter and non-adopter respondents. Becerril and Abdulai (2010), Cariappa et al. (2021), and Ramappa et al. (2022) reported that the most commonly used approaches are Nearest Neighbor Matching (*NNM*), Kernel-Based Matching (*KBM*), and Caliper Matching (*CM*) methods. Similarly, three matching methods were subsequently used to calculate the average treatment effect on the treated *(ATT)* of a certain program used to match the treatment and comparison groups: *NNM*, *KBM*, and *CM* (Ngango and Hong, 2021). The formulation of PSM Equation 6 is as follows:

$$ATT = E\left(y_{d=1} | d = 1, p\left(X\right)\right) - E\left(y_{d=0} | d = 0, p\left(X\right)\right) \qquad (6)$$

ATT is among the subsample of EAFs, whereas $yd = 0|d = 0$ is the change observed in the $yd = 1|d = 1$ is the reported shift in livelihood results seen in LFs. PSM, or $p(X)$, is the chance of being in LF groups under certain conditions, as defined by X. The PSM technique avoids the difficulty of dimensionality-creating covariate matching issues, particularly when matching several variables. As a result, PSM includes a several-step process, which is involved in conducting PSM to evaluate the impact of CAPS adoption, as outlined by Salam and Sarker (2023); Staffa and Zurakowski (2018); and Haile et al. (2024).

According to Figure 1, PSM was conducted through a multi-step process including selecting covariate, selecting a model for estimating PSM, selecting matching methods, checking for matching, evaluating outcome variables, computing PSM, and conducting impact evaluation. This study was conducted with EAFs and LFs, using a probit regression model to estimate the propensity score $[p(X)]$—the probability that a household belongs to the EAFs group. A group of factors thought to impact the decision to use CAPS is contained in vector X. The matching stage of EAFs and FLs was conducted via *NNM, KBM*, and *CM*. This study was conducted with the common support of an unadjusted sample between the two groups (EAFs and FLs). A balancing check was performed to assess the matching quality, followed by an effect analysis. A mean comparison between the EAFs and FLs groups, both before and after matching, was conducted using an independent two-sample *t*-test. *ATT* was computed and an impact evaluation was carried out to assess the outcome variables of this study including productivity, family income, and food security.

3 Methodology

3.1 Study areas and sample size

This study employed a mixed-methods approach, integrating qualitative and quantitative methods. By utilizing multiple data collection techniques, a triangulation protocol was implemented to cross-check findings and ensure the validity and quality of the research (Figure 2) (Amadi, 2023). Data were gathered from Battambang (BTB) and Preah Vihear (PHV) provinces in Cambodia. The implementation of the MetKasekor (MK) Agricultural Extension Model project started in 2021 to promote CAPS in Cambodia. The number of participants who attended the CAPS fields showcase or EAFs was 270 households: 180 households from the BTB, and 90 households from the PHV. The data used in this research were

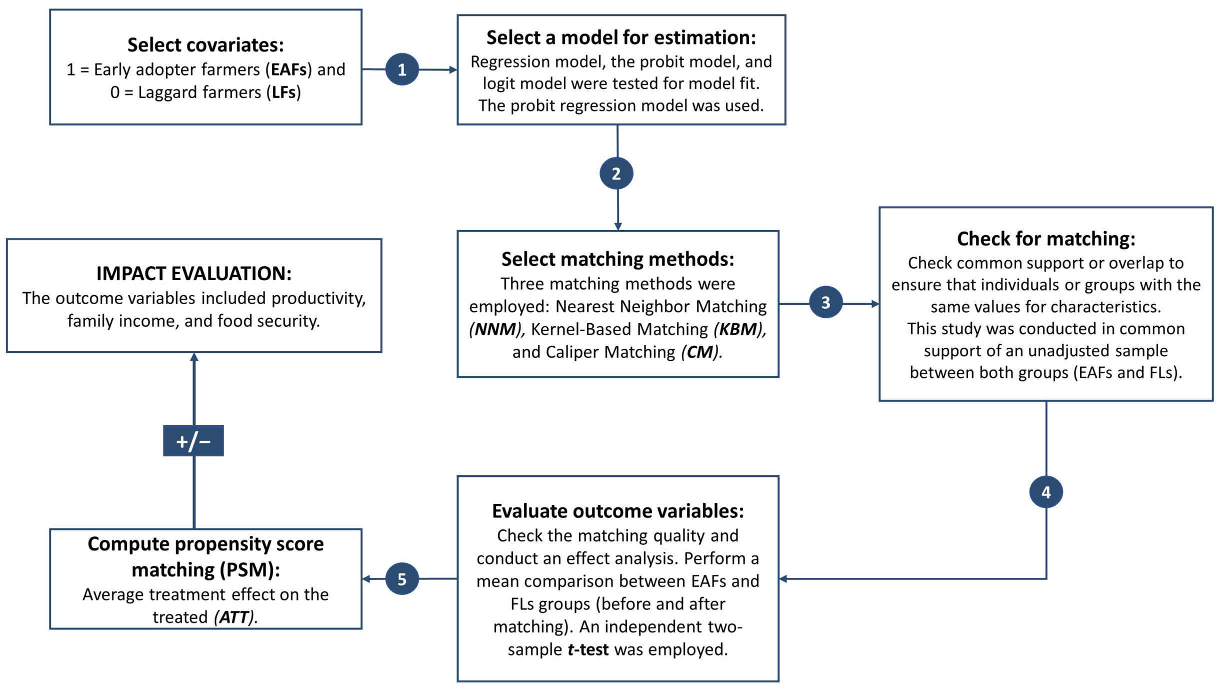

FIGURE 1
The process of conducting propensity score matching to evaluate outcome variables.

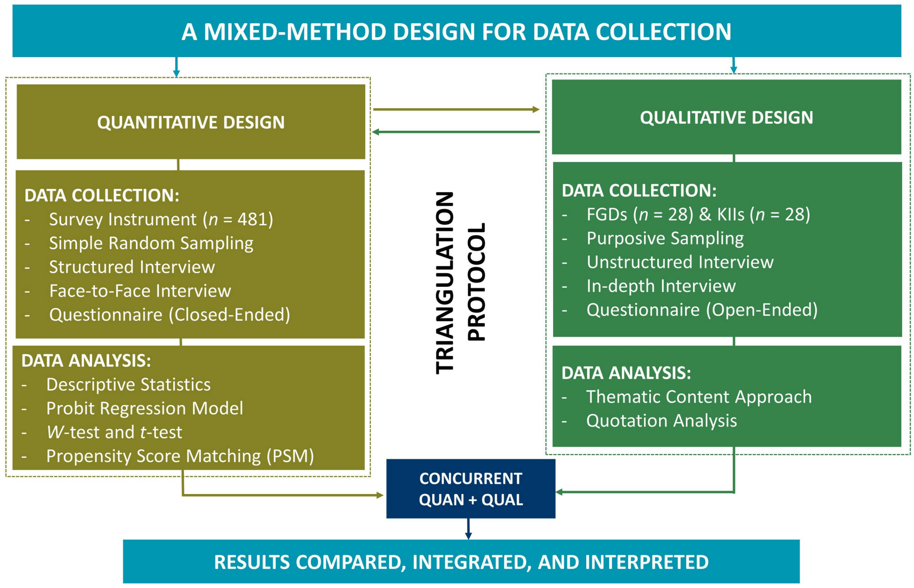

FIGURE 2
Triangulation protocol of research validation for mixed method design. QUAN, Quantitative Approach; QUAL, Qualitative Approach; *n*, Number of observations.

obtained via face-to-face interviews conducted in 2023. In the BTB, only three districts (Rathanak Modul, Banan, and Sangkea) out of the total 13 were selected as the sample. In PHV province, among the eight districts, only one district (Rovieng) was chosen. Detailed information on the farmers who attended or did not attend the CAPS field showcase was collected via a field survey. A total of 481 sample observations were selected for an interview: 242 from EAFs and 239 from LFs, chosen randomly assignment. The response rate of the EAFs was 89.63%.

3.2 Sampling technique and data collection

3.2.1 Survey instrument

This sample is a completed survey instrument of EAFs who attended the CAPS training field showcase in 2021, with 242 observations from the recode list of the randomly selected MK model project. LFs referred to farmers out of the MK model project. The details of the MK model project are described in Men et al. (2024b). The sample size of LFs (239 observations) was assumed to be equal to that of EAFs. Before data collection, a pretest was developed to verify the legitimacy of the survey with 10 respondents. The sample of pretest respondents was not included in the data collection by the survey instrument. Survey instrument was improved and finalized after the pretest. The questions concerning the characteristics of households, farmers' perceptions, agricultural extension methods, and information sources were revised following the pretest section.

3.2.2 Focus group discussions and key informant interviews

Focus group discussions (FGDs) and key informant interviews (KIIs) provided qualitative data. Both methods examine the CAPS adoption and transfer mechanism in the agricultural extension model from EAFs to LFs and discuss information on agricultural sources. KII supplemented the qualitative findings of this research (10 government, six private sectors, eight farmers, and four NGOs). The number of participants in the FGD was equal to that in the KII. The sample size was selected by purposive sampling. An open-ended questionnaire was used to collect the data. The questions included agricultural information sources, agricultural extension methods, and technology transfer mechanisms from EAFs to LFs. Details of KII are described in Men et al. (2024b); and FGD methods are descibred in Men et al. (2024a). Two specific questions related to the research objective were added: What mechanisms are in place to encourage early adopter farmers involved in the CAPS to transfer technology to laggard farmers in the region? Which agricultural extension methods and technology transfer approaches are most suitable for laggard farmers to adopt CAPS?

3.2.3 Statistical analyses

The statistical analysis was performed via the R program (version R 4.3.2) to process the acquired data via descriptive statistical techniques such as frequencies, means, standard deviations, and standard errors. Farmers' characteristics were computed with an independent two-sample *t*-test. *AIC*, *BIC*, and Pseudo-R^2 were used to assess the goodness-of-fit to select the model fit. Factors influencing CAPS adoption and transfer were analyzed using quantitative data through a probit regression model and marginal effects. The impact of CAPS adoption was evaluated using propensity score matching. Consistent with previous studies, a 5-point Likert scale was employed by Azumah et al. (2018) with 1 = strongly disagree, 2 = disagree, 3 = moderate, 4 = agree, and 5 = strongly agree. This Likert scale was used to rank agricultural extension methods and information sources for promoting CAPS among laggard farmers. Kendall's *W*-test was used to identify the priority of agricultural extension methods and information sources for promoting CAPS. The qualitative data were distilled and placed into text, and thematic content methodologies were used to examine the quantitative data from the household surveys. The CAPS adoption and transfer mechanisms in the agricultural extension model were drawn from qualitative data.

4 Results

4.1 Summary statistics of farmer characteristics for promoting CAPS

Descriptive statistics of characteristics of EAFs and LFs regarding the adoption and transfer of CAPS are presented. Outcome variables included productivity, family income, and food security. Explanatory variables comprised of household demographic characteristics: such as gender, age, marital status, education level, and socioeconomic characteristics, including field numbers, soil fertility, type of main crops, off-farm income, distance to the extension office, and distance to markets (Table 1).

The outcome variables from an independent two-sample *t*-test revealed that the average productivity and food security of EAFs and LFs were significantly different ($p < 0.10$; $p < 0.05$, respectively), whereas family income was not significantly different between the two groups ($p \geq 0.10$) (Table 1). The explanatory variables revealed that gender, age, and field numbers were significant between EAFs and LFs ($p < 0.01$). Off-farm income was significantly impacted ($p < 0.10$). However, education level, marital status, type of main crops, distance to markets, and distance to the extension office were nonsignificant between the EAF and LF groups ($p \geq 0.10$).

4.2 Factors influencing the adoption and transfer of CAPS

The estimated coefficients of probit model represent the change in the latent variable (unobserved underlying tendency) associated with a one-unit change in the independent variable, while marginal effects quantify how this change impacts the probability of the dependent variable equaling 1. The model goodness-of-fit indicated that the probit model ($AIC = 649.35$, $BIC = 703.64$, pseudo-$R^2 = 0.12$) was a better fit than the logit model ($AIC = 649.63$, $BIC = 703.92$, pseudo-$R^2 = 0.11$) and regression model ($AIC = 683.10$, $BIC = 741.57$, $R^2 = 0.09$) (Table 2). The explanatory variables were statistically significant (log-likelihood = −311.67, likelihood ratio test = 10.80,

TABLE 1 Differences in the characteristics of early adopters and laggard farmers for promoting CAPS.

Variables	Description	EAFs (n = 242)		LFs (n = 239)		Difference mean	*t*-test (*p*-value)
		$\bar{x}$	*SD*	$\bar{x}$	*SD*		
Outcome variables							
Productivity	1 = if improved	0.92	0.28	0.87	0.34	0.05	0.09*
Family income	1 = if improved	0.91	0.29	0.87	0.34	0.04	0.17^{ns}
Food security	1 = if improved	0.92	0.28	0.86	0.35	0.06	0.03**
Explanatory variables							
Demographic characteristics							
Gender	1 = if male	0.53	0.50	0.38	0.49	0.15	0.00***
Age	Age of household (years old)	49.64	12.11	44.97	13.86	4.67	0.00***
Marital status	1 = if single	1.26	0.82	1.26	0.79	0.00	0.91^{ns}
Education level	Formal grade of education	2.40	0.85	2.49	0.93	−0.09	0.27^{ns}
Socioeconomic characteristics							
Field numbers	Number of field (s)	2.42	1.41	2.08	0.95	0.34	0.00***
Soil fertility	1 = if good	0.63	0.49	0.64	0.48	−0.01	0.78^{ns}
Main crops	Type of main crops						
Rice	1 = if rice is the main crop	0.21	0.41	0.22	0.41	−0.01	0.50^{ns}
Cassava	1 = if cassava is the main crop	0.09	0.29	0.10	0.30	−0.01	0.77^{ns}
Maize	1 = if maize is the main crop	0.01	0.09	0.02	0.13	−0.01	0.72^{ns}
Distance to markets	Distance to the nearest markets (km)	17.83	10.47	18.75	10.22	−0.92	0.33^{ns}
Distance to the extension office	Distance to the extension office (km)	17.70	10.40	18.68	10.23	−0.98	0.30^{ns}
Off-farm income	1 = if the farmer has	0.70	0.46	0.62	0.49	0.08	0.05*

*, **, and *** Indicate significance at 10% ($p < 0.10$), 5% ($p < 0.05$), and 1% ($p < 0.01$) levels, respectively; *SD*, Standard deviation; ns, Not significant ($p \geq 0.10$); *n*, Number of observations; EAFs, Early adopter farmers, LFs, Laggard farmers.

$p < 0.01$) (Table 3). The estimated coefficients and marginal effects of the probit model suggest that four variables were statistically significant at the 5% ($p < 0.05$) and 1% ($p < 0.01$) levels in influencing the probability of the CAPS adoption and transfer. This research revealed that the positive factors influencing the adoption and transfer of CAPS include gender, age, field numbers, and off-farm income (Table 3).

Gender was positively and significantly associated with the likelihood of adopting and transferring CAPS ($p < 0.05$). Male farmers were more likely than female farmers to adopt and transfer CAPS, holding other factors constant. The marginal effect of gender indicated that being a male farmer increased the probability of by 11% compared to being a female farmer. Age was also positively and significantly associated with an increased likelihood of CAPS adoption and transfer ($p < 0.01$). The marginal effect of farmers' age showed that each additional year increased the probability of the CAPS adoption and transfer by 1%. The field numbers by farmers had a positive and significant effect on the likelihood of the CAPS adoption and transfer ($p < 0.01$). The marginal impact suggested that farmers with more fields were 6% more likely to adopt and transfer CAPS than those with fewer fields. Off-farm income was positively and significantly associated with an increased likelihood of adoption and transfer ($p < 0.01$). The marginal effect revealed that farmers with off-farm income were 13% more likely to adopt CAPS.

4.3 Impact evaluation for CAPS adoption

PSM was used to evaluate how CAPS impacted livelihood outcome changes, including improved productivity, family income, and food security resulting from CAPS adoption. Matching methods, including *NNM*, *KBM*, and *CM,* were used to generate sample EAF and LF groups. *ATT* estimation for all three matching algorithms illustrates the impact of adopting CAPS on productivity, family income, and food security. PSM and regional support for two groups, the treatment group or EAFs and the control group or LFs, are displayed in Figure 3. Common support refers to the overlap in propensity score distributions between the treatment and control groups and is typically assessed through visual inspection (Figure 3). This overlap ensures group comparability. Additionally, the propensity scores should exhibit similar distributions to achieve covariate balance (Garrido et al., 2014; Staffa and Zurakowski, 2018). Common support illustrated that before matching (unadjusted sample), there was a significant difference in the probability of propensity values between EAFs and LFs, which could lead to biased estimation results (Figure 3). Conversely, after matching (adjusted sample), the two groups' probability distribution values were very similar, demonstrating an effective matching process and a successful common support test.

CAPS adoption increased productivity in the treatment group by 430 compared with 52 in the control group, family income by 428 versus

TABLE 2 Selection of the model goodness-of-fit for regression, probit, and logit models in propensity score matching.

Explanatory variables	Model 1			Model 2			Model 3		
	Coefficient	*SE*	*p*-value	Coefficient	*SE*	*p*-value	Coefficient	*SE*	*p*-value
Gender	0.11**	0.05	0.02	0.30**	0.13	0.02	0.49**	0.21	0.02
Age	0.01***	0.00	0.00	0.02***	0.00	0.00	0.03***	0.01	0.00
Marital status	−0.01	0.03	0.72	−0.03	0.08	0.71	−0.05	0.12	0.70
Education level	−0.02	0.03	0.57	−0.04	0.07	0.59	−0.07	0.12	0.58
Field numbers	0.06***	0.02	0.00	0.17***	0.05	0.00	0.27***	0.09	0.00
Soil fertility	−0.01	0.05	0.79	−0.03	0.12	0.80	−0.05	0.20	0.79
Rice is the main crop	0.04	0.10	0.66	0.10	0.25	0.68	0.17	0.41	0.69
Cassava is the main crop	0.05	0.10	0.64	0.12	0.27	0.64	0.19	0.44	0.66
Maize is the main crop	0.05	0.12	0.65	0.14	0.31	0.66	0.22	0.50	0.67
Distance to markets	−0.00	0.01	0.87	−0.00	0.04	0.88	−0.00	0.06	0.89
Distance to the extension office	−0.00	0.01	0.96	−0.00	0.04	0.93	−0.00	0.06	0.95
Off-farm income	0.13***	0.05	0.00	0.36***	0.13	0.00	0.58***	0.21	0.00
Constant	− 0.03	0.19	0.88	− 1.44***	0.50	0.00	− 2.32***	0.82	0.00
Number of observations (*n*)	481			481			481		
R^2	0.09								
AIC	683.1			649.35			649.63		
BIC	741.57			703.64			703.92		
Pseudo-R^2				0.12			0.11		

R^2, Coefficient of determination; *AIC*, Akaike information coefficient; *BIC*, Bayesian information criterion; Pseudo-R^2 = Nonlinear determinative coefficient; Model 1 = Regression model; Model 2 = Probit model; Model 3 = Logit model; ** and *** Indicate significance at 5% ($p < 0.05$) and 1% ($p < 0.01$) levels, respectively; SE, Standard error.

TABLE 3 Estimated factors influencing adoption and transfer among early adopter farmers for promoting CAPS.

Explanatory variables	Coefficient of variation				Marginal effects			
	Coefficient	*SE*	*z* values	*p*-value	Coefficient	*SE*	*z* values	*p*-value
Gender	0.30**	0.13	2.32	0.02	0.11**	0.05	2.36	0.02
Age	0.02***	0.00	3.47	0.00	0.01***	0.00	3.61	0.00
Marital status	−0.03	0.08	−0.37	0.71	−0.01	0.03	−0.37	0.72
Education level	−0.04	0.07	−0.54	0.59	−0.02	0.03	−0.55	0.57
Field numbers	0.17***	0.05	3.19	0.00	0.06***	0.02	3.30	0.00
Soil fertility	−0.03	0.12	−0.25	0.80	−0.01	0.05	−0.25	0.79
Rice is the main crop	0.10	0.25	0.41	0.68	0.04	0.09	0.41	0.66
Cassava is the main crop	0.12	0.27	0.46	0.64	0.05	0.10	0.46	0.64
Maize is the main crop	0.14	0.31	0.44	0.66	0.05	0.12	0.44	0.65
Distance to markets	−0.00	0.04	−0.14	0.88	−0.00	0.01	−0.14	0.87
Distance to the extension office	−0.00	0.04	−0.08	0.93	−0.00	0.01	−0.08	0.96
Off-farm income	0.36***	0.13	2.76	0.00	0.13***	0.05	2.83	0.00
Constant	−1.44***	0.50	−2.87	0.00				
Log-likelihood	−311.67							
Likelihood ratio test: χ^2 (13)	10.80							
Number of observations (*n*)	481							

** and ***Indicate significance at 5% ($p < 0.05$) and 1% ($p < 0.01$) levels, respectively; *SE*, Standard error.

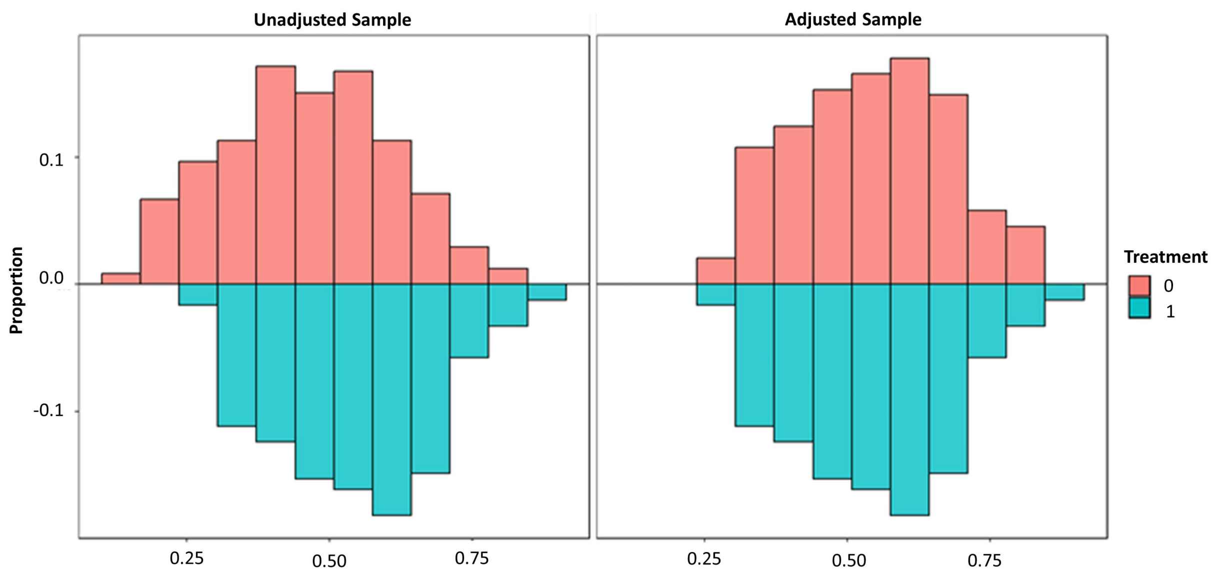

FIGURE 3
Displays of the propensity score distribution and common support of the unadjusted sample between the treatment or early adopter farmers (EAFs) and control or laggard farmers (LFs) groups for propensity score estimation. 1 = Early adopter farmers, 0 = Laggard farmers.

53 in the control group, and food security by 427 in the treatment group compared with 54 in the control group (Table 4). Three matching algorithms indicate that adopting CAPS significantly improves productivity (95% CI: 0.87–0.92) and food security (95% CI: 0.86–0.92), with significance at $p < 0.10$. Specifically, CAPS adoption improved productivity and food security by approximately 4% when *NNM, KBM,* and *CM* were used. In other words, this implies that, on average, EAFs have higher crop productivity than LFs (Table 4). These findings suggest that when accounting for socioeconomic factors, randomly selected EAFs are demonstrated to be 4% more likely to report improvements in

TABLE 4 The average treatment effect on the treated to evaluate the impact of CAPS adoption via the propensity score matching.

Description	Productivity			Family income			Food security		
	NNM	*KBM*	*CM*	*NNM*	*KBM*	*CM*	*NNM*	*KBM*	*CM*
Treatment (EAFs)	0.89	0.89	0.89	0.96	0.89	0.89	0.89	0.89	0.89
Control (LFs)	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
Difference, *ATT*	0.04*	0.04*	0.04*	0.11	0.04	0.04	0.04*	0.04*	0.04*
SE	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
p value	0.09	0.09	0.09	0.13	0.13	0.13	0.05	0.05	0.05
Number of observations (*n*)									
Treatment (EAFs)	430	430	430	428	428	428	427	427	427
Control (LFs)	51	51	51	53	53	53	54	54	54
Common support (*n*)									
Treatment (EAFs)	430	430	430	428	428	428	427	427	427
Control (LFs)	52	52	52	53	53	53	54	54	54

*Indicates significance at 10% ($p < 0.10$) level, respectively; *SE*, Standard error; EAFs, Early adopter farmers; LFs, Laggard farmers; *ATT*, Average treatment effect on the treated; *NNM*, Nearest Neighbor Matching; *KBM*, Kernel-Based Matching; *CM*, Caliper Matching. The confidence intervals (CIs) were as follows: productivity (95% CI: 0.87–0.92), family income (95% CI: 0.86–0.91), and food security (95% CI: 0.86–0.92).

food security than LFs. The standardized mean difference (sometimes referred to as Cohen's d) represents an effect size that indicates the strength of the relationship between variables or the difference between before and after matching (Hedges, 2024). Effect sizes are commonly categorized into three levels: small (Cohen's $d = 0.2$), medium (Cohen's $d = 0.5$), and large (Cohen's $d = 0.8$) (Cohen, 1988). In this study, we observed a small effect size in the standardized mean difference between the treatment and control groups. Gender, age, and field numbers were minimized before matching ($p < 0.01$), whereas all variables with nonsignificant differences ($p \geq 0.10$) were matched (Table 5 and Figure 2). Before matching, the average score of off-farm income was significantly different ($p < 0.10$), but after matching, the average score was the same (Table 5).

4.4 Mechanisms for promoting CAPS in an agricultural extension model

This study utilized data from 239 observations of LFs to identify potential agricultural information sources and extension methods. The number of respondents who are aware of and practice CAPS are shown in Figures 4A,B. This research identified several reasons why farmers who were aware of CAPS did not practice it (Figure 4C). The reasons include limited access to CAPS inputs, limited labor, limited time, family assets, and other factors. CAPS inputs have become a major challenge, with 156 respondents (38%). Among the respondents, 21% ($n = 86$) identified labor as the main challenge, whereas 18% ($n = 77$) considered the time required for practicing to be a concern. Other challenges to CAPS adoption included family assets and additional factors such as a lack of information sources, technology support, and access to resources, with 8% ($n = 33$) and 15% ($n = 63$) of the respondents citing these issues, respectively.

4.4.1 Ranking agricultural information sources for promoting CAPS

Kendall's *W*-test showed agreement among the information sources, indicating that the rankings provided by the information sources were statistically significant [*W*-test = 0.14; $\chi^2(5) = 164.52$; $p < 0.01$] (Table 6). The mean ranks for information sources were as follows: relatives ranked the highest, followed by mass media, research, NGOs, the government, and personal experience, with mean ranks ranging from 2.70 to 4.32.

4.4.2 Ranking agricultural extension methods for promoting CAPS

Kendall's *W*-test showed respectable agreement among agricultural extension method sources, indicating that the rankings provided by the agricultural extension methods were statistically significant [*W*-test = 0.10; $\chi^2(5) = 114.67$; $p < 0.01$] (Table 7). The mean ranks for extension methods were as follows: F2F, demonstration plots, farm or home visits, workshops or discussions, local agricultural fairs, and office calls, with mean ranks ranging from 2.94 to 3.96.

4.4.3 Mechanisms for CAPS promotion activity in an agricultural extension model

FGD and KII examined mechanisms for promoting CAPS: (1) support mechanism, (2) transfer mechanism, (3) receiving mechanism, and (4) adoption mechanism (Figure 5). These mechanisms are correlated with CAPS promotion to improve productivity and food security. Several quotes from FGDs and KIIs are shown below.

Key stakeholders and FGDs from the BTB and PHV provinces stated the following:

> "NGOs should support technical CAPS training to EAFs. Information on CAPS, including details on the location, date, goals, benefits, subsidies, incentives, and extensive training, should be provided by NGOs. The government should share relevant information with farmers interested in attending CAPS training to aid in participant recruitment. Agricultural extension methods should focus on F2F, demonstration plots, and local training for transferring CAPS. Engaging farmers with NGOs is a good way to promote CAPS; however, it also requires support from the government."

TABLE 5 Testing factors balancing check both mean before and after matching between the treatment and control groups to check matching quality for PSM.

Explanatory variables	Mean before match				Mean after match			
	EAFs	LFs	Difference	*t*-test (*p*-value)	EAFs	LFs	Difference	*t*-test (*p*-value)
Gender	0.53	0.38	0.15	0.00***	0.53	0.56	−0.03	0.16ns
Age	49.64	44.97	4.67	0.00***	49.65	49.96	−0.31	0.74ns
Marital status	1.26	1.26	0.00	0.99ns	1.26	1.28	−0.02	0.76ns
Education level	2.40	2.49	−0.09	0.25ns	2.40	2.38	0.02	0.80ns
Field numbers	2.42	2.08	0.34	0.00***	2.42	2.44	−0.02	0.80ns
Soil fertility	0.63	0.64	−0.01	0.78ns	0.63	0.58	0.05	0.28ns
Rice is the main crop	0.64	0.62	0.02	0.50ns	0.64	0.61	0.03	0.45ns
Cassava is the main crop	0.21	0.22	−0.01	0.77ns	0.21	0.22	−0.01	0.72ns
Maize is the main crop	0.09	0.10	−0.01	0.72ns	0.09	0.14	−0.05	0.10ns
Distance to markets	17.83	18.75	−0.92	0.33ns	17.83	18.50	−0.67	0.45ns
Distance to the extension office	17.70	18.68	−0.98	0.29ns	17.70	18.47	−0.77	0.38ns
Off-farm income	0.70	0.62	0.08	0.05*	0.70	0.64	0.06	0.10ns

EAFs, Early adopter farmers; LFs, Laggard farmers; * and *** Indicate significance at 10% ($p < 0.10$) and 1% ($p < 0.01$) levels, respectively; ns, No significance ($p \geq 0.10$).

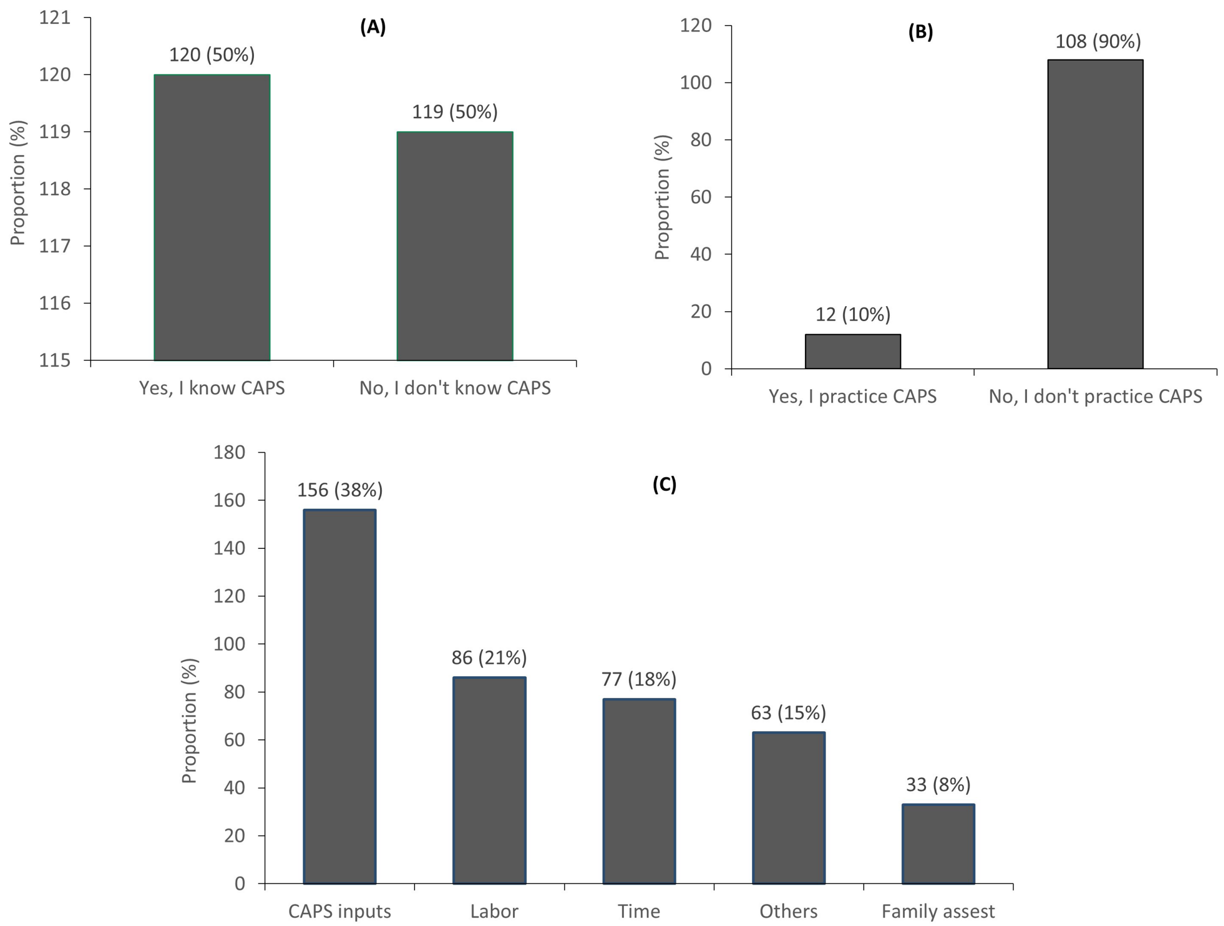

FIGURE 4
(A) Proportion of laggard farmer respondents aware of CAPS (n = 239); **(B)** proportion of laggard farmers practicing CAPS (n = 120); and **(C)** reasons for farmers not practicing CAPS.

TABLE 6 Agricultural information sources utilized by laggard farmers for promoting CAPS.

Agricultural information sources	Mean rank	*SD*	Ranking
Relatives	2.70	0.98	1st
Mass media	3.23	0.91	2nd
Research	3.36	0.82	3rd
NGOs	3.61	0.78	4th
Government	3.77	0.78	5th
Own experience	4.32	0.65	6th
Number of observations (*n*)	239		
Kendall's *W-test*	0.14***		
Chi-square (χ^2)	164.52		
Degree of freedom (df)	5		

The ranking was 1–6, with 1 being the most significant in importance and 6 being the least significant. The means were measured on a 5-point Likert scale (1 = Strongly disagree, 2 = Disagree, 3 = Moderate, 4 = Agree, 5 = Strongly agree); *** Indicates significance at 1% ($p < 0.01$) level, respectively; *SD*, Standard deviation.

TABLE 7 Agricultural extension methods used by laggard farmers for promoting CAPS.

Agricultural extension methods	Mean rank	*SD*	Ranking
Farmer-to-farmer (F2F)	2.94	0.95	1st
Demonstration plots	3.19	0.80	2nd
Farm or home visits	3.38	0.82	3rd
Workshops or discussions	3.62	0.71	4th
Local agriculture fairs	3.92	0.72	5th
Office calls	3.96	0.74	6th
Number of observations (n)	239		
Kendall's *W-test*	0.10***		
Chi-square (χ^2)	114.67		
Degree of freedom (df)	5		

The ranking was 1–6, with 1 being the most significant in importance and 6 being the least significant. The means were measured on a 5-point Likert scale (1 = Strongly disagree, 2 = Disagree, 3 = Moderate, 4 = Agree, 5 = Strongly agree); *** Indicates significance at 1% ($p < 0.01$) level, respectively; *SD*, Standard deviation.

Multiple key informants in the BTB and PHV provinces stated the following:

> "Incentives and subsidy support should be provided to promote EAFs to become farmer advisors because this persuades them to transfer CAPS to LFs in the community. Transferring CAPS from EAFs to LFs should include benefits and incentives for farmer advisors. When we understand the benefits of CAPS, we will decide whether to adopt or reject it. The government should share the benefits of CAPS with farmers in the community, whereas NGOs should encourage EAFs to become farmer advisors by providing technical and incentive support. We need to see the results before accepting or rejecting new technology. Learning from other farmers is the best mechanism for transferring new technology. We will conduct training sessions with LFs to share knowledge. Seeing is believing and learning by doing."

KIIs and FGDs in the BTB and PHV provinces confirmed the following:

> "The mechanisms to promote CAPS include the transfer mechanism by using F2F and demonstrate plots. Demonstration plots are the best way to learn about CAPS from EAFs. We would believe a farmer in the commune if we saw the result during the harvest stage. Farmers learn faster from each other through observation. The problems preventing us from joining a CAPS include time constraints and the required CAPS inputs. Learning from EAFs and extension agents would be beneficial. We would trust a farmer's advisor if we saw the farmer's results. Farmer advisors should be provided incentives by NGOs and the government. Training should be scheduled at convenient times for farmers. F2F should be conducted because farmers learn easily from relatives in the local area. The mechanism to promote CAPS from EAFs to LFs is to increase the capacity of farmer advisors. Farmers' knowledge can be impacted by technology adaptation. Adopting and transferring CAPS will increase productivity by improving food security."

5 Discussion

5.1 Factors influencing the adoption and transfer of CAPS promotion

Several factors influence adoption and transfer, including gender, age, number of fields, and off-farm income. Gender disparity in adopting agricultural technologies affects productivity, with men being more likely to adopt these innovations than women (Hirpa Tufa et al., 2022). Gender positively and significantly influenced adoption ($p < 0.10$). This finding is consistent with Ojo et al. (2023) and Ngaiwi et al. (2023), who reported that gender impacts agricultural technology interventions, with men being more willing to adopt technology. Similar findings were highlighted by Manda et al. (2016) in rural Zambia. This prediction supports an earlier study by Negera et al. (2017) in Ethiopia, which shows that men manage agricultural resources and are more likely to adopt agriculture practices that require more resources. Focusing on gender to promote CAPS can significantly accelerate adoption and influence farmer characteristics, including productivity, family income, and food security.

This study revealed that the average age of farmers was approximately 50 years old, which influenced their adoption and transfer. Age had a significantly positive effect on the adoption and transfer of CAPS. This result aligns with findings from Belay et al. (2023) in southern Ethiopia and Mugandani and Mafongoya (2019) in Zimbabwe. In another study, Simtowe et al. (2011) and Tufa et al. (2023) noted that older farmers in Tanzania and southern Africa were more inclined to adopt new technologies. However, these results contrast with those of Ali and Erenstein (2017) in Pakistan, which

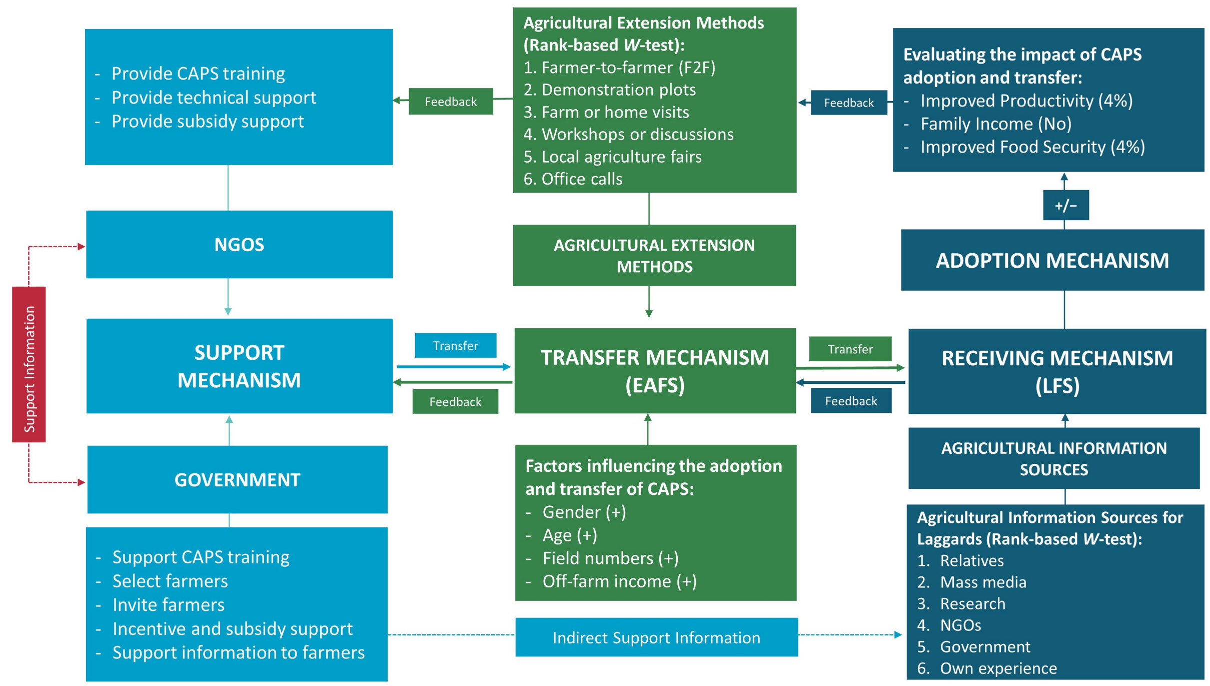

FIGURE 5
Mechanisms for promoting conservation agriculture production systems (CAPS). EAFs, Early adopter farmers; LFs, Laggard farmers; NGOs, Nongovernmental organizations.

suggest that younger farmers are more likely to adopt and experiment with new technologies to enhance agricultural productivity. In addition to age, field numbers play a fundamental role in adopting agricultural technologies (Krishna et al., 2022).

Field numbers are related to farm size; i.e., if farmers have more fields, they are likely to have larger farms, which allows them to practice new technologies. As expected, this study demonstrated that farmers' field numbers were significantly positive factors in the CAPS adoption and transfer. This result supports the findings of Gao et al. (2020), who reported that having more field numbers positively affects technology adoption. For example, large-scale farms are more likely to adopt and transfer technology than smaller farms because they can test the technology on a small part of their field before deciding to implement it on a larger scale (Akudugu et al., 2023). Similar results were reported by Kifle et al. (2022) in Ethiopia and Tufa et al. (2019) in Malawi, supporting the present finding. According to Li et al. (2020), farm size positively impacts adoption and transfer. In addition to farmers' demographic characteristics, socioeconomic factors such as off-farm income are also crucial.

Off-farm income is identified as a significant factor that directly influences farmers' decisions to adopt agricultural technology (Nkhoma et al., 2017). This study also indicated that off-farm income significantly influence on farmers' decision-making regarding the CAPS adoption and transfer. These results aligns with the findings of Amankwah (2023) in rural Nigeria and Knowler and Bradshaw (2007), who found that off-farm activities had a significantly positive effect on technology adoption and transfer. Nevertheless, this result was argued by Tambo and Mockshell (2018) in Sub-Saharan Africa and Chichongue et al. (2020) in Mozambique. Off-farm employment provides families with income. For example, smallholder farmers earning more money from off-farm employment find adopting easier (Kifle et al., 2022; Tadesse and Ahmed, 2023). Farmers with off-farm income were more likely to adopt new technologies, as this income allowed them to pay for CAPS inputs such as agricultural machinery, land preparation, cover crops, main crops, and harvest. Farmers' demographic and socioeconomic characteristics, including gender, age, field numbers, and off-farm income, influence the adoption and transfer of CAPS. These factors encourage farmers to adopt and transfer CAPS, which improves productivity, family income, and food security. Stakeholders should provide technology support via appropriate extension methods, which would also increase the number of farmers adopting and transferring CAPS.

5.2 Impact evaluation of CAPS adoption

CAPS adoption is essential in enhancing productivity as new technologies are developed to address farmers' problems (Hobbs et al., 2007). Productivity serves as a reliable measure of land conditions, as it directly reflects variations in land quality and its limitations, including the need to ensure optimal conditions for crop growth from planting to harvest (FAO, 2024). This research showed that EAFs who adopted CAPS had approximately 4% higher productivity than LFs. This finding is consistent with Nkala et al. (2011), who pointed out that technology adoption has a positive effect on improving crop production in central Mozambique. Similarly, this result is also consistent with several previous studies by Nkhoma et al. (2017) in Zambia, Gebeyehu (2023) in southern Ethiopia, Mideksa et al. (2023) in eastern Ethiopia, and Siziba et al. (2019) in Zimbabwe, which showed that CAPS adoption improves crop productivity and food security because it enhances soil health, reduces input costs, and increases water use efficiency—factors that contribute to yield stability, long-term sustainability, and diversification of food production. Enhancing agricultural productivity and profitability is essential to meet the food security needs of smallholder farmers (Asfaw et al., 2012; Miah et al., 2023; Mideksa et al., 2023).

Sometimes, CAPS adoption impacts crop productivity but does not impact household income because the initial costs and investments required for CAPS inputs such as agricultural machinery, land preparation, cover crops, and harvesting the main crops necessitate upfront funds from farmers (Sims and Kienzle, 2015). The investment cost would typically be too steep, and the opportunity cost for the available capital is significant. This present research revealed that adopting CAPS did not affect family income. Results align with that of Nkala et al. (2011) in central Mozambique. However, this contrasts with the findings of Tambo and Mockshell (2018), who found that CAPS adoption significantly enhances total family income in Sub-Saharan Africa, as adoption of CAPS components in combination is associated with greater income gains compared to when the components are adopted in isolation.

Food security is defined as having an adequate and high-quality food supply that ensures continuous nutritional wellbeing and meets all physiological needs (FAO, 2006). Adoption of CAPS is crucial for increasing crop production and positively impacts household livelihoods by improving food security (Mango et al., 2017; Mgolozeli et al., 2020). This study revealed that EAFs improved food security by approximately 4% compared with LFs. This result aligns with the findings of Opoku-Acheampong et al. (2024), who discovered that adopting CAPS practices significantly impacts household food security levels in Ghana. Consistent with previous studies, including those by Mideksa et al. (2023) in Ethiopia, Sileshi et al. (2019) in eastern Ethiopia, Anghinoni et al. (2021) in central Brazil, and Pradhan et al. (2018) in India. Similarly, Fentie and Beyene (2019) stated that adopting new technology enhances yield productivity and food security. The positive effects of adopting new technology encourage more farmers to embrace these innovations, ultimately improving family food security (Belay et al., 2023; Yang et al., 2023).

Agricultural technology adoption integrates decision-making theory and the diffusion of innovations theory to explain why some farmers adopt new technologies while others resist them (Ruzzante et al., 2021). CAPS is a package that includes reducing soil disturbance, adding organic materials to the soil, and diversifying crops (Hobbs et al., 2007). This study demonstrated that EAFs who adopted CAPS experienced a 4% improvement in productivity and food security compared with LFs. This information would be valuable for stakeholders in providing technology training to farmers interested in practicing CAPS. The government should implement long-term policy measures to support and promote the adoption of CAPS. The agricultural extension model should be considered for technology transfer to smallholder farmers, as it significantly impacts the adoption of agricultural practices. This study evaluated the impact of CAPS adoption during the short duration of the MK agricultural extension model project, which may have influenced the number of farmers adopting the practices. An evaluation conducted at the end of the project would likely reveal a greater impact, exceeding 4%, in terms of improving productivity and food security. Furthermore, after the project concludes, family income is expected to be positively affected by the CAPS adoption.

5.3 Mechanisms for promoting CAPS in the agricultural extension model

Agricultural extension methods improve the level of technology adoption by farmers to a certain extent, with a partial spillover effect promoting these technologies within the community (Gao et al., 2020). Agricultural information sources are essential in encouraging farmers to adopt new technology because information is required to make decisions (Caffaro et al., 2020). Problems of technology adoption include a lack of access to inputs for CAPS, limited labor, limited time, family assets, and other factors. This result is similar to the findings of Bhan and Behera (2014) in India, which explored the challenges, opportunities, and policy implications of conservation agriculture.

The labor demand associated with CAPS implementation is significant, but labor needs are particularly critical during key times in farm management and practices (Silva et al., 2023). For example, limited time and labor can affect crop management and practices, as delayed operations may lead to reduced crop productivity, impacting food security (Silva et al., 2023). Prioritizing agricultural information sources and extension methods would be valuable for promoting CAPS. These methods impact the adoption of CAPS by improving crop productivity and food security, especially for smallholder farmers.

5.3.1 Agricultural information sources for promoting CAPS

Relatives were the highest-ranked potential information sources for farmers as indicated in the present study. Asule et al. (2023) stated that in the central highlands of Kenya, local information included family members, friends, and neighbors, as farmers believed that fellow farmers possessed valuable knowledge to share, particularly regarding agricultural practices. In developing countries, local information sources had a positive effect on providing information to smallholder farmers, as reported in several studies by Lambrecht et al. (2016) in the Republic of Congo, Ndimbwa et al. (2020) in Tanzania, and Brown et al. (2018a) in Eastern and Southern Africa. Wani et al. (2021) pointed out that farmers adopted new technologies, such as increased crop improvement and family food security, by observing the benefits to other farmers. This illustrates that “seeing is believing”—farmers would trust in innovation if they witnessed its success firsthand.

Mass media is also a powerful information source for farmers because it provides accessible and easy-to-understand information (Fan et al., 2022). This research presented that mass media was the second most important information source. Wale and Mkuna (2023) found that mass media sources include newspapers, magazines, posters, and social media platforms—serve as important and timely sources of information for the majority of farmers. Additionally, media such as radio, television, and smartphones are effective information sources, positively influencing adoption (Ben-Enukora et al., 2023). Farmers can learn about new farming technologies and their applications through radio and television, which act as intermediaries (Das et al., 2021). These media sources are utilized in information-sharing channels, which include formal channels such as local officials, print media (i.e., newspapers), information and communication technology (i.e., radio and mobile phones), and national meteorological services (Friedman et al., 2023). Innovations from agricultural research offer valuable information sources for farmers (Alexander et al., 2020). This present study revealed that research was the third most important information source. The research referred to universities, institutes, and human resources for agricultural research. Participatory research systems cannot be effectively implemented if researchers are unable to communicate properly with farmers (Brown et al., 2018b).

NGOs and agricultural extension agents play pivotal roles in providing agricultural information sources to farmers and encouraging their technology adoption. NGOs offered support services such as information, input supply, technical training, technology transfer, credit, and oversight of extension activities. Farmers typically view these services as valuable and applicable to their needs (Buadi et al., 2013). The present study showed that the information source by NGOs ranked fourth. In developing countries, NGOs are a potential source of information for small-scale farmers (Tandi Lwoga et al., 2011). Promoting new technologies requires engaging both the private sector and NGOs, which need government support for information sharing (Nickens et al., 2023). Agricultural extension agents are key government actors responsible for transferring agricultural information sources to smallholder farmers. The government is also a significant information source, ranking fifth in importance. Agricultural extension agents need to provide essential information to farmers and play a crucial role in technology transfer and information dissemination (Lee et al., 2023; Ragasa, 2020).

Aligned with the initiative of the Royal Government of Cambodia, the development of professional extension agents, particularly commune agriculture officers, is expected to grow, as they serve as vital links between farmers and essential agricultural information. Own experience including conducting field trials and experiments on farms and learning from past agricultural seasons (Garner, 2022; Phiri et al., 2019) was a part of the information source for accepting or rejecting new technologies. Own experience is the last rank of information source. Models of the production process that incorporate knowledge gained through experience are known as learning by doing in another area of knowledge literature (Levitt et al., 2013; Nemet, 2012; Yang and Shumway, 2020). The present research indicated that relatives were a significant source of agricultural information, as most farmers in the Cambodian context are more likely to adopt or learn new practices from their relatives, including family members, friends, and neighbors. The principle of 'seeing is believing' further supports the effectiveness of using relatives as a channel for promoting new technologies.

5.3.2 Agricultural extension methods for promoting CAPS

F2F complements formal agricultural extension methods by helping disseminate agricultural technologies and enhancing farmers' skills to improve production (Kiptot and Franzel, 2015). This study highlighted that F2F ranked highest among extension methods for delivering information to farmers. These results align with the findings of Nakano et al. (2018) in Tanzania. Kansanga et al. (2021) and Nakano et al. (2018) stated that farmer training is generally a more affordable way to reach a variety of farmers in smallholder agricultural situations. Dosso et al. (2023) pointed out that effective communication enhances farmers' adaptability and problem-solving skills. The F2F system is a collaborative strategy (Martini et al., 2023) which offers several benefits, including the widespread adoption through farmer training, as it is a cost-effective and straightforward method for technology transfer (Bourne et al., 2021; Nakano et al., 2018).

Demonstration plots are considered the most effective agricultural extension method for promoting technology (Dhehibi et al., 2020; Kuhl, 2020). In this present research, the average score for the demonstration plots ranked second. This finding is consistent with the results of Dhehibi et al. (2020) in Tunisia. These demonstration plots are typically farmer-owned and farmer-managed, with support from extension agents (Sseguya et al., 2021). Agricultural extension agents are more likely to select experienced farmers as key organizers for agricultural events, such as demonstration farms and field visits, to facilitate knowledge sharing with other farmers in their communities (Gido et al., 2015; Lee et al., 2023). This method requires substantial financial resources but results in improved outcomes; i.e., the demonstration plot approach has delivered significant benefits to smallholder farmers, such as improved decision-making and marketing skills, contributing to increased profits (Parven et al., 2023).

Extension access ratings for technology transfer methods and adoption were positively correlated with the number of agricultural commodities, extension agents, demonstration plots, and farm or home visits (Lee et al., 2023). The mean score for farm or home visits ranked third among agricultural extension methods, followed by workshops or discussions, local agricultural fairs, and office calls. Agricultural extension agents either visit farms to address regular farming activities or to deliver timely agricultural messages (Tegene et al., 2023). Farm or home visits are valuable for smallholder farmers facing challenges with agricultural practices, as they provide an opportunity to discuss these issues directly with agricultural extension agents, who can then share their expertise to improve agricultural outcomes. In contrast, workshops or discussions and local agriculture fairs are considered one component of agricultural extension methods, allowing smallholder farmers to learn new information through knowledge sharing sessions organized by agricultural extension agents.

The increasing adoption of smartphones offers the possibility of turning traditional extension services into digital extension services (Abebe, 2023). Phone calls are agricultural extension methods in which smallholders receive information quickly from the agricultural extension agents. Smallholder farmers were not interested in the phone call approach because they found it difficult to explain their field problems to experts over the phone. This approach may prove useful for solving problems for small-scale farmers in the future. Technology transfer and adoption methods in agricultural extension methods, such as F2F, demonstration plots, farm or home visits, workshops or discussions, local agriculture fairs, and phone calls, would be valuable for smallholder farmers. Among agricultural extension methods, F2F has become an extension method for transferring CAPS to laggard or smallholder farmer in Cambodia. To effectively promote CAPS, it is important to prioritize the F2F methods to encourage technology adoption among farmers.

5.3.3 Mechanisms for promoting CAPS in an agricultural extension model

Support mechanism actors, including the government and NGOs, provide information and technical support to EAFs through training. For example, governance actors provide information-sharing support and NGOs provide technology support to farmers (Vignola et al., 2013). NGOs support technical training and offer subsidies to EAFs, whereas the government needs support for training in areas such as disseminating information, selecting farmers, inviting farmers, and providing incentives to farmers. NGOs should coordinate with the government by providing detailed information on training activities, including the topic, objectives, location, date, participant selection criteria, and associated benefits. This enables the government, through local authorities such as village chiefs, to appropriately identify and invite eligible farmers to participate. NGOs should provide the government with information for participant recruitment, such as the training topic, goals, location, date, participant criteria, and benefits of the training. This information impacts the quality of technology transfer and adoption for promoting CAPS. Based on the information provided by NGOs, the government would invite the participants for information sharing. The government processed the paperwork to invite participants and other relevant stakeholders for training. This study revealed that subsidies and incentive support would be obtained by collaborating with private sector actors to persuade EAFs to adopt practices that enhance crop production and food security. NGOs provide technical support to farmers on the training day, which is supported by the government (Lukuyu et al., 2012). Farmers can discuss their problems with the technical staff and learn through hands-on experience such as F2F and demonstration plots.

The transfer mechanism is important in encouraging EAFs to adopt CAPS and in facilitating its dissemination to LFs. Farmers who are early adopters, frequently regarded as leaders in innovation, constitute the initial quarter of adopters within the broader population of potential users (Diederen et al., 2003). Face-to-face interviews found several factors that influence EAFs in adopting CAPS, including gender, age, field numbers, and off-farm income. These factors impact adoption, which in turn affects productivity and food security. The mechanism of EAFs engaging with information sharing serves as an incentive or benefit to convey to farmers' advisors. The purpose of providing incentives is to develop farmer advisors for knowledge-sharing or technology transfer. Incentives would be provided for the efforts of EAFs to implement more efficient practices and new technologies, and they would transfer this technology to LFs (Fisher et al., 2018; Levidow et al., 2014). Kansiime et al. (2018) concluded that incentives included higher yields, increased land productivity, and labor savings. The farmers who attended the training observed all the training processes and steps. The survey procedure highlighted that agricultural information sources, such as relatives, NGOs, mass media, research, and personal experience, were confirmed by EAFs. The technology transfer methods included F2F, demonstration plots, farm or home visits, workshops or discussions, local agriculture fairs, and office calls for promoting CAPS. EAFs emphasized that farmer training programs should serve as effective platforms for sharing agricultural technologies and innovations.

The mechanisms of promoting CAPS are important. These mechanisms need direct support from the transfer mechanism and indirect support from the support mechanism. LFs are those who either adopt new technologies with significant delay or do not adopt them at all. This group can be categorized into two distinct segments: late adopters and non-adopters. Late adopters eventually implement an innovation but do not fall within the initial quarter of potential adopters. In contrast, non-adopters are individuals who refrain from adopting any new technologies (Diederen et al., 2003). LFs in this study refer to those who did not participate in the MK agricultural extension model project activities. Face-to-face interviews revealed that while most of them were aware of CAPS (50% out of 120 respondents), 10% practiced it. Several factors, such as limited CAPS inputs, time, labor, information, and family assets, were identified as challenges for practicing CAPS. LFs receive information about technology directly from EAFs, and they provide feedback to them. The government also provides information support to LFs. Additionally, LFs receive agricultural information from various sources such as relatives, mass media, research, NGOs, government, and own experience.

The adoption mechanism is influenced by the support mechanism, transfer mechanism, and receiving mechanism. Providing the right extension methods would be valuable for promoting CAPS from EAFs to LFs. The promotion requires the engagement of multiple actors, including the government, NGOs, EAFs, and LFs, as their involvement can impact agricultural outcomes such as productivity and food security. Stakeholders of CAPS should recognize the value of agricultural extension methods in promoting CAPS, which could lead to an increase in the number of EAFs and, consequently, more widespread CAPS adoption across Cambodia.

6 Conclusion

Key factors influencing adoption and transfer mechanisms for CAPS include gender, age, field numbers, and off-farm income, which demonstrate positive impacts. The results showed that early adopter farmers who attended CAPS training experienced significantly improved productivity (95% CI: 0.87–0.92) and food security (95% CI: 0.86–0.92) compared to laggard farmers, with a 4% improvement. The mechanisms of CAPS promotion include support, transfer, receiving, and adoption mechanisms. These mechanisms involve several primary actors: the government, NGOs, early adopter farmers, and laggard farmers. The farmer-to-farmer approach emerged as the most effective agricultural extension method for promoting CAPS, followed by demonstration plots, farm or home visits, workshops or discussions, local agriculture fairs, and office calls. Laggard farmers primarily sourced agricultural information from relatives, mass media, research, NGOs, the government, and their personal experience. This study is constrained by small effect sizes and limitation of only two provinces covered by the MK agricultural extension model activities. Future studies should consider including a broader and more diverse groups of farmers to strengthen scientific evidence for promoting CAPS adoption in Cambodia. Additionally, this current research only captures the impact on technology adoption during the project implementation phase. Thus, longitudinal assessment is needed to examine post-project effect, particularly tracking evolving outcomes which could potentially affect family income.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Ethics statement

The studies involving humans were approved by the Research Ethics Committee of Kasetsart University, Thailand. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

PM: Conceptualization, Data curation, Formal analysis, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing, Project administration. LH: Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Validation, Visualization, Writing – review & editing. PS: Methodology, Supervision, Validation, Writing – review & editing. BM: Funding acquisition, Methodology, Supervision, Validation, Writing – review & editing. FK: Writing – review & editing. PP: Funding acquisition, Writing – review & editing. RD: Conceptualization, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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