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Adoption and intensity of pearl millet technology packages in drought-prone areas of the Waghimra Zone, Ethiopia: A transition pathway for assuring food security

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Pearl millet, a climate-resilient crop, is advocated for combating food insecurity in drought-prone areas. To that end, the Ethiopian Agricultural Research Institute and agricultural extensions have been instrumental in promoting pearl millet technology packages. However, a more detailed understanding of the adoption and impact of these packages on the food security of farm households in Ethiopia is needed. This study investigated the factors influencing the adoption of pearl millet technology packages and their impact on food security in drought-prone areas of the Waghimra Zone. Data were collected from 172 farmers through systematic random sampling in 2018. Double-hurdle and generalized propensity score approaches were employed. The results from the double-hurdle regression revealed that gender, education, age, number of oxen, extension services, training, distance to the primary market, and participation in farm field demonstrations were the primary factors influencing adoption decisions and the intensity of pearl millet technology packages. The analysis using generalized propensity scores emphasized that adopting pearl millet technology packages had a significant positive effect on the food security of farm households. Therefore, research institutes and extension agents should pay special attention to popularizing pearl millet technology packages to increase household food security in Ethiopia and similar contexts.

Keywords: adoption, double hurdle, Ethiopia, food security, generalized propensity score, pearl millet

JEL Classification: B21, C01, C21, D22, Q16, Q18

Introduction

Pearl millet (with its scientific name *Pennisetum glaucum L.*) is a widely produced staple food crop in Africa and India and is ranked as the world's 6th most essential cereal crop (Mason, Maman, and Pale 2015; Matuschke and Qaim 2008). It is predominantly grown by farm households in marginal areas of the Waghimra Zone region in Ethiopia because of its exceptional adaptability to harsh climatic environments, rich nutritional content, and low input requirements (FAO 2021; Gari 2001; Jukanti et al. 2016; Mason, Maman, and Pale 2015). Over 500 million people around the globe depend on pearl millet since it is considered a climate-resilient crop (Gari 2001; Khairwal et al. 2007; Mustafa and Dangaladima 2008; Satyavathi et al. 2021).

Agricultural production growth cannot come only from cultivation area expansion; instead, sustainable agricultural production growth will have to come from growth in yields arising from plant breeding and other scientific advances presented by biotechnology (De Janvry et al., 2001). In line with this, a pearl millet program targeting drought-prone areas of Ethiopia has focused on releasing genotypes that yield high yields under harsh growing conditions (erratic and small amounts of rainfall distribution). As a result, one drought-tolerant pearl millet variety (named 'Kola-1') was introduced in collaborative efforts by the Melkassa Agriculture Research Center and Ethiopian Institute of Agriculture Research (EIAR) (Adugna et al. 2011). Furthermore, Ethiopian regional agriculture research centers, including the Sekota Dryland Agriculture Center, prescaled this drought-tolerant pearl millet variety with its agronomic packages in drought-prone areas of the country to improve household food security.

Recent research and extension initiatives have enhanced the adoption of improved and new crop varieties, soil and water management techniques, and agricultural practices. In line with this, several studies have focused on mapping the patterns of pearl millet technology adoption (Faye et al. 2018; Galadima et al. 2019; Munasib, Roy, and Birol 2015; Vabi et al. 2020). They investigate associated factors to improve the adoption level, aiming to have visible impacts on household food security. For example, one study measured adoption intensity in terms of the proportion of the area grown with improved pearl millet varieties in Nigeria (Vabi et al. 2020). Likewise, other studies have focused on measuring agricultural technology adoption with or without acceptance of the technology, which has a dummy nature of interest (Anaeto et al. 2012; Galadima et al. 2019). However, adoption has multidimensional aspects. For example, an improved pearl millet variety would not perform well without the need to integrate different agronomic packages, such as sowing, plowing, fertilizer, crop rotation, seed rate, tie ridge[1] use, and weed management (Berhanu, Beshir, and Lakew 2020). Therefore, the adoption of pearl millet technology packages should be considered and prioritized.

One of the main objectives of this study was to analyze the factors influencing the adoption and level of pearl millet technology packages tested and promoted by the Sekota Dryland Agriculture Research Center for drought-prone areas of the Waghimra Zone, Ethiopia. Although pearl millet has been produced and accepted by farm households and has great importance for food security in the drought-prone areas of the zone, only a limited number of empirical studies have investigated farmers' adoption decisions and their respective adoption intensities of pearl millet technology packages. Previous studies have focused on analyzing farm households' perceptions of pearl millet technology in Ethiopia via simple descriptive analysis (Mihiretu, Asefa, and Wubet 2020; Siyum et al. 2017). However, we go beyond the classical approach of measuring and analyzing the adoption level of farm households by constructing an adoption index for multiple agronomic packages associated with improved pearl millet varieties (Kola-1). In our study, pearl millet production was a common boundary for all the sample farm households, but different agronomic packages related to pearl millet technology were used. Hence, we constructed an index that included the fertilizer rate, seed rate, sowing method, weeding frequency, plowing frequency, crop rotation, and tie ridges to define adoption and understand farmers' level of adoption.

Another goal of this study was to estimate the impact of the adoption intensity (dose) of pearl millet technology packages on farmers' food security. The benefits of the adoption of pearl millet technology packages might vary across farm households. We used a continuous treatment effect because of heterogeneous responses among the farm households on the basis of Hirano and Imbens (2004). Many adoption studies rely on a binary treatment framework to examine the impact of technology adoption on household food security by deriving a single average treatment effect (Faye et al. 2018; Galadima et al. 2019; Vabi et al. 2020; Wordofa et al. 2021). Similarly, a study on the adoption of improved teff varieties in Ethiopia revealed that the intensity of adoption is assessed on the basis of land allocation for improved variety (Teshome and Tegegne 2020; Vabi et al. 2020). However, farm households have different responses to technology adoption, particularly for pearl millet technology packages; thus, following a continuous treatment variable requires quantifying the average treatment effect at different adoption intensities or dose levels. As a result, we applied a generalized propensity score via a dose–response model to quantify the heterogeneous impact of adoption intensity on household food security via a household diet diversity score. Thus, we have clearly outlined two research questions to address these two primary research objectives: (1) What factors affect adoption decisions as well as the intensity of adoption of pearl millet technology packages? (2) Does the intensity of the adoption of pearl millet technology packages impact farm household food security?

This study contributes to the literature by focusing on the adoption intensity of pearl millet technology packages among farm households. Instead of merely categorizing households as adopters or nonadopters, the study investigates the nuanced aspects of continuous exposure. This highlights that farm households embrace a singular pearl millet production package and adopt multiple packages at varying intensities, incorporating several associated packages. This approach provides empirical evidence for diverse responses to different levels of technology adoption. Thus, this study underscores the importance of treatment intensity (dose) in elucidating how pearl millet technology packages impact the diet diversity of farm households. In the following section, section two provides the theoretical and empirical framework of the study; section three presents a brief overview of the research methods (sample design, model specification, and data); section four presents the results and discussion; and conclusions and policy implications are presented in section five.

Theoretical framework

Innovation diffusion theory

Roger's innovation diffusion theory (IDT) explains that innovation and adoption occur through several steps, including understanding, persuasion, decision, and confirmation. These steps form the S-shaped adoption curvature for laggards, the late majority, the early majority, early adopters, and innovators. The S-shaped diffusion curvature indicates that only a few people are initially exposed to innovation (Figure 1). However, individuals within the social system play an essential role in accelerating the diffusion of agricultural technology across society. As they start accepting the innovation, they bring it into contact with more people, thereby influencing the spread of the innovation. Eventually, innovation gains acceptance from most members within the social system, lowering the spread rate as it approaches diminishing returns; once there are no remaining members to accept the innovation, the spread ceases (Rogers 2003). Rogers proposed that IDT provides the foundation for researching innovation acceptance and adoption by synthesizing findings from over 580 diffusion research studies. He developed diffusion innovation theory, highlighting the innovation adoption process among individuals and organizations. As shown in Figure 2, the theory explains how innovation is interconnected through specific channels over time among the constituents of a social structure (Rogers 1983).

The theory of reasoned action (TRA) is a significant theoretical framework that aids in understanding individuals' adoption behaviour. With its roots in social

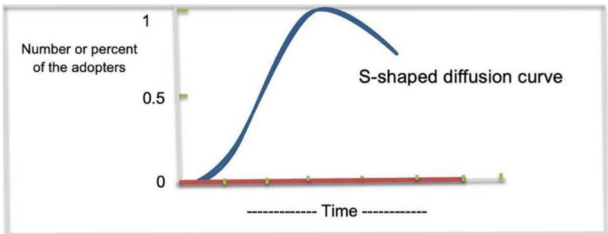

Figure 1: S-shaped diffusion curve.
Source: Adapted from Rogers (2003).

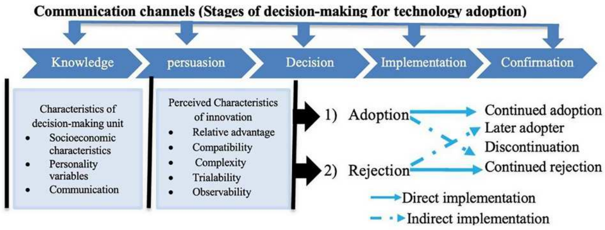

Figure 2: Innovation diffusion theory.
Source: adapted from Rogers (2003).

psychology, TRA reveals that individuals are logical decision-makers who constantly calculate and evaluate relevant behavioural beliefs to form their attitudes regarding behaviour. The theory proposed three general constructs: 'behavioural intention', 'attitude', and 'subjective norm'. On the basis of the TRA, an individual's behavioural intentions determine his or her actual behaviour. This indicates, as explained in Figure 3, that a person's behavioural intention depends on subjective norms and attitudes. Behavioural intention can be mathematically measured as the summation of subjective norms and attitudes. Furthermore, an individual's intention is more likely to translate into action when the desire to engage in a specific behaviour is sufficiently strong (Ajzen and Fishbein 1975). This comprehensive framework provides a profound understanding of the factors influencing individual behaviour in adoption and diffusion analysis.

The adoption index is linked to farmers' behaviour since it is a quantitative measure capturing the intensity and extent of their acceptance and implementation of Pearl Millet technology packages. Analyzing this index provides valuable insights into the behavioural patterns and motivations that drive farmers' adoption of these technology packages. This association between the adoption index and farmers' behaviour enables a wide-ranging understanding of the dynamics of agricultural innovation, with a focus on the concepts of IDT and TRA.

The impact evaluations of various proven agricultural technologies mostly require panel data rather than cross-sectional data because farmers need time for full adoption of the given technology. It is difficult to capture the time effect through cross-sectional survey data. However, recent econometric models, such as the generalized propensity score (GPS), endogenous switching regression, propensity score matching, double-hurdle, and other impact evaluation econometric models, have the ability to capture and/or control unobserved factors that are thorough when balance scores are made and appropriate counterfactuals are found. Thus, the GPS model helps capture Roger's innovation theory by finding counterfactual groups and capturing unobserved factors, including time effects.

Empirical framework: an iterative process of pearl millet technology adoption

An iterative process calculates the desired result via a repeated cycle of operations. An iterative process should exhibit convergence, progressively approaching the desired result as the number of iterations increases. On the basis of this general definition of the iterative process, there is a limited but repeated cycle of procedures from innovating new ideas until their popularization through learning and monitoring of agricultural technology promotion (Johannes 2014), which leads to the adoption of agricultural technology and the improvement of household food security. The initial step is called the innovation stage; in this step, a needs assessment survey is conducted, new ideas are generated, and an appropriate approach is developed through the survey findings (Figure 3). The second step involves a pilot project, including a farm field demonstration with a small number of farmers and little farmland coverage; this step is called the learning stage. Stakeholders, such as extension experts, development agents, farmers, researchers, and other concerned bodies (input providers), have participated. Hence, farmers have the skills, experience, and know-how to implement the new technology on their farms. This step is also a so-called demand creation step through farmers' field day, monitoring, and evaluation workshops, meaning that farmers observe how the new technology looks in the field and acquire knowledge of it. This knowledge came from farmers' internal learning, external or from their neighboring model farmers. The second step involves the possibility of achieving a minimal impact on the technology, such as increasing yield. Once the demand for technology is created, the next step is to popularize the technology for many farmers and broaden farmland coverage. The third step is the final step in the iterative process of technology popularization; in this step, a better impact is observed

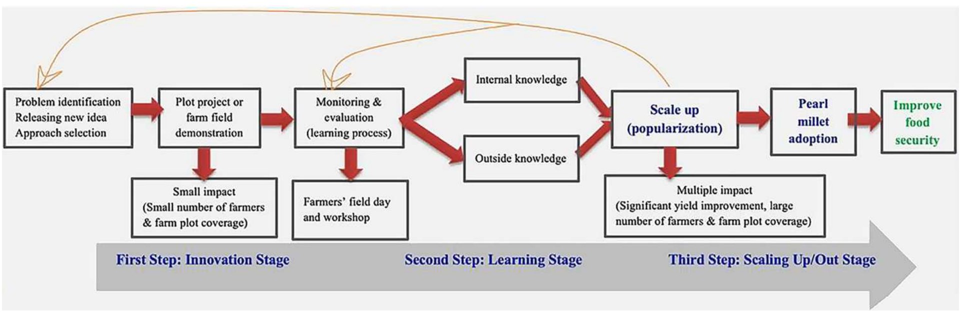

Figure 3: An iterative process for scaling up agricultural technology (popularization), which is linked with food security.
Source: authors modified from (Johannes 2014).

because of the involvement of a relatively large number of farmers and ample farmland coverage. Farmers might be eager to implement a new technology efficiently as quickly as they acquire skills through technology diffusion, which contributes to agricultural productivity and economic growth (Matuschke and Qaim 2008).

This iterative process of technology popularization is cyclical since the farming system has always faced new challenges. Thus, the steps might be repeated many more times to respond to risks and uncertainties (Feder, Just, and Zilberman 1985) and improve household food security. In each step, village-based advisors, or development agents (DAs), are more relevant for making sustainable pearl millet production in areas prone to drought and similar settings in Ethiopia since farmers easily understand and trust those DAs (Monica et al. 2018).

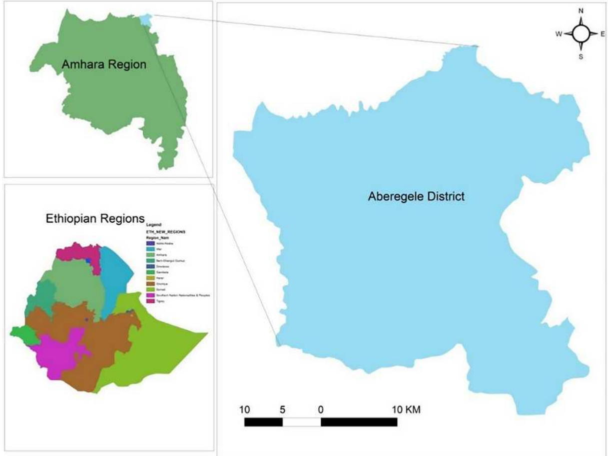

Figure 4: Map of the study area.
Source: Authors' sketch (2021) via ArcGIS V. 10.3.

Research methods

Study area and sampling procedures

The study was conducted in the Abergele district in the Eastern Amhara region of Ethiopia (Figure 4). The area is generally characterized by moisture stress and is one of the country's most drought-prone areas. The district is approximately 1495 m above sea level, with a minimum temperature of 28°C, a maximum temperature of 42°C, and an average rainfall distribution of 250–650 mm (Lakew and Berhanu 2019). Three-stage sampling was employed to collect survey data in 2018. First, the Abergele district was purposively selected because of its potential for pearl millet production. Second, two kebeles were purposively selected from the 15 kebeles in the district on the basis of their potential for pearl millet production. Third, the respondents were selected via a systematic random sampling technique from the selected kebeles, as the populations in the study areas are known and have homogeneous socioeconomic characteristics (Allan 2007). The sample size was calculated on the basis of the population proportion from each selected kebele. The data were accessed from kebele agricultural offices. We used pearl millet-producing farmers as the population frame to select the final sample unit, and the sample size was calculated via Yamane's sampling size determination formula (Yemane 1967) because of its simplicity.

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

In equation (1), n represents the sample size, N represents the entire number of pearl millet-producing farmers (1085) during the survey year (2018, as reported by the Abergele District Agriculture Office [ADAO] 2018), and e represents the precision level or the error that the researcher will tolerate. In this study, e was set at 0.07, as we assumed that the variability of the population was not heterogeneous in terms of agroecological, institutional, and socioeconomic characteristics. Therefore, approximately 172 sample farmers were selected for this study via equation (1).

Data collection methods

The quantitative data were collected through a structured questionnaire, which was pretested with five households before the actual survey. Pretesting the questionnaires helped us improve the flow of ideas and maintain consistency in the survey.

Methods of data analysis

Descriptive and inferential analysis

Descriptive statistics were used to describe the sociodemographic and institutional characteristics of the sample farm households. Inferential statistics, including t tests and chi-square tests, were employed to assess the mean difference and determine interdependencies between adoption categories. Finally, Pearson correlation analysis was used to illustrate the associations between continuous variables and the level of adoption of pearl millet technology packages.

Econometric analysis

Double-hurdle regression model: The incidence of a zero value in the dependent variable, such as the adoption index, can create difficulties when analyzing microdata. In such cases, using ordinary least square regression can lead to biased results of the parameters, as the estimated regression line fits the scatter of points without considering that the data are limited at one end. The bias can be severe when the dependent variable is zero for a significant proportion of the sample. There are three major scenarios in which the dependent variable can become zero: corner solutions, nonparticipation in the program, and infrequent participation in the program (Newman, Henchion, and Matthews 2001). Corner solutions occur when households do not use pearl millet technology packages at the recommended levels. Nonparticipation in pearl millet technology intervention indicates that households refrain from implementing pearl millet technology packages due to various factors, such as the high cost of chemical fertilizers and improved seeds. Finally, infrequent participation in the pearl millet adoption process requires that farmers sometimes apply chemical fertilizers and other packages.

Wooldridge mentioned that the econometric model specification depends on the data structure and the study's objective (Wooldridge 2020). Various options are available to analyze the adoption decision and intensity of pearl millet technology packages, including the double hurdle, Tobit, and Heckman's two-stage selection models. The decisions to adopt and the level of adoption for a specific agricultural technology might be made separately or jointly (Berhanu and Swinton 2003). The Tobit model assumes that a similar set of determinants affects two decisions (adoption decision and level of adoption) (Green 1993). However, the double-hurdle regression model assumes that the likelihood of adoption decision, as well as the level of adoption of pearl millet technology packages, is influenced by separate sets of factors explained by Cragg (1971), which indicates that there is no restriction on the independent variables in each stage of the model estimation. The double-hurdle model serves as a parametric extension of the Tobit model, employing two separate stochastic processes to estimate the likelihood of adoption decision and the level of adoption of the pearl millet technology packages.

In double-hurdle model estimation, two stages of estimation are needed. First, with respect to overall sample sizes, the probit model is applied to identify the driving factors of the probability of decision to adopt pearl millet technology packages. This study defined adopters as farmers who applied at least two technology packages for pearl millet production. Additionally, nonadopters were farmers who did not apply any recommended technology packages mentioned in Table 2. However, the nonadopters are still growing pearl millet without considering the recommended packages, which means that their adoption index becomes zero. Second, the truncated regression model estimates the adoption intensity of pearl millet technology packages among the adopters, or the adoption index values are greater than zero. In the double-hurdle framework, the probit model estimation represents the likelihood of the decision to adopt (Di) pearl millet technology packages, mathematically expressed in equation (2).

$$\begin{array}{c} D_i^* = \alpha X_i + + \varepsilon_i \\ D_i = i \; if \; D_i^* > 0 \\ D_i = 0 \; if \; D_i^* \le 0 \end{array} \tag{2}$$

where D^*_i is the unobserved or latent variable; D_i is the observed variable that takes a value of 1 if a farmer adopts the pearl millet technology package or whose adoption index is positive ($D^* > 0$) and 0 if a farmer does not adopt any pearl millet technology package or whose adoption index is zero ($D^* = 0$), which might be due to corner solution and/or infrequency problems; X is a vector of farmer variables that affect the adoption of the pearl millet technology package; α represents a set of parameters; and ε is the random error for the first hurdle (probit model estimation). The second stage of the double-hurdle model (truncated regression) is mathematically derived in equation (3).

$$\begin{array}{ll} Y_i^* = \beta Z_i + v_i \; and \; D_i^* = \alpha X_i + + \varepsilon_i & \\ Y_i^* = 0 & if \; D_i^* = 0 \\ Y_i = Y_i^* & if \; D_i^* = 1 \\ \text{and } Y_i = 0 & \text{if } D_i^* = 0 \end{array} \tag{3}$$

where Y^*_i is the unobserved or latent variable that illustrates the intensity use of pearl millet technology packages; Y_i is the observed outcome variable (adoption index in terms of continuous scale); Z_i represents the set of independent variables that influence how much the farmers use the technology; ß represents the coefficients of the variables to be estimated; and v_i represents the error term from the second hurdle (truncated regression). Since double-hurdle model estimation assumes two error terms, those two errors (ε and ß) are assumed to be independent and normally distributed.

Generalized propensity score (GPS): Different econometric methods have been developed to analyze the effects of a certain proven agricultural technology on a farm household's food security; for example, propensity score matching (PSM) in a binary treatment framework in which the treatment is not randomized and the generalized propensity score (GPS) is suitable for a continuous treatment framework. GPS estimation was used to investigate the effects of improved pearl millet technology adoption on household food security. The PSM model mimics randomization to create a control or counterfactual group that is closely similar to the treatment group using observed characteristics and assesses the treatment effect. This approach is employed in impact evaluation analysis if the treatment variable, 'adoption index', is binary, indicating that the average treatment effect is appropriate with the assumption that all farmers are occupied with the same amount but that all farmers do not have a similar intensity or that they do not apply the given technology packages, which are confirmed by Rogers (2003) in IDT (see Figures 1 and 2). These findings indicate that some farmers partially used pearl millet technology packages, whereas others used full technology packages for pearl millet production. For this reason, a single average impact evaluation through a conventional binary treatment approach is not a detailed analysis (Bia and Mattei 2007; Kluve et al. 2012; Li and Fraser 2015; Menale, Moti, and Mattei 2014). As a result, GPS estimation is appropriate for analyzing the effects of the adoption index for the pearl millet technology package at different continuous treatment intervals or cutting points.

The concept of the GPS approach to estimate the entire dose–response function for continuous treatment was introduced by Hirano and Imbens (2004). It extended the confoundedness assumption from binary treatment to continuous and multivalued treatments, defining the GPS function as the conditional density of the actual treatment given the observed covariates. Recently, Gebre et al. (2021) and Manda et al. (2020) applied a dose–response model to analyze the effects of the adoption of stress-tolerant maize varieties on maize productivity and household income in Tanzania and the effects of cowpea market participation on food security and income in northern Nigeria. The GPS method has a similar balancing property to the standard propensity score by eliminating bias related to systematic differences in the covariates. In the GPS estimation, we followed the procedure of Hirano and Imbens (2004), which revealed that the matching property of the GPS, in this study, was assessed by cutting the spreading of the adoption index at the 30th and 70th percentiles. Thus, we grouped the sample farm households into three levels: First, the households whose adoption index was ≤ 20% were in group one; second, the households whose adoption index was between 20% and 80% were in group two; and third, the households whose adoption index was ≥ 80% were in group three.

The GPS model analysis involved four key steps.

First, the generalized propensity score (GPS) was calculated as a conditional density of intensity if the covariates followed a normal distribution of intensity, which can be expressed as:

$$(\beta(t.r) = E[Y|T = t,\ R = r]) \tag{4}$$

This assumption was evaluated via the Kolmogorov–Smirnov (K–S) goodness-of-fit test to verify whether the observed random sample originated from the assumed normal continuous distribution.

Second, equation (6) describes the parameters beta sub 0, beta sub 1, and delta squared (representing the conditional distribution of the intensity of the adoption index value).

$$T_i|X_i \sim N = [\beta_0\ +\ \beta_1 X_i,\ \delta^2] \tag{5}$$

Third, balancing independent variables along the intensity categories is a critical procedure. After the parameters of the intensity function in equation (5) were estimated, the GPS was calculated via equation (6).

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\delta^2}} exp\left[-\frac{1}{2\delta^2}\left(T_i - \hat{\beta}_0 - \hat{\beta}_1 X_i\right)^2\right] \tag{6}$$

Fourth, modelling the conditional expectations of the farmers' HDDS (Y_i) as quadratic functions of the observed treatment (T_i), estimation of GPS [$\widehat{R_i}$], and interaction analysis are illustrated in equation (7).

$$\begin{aligned}(\beta(t.r) &= g([Y_i|T_i,\quad \hat{R}_i])\\ &= \alpha_0 +\ \alpha_1 T_i +\ \alpha_2 T_i^2 + \alpha_3 \hat{R}_i +\ \alpha_4 \hat{R}_i^2\\ &\quad +\ \alpha_5 T_i \hat{R}_i\end{aligned} \tag{7}$$

where g was estimated through a normal regression model because the outcome variable is continuous. Finally, the average dose–response function at a specific value of the adoption intensity (t) was predicted by averaging the conditional expectation μ(t) over the GPS at the given specific adoption intensity, or the dose of the pearl millet technology package was derived via equation (8).

$$\begin{aligned}\mu(t) &= E[\hat{Y}_{(t)}]\\ &= \frac{1}{N}\sum_{i=1}^{N} g^{-1}[\ \hat{\alpha}_0 +\ \hat{\alpha}_1 t +\ \hat{\alpha}_2 t^2 + \hat{\alpha}_3 \widehat{r(t, X_i)}\\ &\quad + \hat{\alpha}_4 \widehat{r(t, X_i)}^2 + \hat{\alpha}_5 t\hat{r}(t, X_i)]\end{aligned} \tag{8}$$

where $\hat{\alpha}$ denotes the set of parameters estimated in the second step and where $\widehat{r(t, X_i)}$ is the predicted value of $r(t.X_i)$ at level 't' of the treatment or adoption intensity (dose). This value is assumed to take ten values strictly within the continuous range of [0–100] or 0.1, 0.2, 0.3, … , 1, representing a continuous treatment indicator.

The entire dose–response function was acquired by estimating the average potential outcome variable (HDDS) for each specific level of the adoption index intensity for pearl millet production. Graphical illustrations of the marginal treatment impact and average dose–response functions were computed as derivatives of their corresponding dose–response functions.

The average dose–response function illustrates the magnitude and nature of the causal relationship between adoption level and farmers' HDDS. In contrast, the marginal treatment effect function reveals the marginal effects of the adoption index on farmers' HDDS (Bia and Mattei 2007).

Treatment variable

We calculated the adoption index of pearl millet technology packages on the basis of the pearl millet production manual prepared by the Sekota Dryland Agriculture Research Center (SDARC 2013). In many studies, weight has been given to each package to acquire the intensity of adoption of a given technology (Julius and Jimoh 2020; Ogunya, Simeon, and Ayodeji 2017; Wuletaw and Daniel 2015). Thus, different weights for every package of pearl millet production have been applied to obtain farmers' adoption intensity in pearl millet farming (Table 1). The mathematical notion of the adoption index is illustrated in equation (9).

$$AI_i = \sum \frac{AT_i}{RT_i} * IS_i \tag{9}$$

where AI_i denotes the adoption index of pearl millet technology of the i^{th} farmer; AT_i is the list of packages (fertilizer rate, sowing method, seed rate, weeding frequency, plowing frequency, crop rotation, tie ridges) of the sample i^{th} farmer who applied; RT_i is the suggested number or level of packages to be applied; and IS_i is the weight or proportion score for each package in pearl millet production.

Outcome variable: measurements of food security at the household level

Food security remains a multifaceted and complex concept encompassing access, availability, stability, and utilization, which can be measured through various indicators (Jones et al. 2013; Tadesse, Abate, and Zewdie 2020). Experts employ different sets of proxy indicators to examine the dimensions of food security, with the primary indicators being objective or subjective. Objective food security measures include calorie intake, dietary diversity, and monetary poverty thresholds closely tied to income or consumption approaches (Headey and Ecker 2012; Tadesse et al. 2020). For example, consumption data collection for food security research faces significant challenges, including seasonal volatility and single-round survey limitations. Data

Table 1: Weights and methods used to calculate the adoption indices of the pearl millet technology packages.

Packages	Recommended level	Weight	Method of rating
Sowing method	Row sowing with 50 cm and 5 cm inter and intra row spacing	0.10	Ratio of the area covered by row to total area covered by pearl millet
Plowing frequency	≥ 4 frequencies	0.05	The ratio of average plowing frequency plot^{-1} to recommendation frequency
Seed rate	Broadcast: 8–10 kg ha^{-1} and Row: 3–5 kg ha^{-1}	0.15	Ratio of recommendation seed rate ha^{-1} to farmers' actual application of seed ha^{-1}
Fertilizer rate application	Urea: 50 kg ha^{-1}	0.125	Ratio of actual amount of urea applied ha^{-1} to recommendation amount of urea ha^{-1}
	DAP: 100 kg ha^{-1}	0.125	Ratio of actual application of DAP ha^{-1} to recommendation amount of DAP ha^{-1}
Tie ridges application	Apply appropriate tie ridge structure	0.30	Ratio of actual pearl millet cultivated plot that has been covered by tie ridge structure to the total pearl millet plot cultivated
Crop rotation	Rotate with legume crops including Sesame	0.025	Ratio of actual crop rotated pearl millet plot to total pearl millet plot cultivated
Weed management	Manual weeding (3X)	0.125	Ratio of average weeding frequency plot^{-1} to recommendation weeding frequency plot^{-1}
Total		1.00	

Source: Sekota Dryland Agriculture Research Center [SDARC] (2013).

typically covering short periods before interviews are susceptible to irregular purchases and price fluctuations. Measurement errors may arise from reporting bias or imperfect recall, potentially leading to systematic misrepresentation of household food security situations (Gebre et al. 2021). Thus, objective indicators struggle to capture shock effects without frequent surveys (Tadesse et al. 2020). Despite these challenges, such data remain valuable for measuring food security. Subjective-based or experimental measures of food in/security are based on respondents' experiences or perceptions regarding the availability and accessibility of sufficient food. These measures gather data on individual or household experiences related to the frequency of food in/security incidents. In contrast to objective indicators, subjective indicators are derived from self-reported responses to questions about food shortages and their consequences. These questions assess the severity of food insecurity, ranging from psychological impacts to more tangible physical effects experienced by respondents (Headey and Ecker 2012).

Subjective-based food/security, including the household dietary diversity score (HDDS), can be measured differently. The HDDS is a qualitative-based measure of food consumption that reveals households' access to diverse foods and serves as a proxy for nutrient sufficiency in individuals' diets. Swindale and Bilinsky (2006) pioneered the measurement of household food diversity scores using 12 food groups over a 24-hour recall period. Many scholars have modified this approach slightly (FAO 2010; Mehariw 2020). The HDDS focuses on whether a household has consumed food from various food groups within a 24-hour, resulting in a simple count of the consumed food groups (FAO 2010; Mehariw 2020; Swindale and Bilinsky 2006). This study used HDDS to assess household food security in the study area. Following Mehariw (2020), households were asked whether they had consumed from any of the 12 food groups in the past 24 h, with 'yes' responses coded as 1 and 'no' responses as 0 (see Table 2). The dietary diversity score is then calculated by summing the values of all the food groups, resulting in total scores between 0 and 12. Higher scores indicate greater dietary diversity, whereas lower scores indicate less diversity. The HDDS scale is categorized as follows: ≤ 3 indicates low diversity, 4–5 indicates medium diversity, and ≥ 6 indicates high diversity (Kennedy, Ballard, and Dop 2011). The findings revealed that 59 households (34%) had high dietary diversity scores, 73 households (43%) had medium scores, and 40 households (23%) had low scores. Additionally, adopters of the intervention presented higher dietary diversity scores than nonadopters (Figure 5).

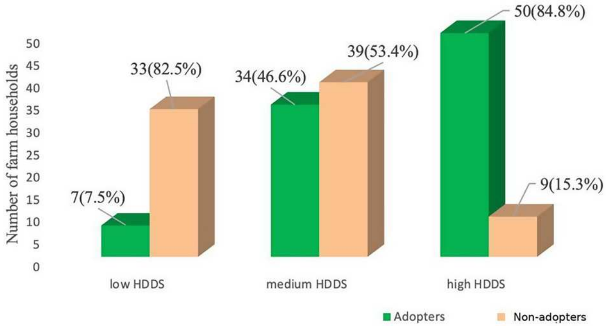

Figure 5: The household dietary diversity score (HDDS) across adopters and nonadopters.

Results and discussions

Descriptive results

We found that 91 (53%) of the sample farm households adopted pearl millet technology packages, whereas the remaining 81 (47%) did not adopt pearl millet technology packages (Table 3). Approximately 136 (79.1%) were male-headed, and 36 (20.9%) were female-headed. Among these, approximately 82 (90.1%) of the male-headed and 9 (9.9%) of the female-headed farm households were adopters; in accordance with this, there is a significant and positive association between gender and the adoption of pearl millet technology packages. The results of the $\chi 2$ test revealed a significant association between access to training services and pearl millet technology adoption, which was significant at less than the 1%

Table 2: Questions for measuring Household Food Dietary Diversity Score (HDDS).
Fill in the types of foods that you or anyone in your household ate over the last 24 hours. Please say “YES” if anyone in the household ate the food in each food group, while say “NO” if no one ate the food.

No.	Food groups	Description of each food group Did you or any member of the household consume … food group over the last 24 hours? (1 = yes; 0 = no)
1	Cereals	Millet (pearl millet, finger millet), teff, barley, wheat, maize, sorghum, rice, oats (Aja”)
2	Tuber and root crops	Beetroot, carrot, potato, sweet potato, onion, garlic, taro or godere
3	Fruits	Banana, avocado, mango, papaya, guava, orange, Pineapple, lemon
4	Vegetables	Lettuce, green pepper, head cabbage, tomato, Swiss chard
5	Meat and poultry	Goat, beef, poultry, lamb, or any other organ meat
6	Fish and seafood	Fish
7	Egg	Egg
8	Milk and milk products	Milk, yogurt, cheese, and other milk products
9	Pulse, nuts, and legume	Faba bean, Chickpea, field pea, lentils, haricot bean, grass pea, soya bean, Mung bean, Fenugreek
10	Oil or fat	Oil, butter or fat
11	Sugar or honey	Honey, sugar
12	Miscellaneous	Other foods such as spices, salt, tea, coffee, chat

Source: Authors adapted from (FAO 2010; Mehariw 2020; Swindale and Bilinsky 2006).

level. Moreover, we found a significant association between nonadopters and adopters of pearl millet technology packages toward participation in farm field demonstrations, off-farm activities, and credit access.

The average household head ages of the adopters, nonadopters, and joint farm household heads were 44, 42, and 43 years, respectively, which is statistically insignificant. The average number of oxen for adopters, nonadopters, and joint farm households was 2.24, 1.44, and 1.87, respectively, and the mean difference was statistically significant at the 1% level. There was a substantial mean difference between nonadopters and adopters in terms of extension service provision, plot fragmentation, number of livestock, and distance from the household’s dwelling to the nearest primary market.

The average pearl millet yields for adopters, nonadopters, and overall farm heads were 1.14, 1.03, and 1.08 tons per hectare, respectively. This shows a significant mean yield difference between nonadopters and adopters. We also reported that this value is less than the national productivity of 2.26 tons ha-1 (CSA 2018).

The adoption index for pearl millet technology packages ranged between 0 and 0.99, whereas the average value among adopters was 0.69 (Figure 6). This figure shows the extent to which farm households adopted pearl millet technology at the time of the survey. Hence, this result follows the concepts of the IDT and

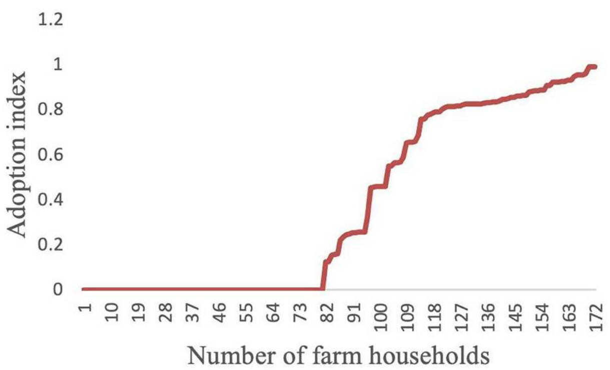

Figure 6: The distribution of the adoption index across the farm households.

TRA theories. Among the adopters, approximately 53 (30.8%) have over 80% (0.8) of the adoption index.

The role of pearl millet in household diet diversity

The farm households use pearl millet for different food meals on the basis of their preferences. The four most common food items are mentioned via simple pairwise ranking, such as [2]Injera, [3]Porridge, Bread, and [4]Tell. Therefore, the farm households ranked the food items from pearl millet, such as Injera, Porridge, Tella, and bread, as the 1st, 2nd, 3rd, and 4th food items, respectively (Table 4).

Determinants of pearl millet technology package adoption

The first hurdle assesses how the given independent variables predict the likelihood of adopting pearl millet technology packages, whereas the second hurdle examines how these variables affect the intensity or level of adoption. The Wald chi-square value for the first hurdle is 66.25 with a 1% significance level, suggesting that the explanatory variables collectively account for the likelihood of adopting pearl millet production technology. Similarly, the Wald chi-square value for the second hurdle is 115.55, which is also statistically significant at the 1% level, suggesting that the explanatory variables collectively explain the intensity of adoption of pearl millet production technology (Table 5).

The gender of the household head positively and significantly influenced the likelihood of the decision to adopt pearl millet technology packages at the 10% significance level. The marginal effect presented here shows that male-headed households increase the probability of adopting pearl millet technology by 25.3%, ceteris paribus.

The age of the household head positively and significantly affected the probability of the decision to adopt pearl millet production technology at the 5% significance level. In contrast, its square is negatively influenced, indicating that age has a parabolic effect on the adoption of pearl millet production technology, with a turning point of 41 years (Figure 7). These findings indicate that farm households above 41 years of age are the most likely to

Table 3: Summary statistics of the demographic, socioeconomic, and institutional variables.

Variables		Adopters (N = 91) s(52.91%)	Non-Adopters (N = 81) (47.09%)	Combined (N = 172) (100%)	χ^2 -value
Dummy variables	Description				
Sex of the household head (1 = male and 0 = female)	Male	82 (90.11%)	54 (66.67%)	136 (79.07%)	(14.2314)***
	Female	9 (9.89%)	27 (33.33%)	36 (20.93%)	
	Total	91 (100%)	81 (100%)	172 (100%)	
Training service provision on pearl millet production (1 = get training and 0 = did not get training)	Getting training	84	49	133	(24.7384)***
	Didn't get training	7	32	39	
	Total	91	81	172	
Participation in farm field demonstration (1 = yes and 0 = no)	Yes	67	47	114	(4.6673)**
	No	24	34	58	
	Total	91	81	172	
Off-farm activity participation (1 = yes and 0 = no)	Yes	63	39	102	(7.8923)**
	No	28	42	70	
	Total	91	81	172	
Credit service provision (1 = get credit service and 0 = didn't get credit)	Getting credit	70	50	120	(4.6909)**
	Didn't get a credit	21	31	52	
	Total	91	81	172	
Continuous variables		**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**t value(SE)**
Grain yield for pearl millet (measured in ton ha. $^{-1}$)		1.138 (0.233)	1.033 (0.218)	1.088 (0.231)	3.015 (0.035)***
Age of the household head (measure in years)		44.209 (7.411)	42.889 (9.655)	43.587 (8.542)	1.012 (1.305)
Education level of the household head (measure in years of schooling)		1.813 (1.053)	1.543 (1.118)	1.686 (1.089)	1.629 (0.166)
Labor force in the household (measure in man-equivalent)		4.978 (2.181)	4.556 (2.504)	4.779 (2.342)	1.183 (0.357)
Number of Oxen (measure in number)		2.242 (0.638)	1.444 (0.894)	1.866 (0.865)	6.782 (0.118)***
Total farmland (measure in hectare)		3.236 (0.880)	3.136 (0.889)	3.189 (0.884)	0.741 (0.135)
Extension service provision (measure in frequency or number)		7.242 (3.631)	2.395 (2.625)	4.959 (4.006)	9.922 (0.488)***
Plot fragmentation (measure in number of plots covered by Pearl millet)		2.341 (0.763)	3.185 (1.026)	2.738 (0.988)	−6.166 (0.137)***
Distance from home to the local market (measure in minutes)		37.571 (19.104)	72.383 (52.749)	53.965 (42.397)	−5.879 (5.921)***
Number of livestock (measure in number; it is not included oxen)		7.426 (2.037)	5.895 (2.708)	6.705 (2.491)	4.216 (0.363)***

Note: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively; the numbers in the brackets are the standard deviation (SD) and standard error (SE).

have a lower probability of adopting pearl millet technology packages because they are afraid of labor shortages, tedious management, and other risks. This finding aligns with the studies by Gebre et al. (2021) and Fikadu et al. (2017).

The number of oxen significantly increased the likelihood of pearl millet technology adoption at the 5% significance level. The marginal effect indicates that for each additional ox owned by a farm household, the probability of adopting pearl millet technology increases by 22.8%, assuming that all other variables remain constant. This finding suggests that farmers with more oxen might have a greater probability of adopting pearl millet production technology.

The number of extension contacts positively and significantly influences the probability of adopting pearl millet technology packages at the 1% significance level. The marginal effect reveals that each additional extension contact with development agents and agricultural extension experts enhances the likelihood of adopting pearl millet technology packages, with other variables held constant. These findings indicate that frequent extension contact provides up-to-date agricultural information about pearl millet production technology, which is consistent with The findings of Debelo (2015) and Mihretie, Abebe, and Misganaw (2021).

Participation in training about pearl millet production significantly improved the probability of adopting pearl millet technology packages at the 10% significance level. The marginal effect shows that training enhances the probability of adopting pearl millet production technology by 20.9%, assuming that other factors remain constant. These findings suggest that training helps farmers acquire the skills and knowledge needed for improved pearl millet technology packages, increasing their likelihood of adopting the technology. This result aligns with the studies by Mihretie, Abebe, and Misganaw (2021) and Bayissa (2014).

As expected, the negative influence of plot fragmentation and distance from home to the local market

Table 4: Farmers' food item preferences for pearl millet.

Food items	Tella	Porridge	Bread	Injera	Score	Rank
Tella	***	porridge	Tella	Injera	1	3rd
Porridge		***	Porridge	Injera	2	2nd
Bread			***	Injera	0	4th
Injera				***	3	1st

significantly affects the decision to adopt pearl millet technology packages. The marginal effects show that fragmented plots and distant local markets decrease the probability of pearl millet technology adoption by 18.3% and 0.3%, respectively, with other variables held constant. These findings emphasize that farmers with fragmented land may need help in managing and implementing appropriate pearl millet technology packages. Additionally, obtaining inputs for pearl millet production may be challenging if the local market is too distant. These findings are consistent with those of Tesfaye, Ayele, and Adam (2014) and Mihretie, Abebe, and Misganaw (2021).

Factors affecting the intensity of pearl millet technology package adoption

As illustrated in the second hurdle estimation, five explanatory variables significantly influenced the intensity of the recommended pearl millet technology package adoption (Table 5). Among these factors, the age of the household head negatively influences adoption intensity at the 5% significance level. This finding suggests that farmers over 41 years of age are less likely to adopt pearl millet technology packages extensively.

The household head's education level was found to influence the intensity of adoption of pearl millet technology packages positively and significantly at the 1% significance level. This finding indicates that the household head's education level increases with one year of schooling. The intensity of the use of pearl millet technology packages increased by 9.5%, ceteris paribus. The justification behind this is that education is the paramount proxy of knowledge, skill, and farm experience, which helps to develop an understanding of proven new agricultural technologies, including pearl millet production.

Table 5: Maximum likelihood estimation of the double-hurdle model of the adoption decision and intensity use of pearl millet technology packages among smallholder farming households in the Abergele district, Amhara Region, Ethiopia.

Variables	1st Hurdle (Probit)	ME in Probit model	2nd Hurdle (truncated model)
Sex of the household head (1 = male and 0 = female)	0.677 (0.377)*	0.253(0.124)	0.117 (0.074)
Age of the household head (measure in years)	0.357 (0.175)**	0.142 (0.069)	0.065 (0.028)**
Age square for the household head	−0.004 (0.002)**	−0.002 (0.0008)	−0.0008 (0.0003)**
Education level of the household head (measure in years of schooling)	0.159 (0.127)	0.063 (0.050)	0.095 (0.020)***
Labor force in the household (measure in man-equivalent)	0.029 (0.057)	0.011 (0.023)	0.009 (0.011)
Number of Oxen (measure in number)	0.575 (0.227)**	0.228 (0.089)	0.030 (0.034)
Total farmland (measure in hectare)	−0.081 (0.165)	−0.032 (0.066)	−0.004 (0.024)
Extension service provision (measure in frequency or number)	0.169 (0.033)***	0.067 (0.013)	0.010 (0.006)*
Training service provision for pearl millet production (1 = get training and 0 = did not get training)	0.551 (0.306)*	0.209 (0.111)	0.069 (0.073)
Participation in farm field demonstration (1 = yes and 0 = no)	–	–	0.165 (0.058)***
Plot fragmentation (measure in number of plots covered by Pearl millet)	−0.463 (0.158)***	−0.183 (0.062)	−0.039 (0.032)
Distance from home to local market (measure in minutes)	−0.009 (0.005) *	−0.003 (0.002)	−0.003 (0.001)***
Off farm activity participation (1 = yes and 0 = no)	−0.044 (0.275)	−0.017 (0.109)	−0.010 (0.047)
Number of livestock (measure in number, which did not include Oxen)	0.014 (0.061)	0.006 (0.024)	−0.007 (0.013)
Credit service provision (1 = get credit service and 0 = didn't get credit)	–	–	−0.010 (0.045)
Constant	−8.907 (3.740)**	–	−0.949 (0.653)
/Sigma			0.185 (0.014)***
Number of observations = 81	Number of observations = 91		
Log-Likelihood = -58.632875	Log pseudolikelihood= 25.709691		
Wald chi2(13) = 66.25	Wald chi2(15) = 115.55		
Prob > chi2 = 0.0000	Prob > chi2 = 0.0000		
Pseudo R2 = 0.5070	Limit: lower = 0 and upper = +inf		

Note: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively; the numbers in the brackets are the robust standard errors of the mean; ME shows the marginal effects of the variables.

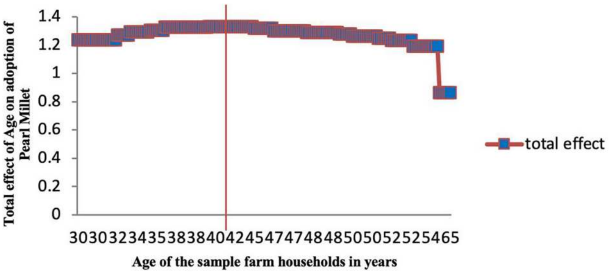

Figure 7: Turning point of the age of the farm households in terms of pearl millet technology adoption.

Participation in on-farm field demonstrations and the number of extension contacts significantly increased the intensity of the use of pearl millet technology packages at the 1% significance level. These findings indicate that, compared with nonparticipants, farm households participating in farm field demonstrations increased the intensity of the adoption of pearl millet technology packages by 16.5%, with other variables remaining constant. This occurred because farm field demonstrations increase farmers' confidence in the production of pearl millet. After all, seeing is more likely to mean believing than hearing or listening. Farm field demonstrations facilitate farmers' knowledge and farm experience by learning by doing so. This result aligns with previous adoption studies by Danso-Abbeam et al. (2017).

The number of extension contacts was found to influence the intensity of the use of pearl millet technology packages positively and significantly at the 10% significance level. These findings indicate that each additional extension contact between the farmers, development agents, and extension experts improves the intensity of the use of pearl millet technology packages by 1%, with other variables held constant. The reason is that if farm households have frequent extension contact, they will have more confidence and be more aware of the application of pearl millet technology packages. This result is comparable with that of another adoption study by Teshome and Tegegne (2020).

Distance to the local market influenced the intensity of adoption of pearl millet technology packages negatively and significantly at the 1% significance level. This shows that with a one-minute increase in the distance of the local market from farmers' dwellings, the intensity of the use of pearl millet technology packages decreases by 0.3%, ceteris paribus. The reason is that the farmers near the market can obtain sufficient market information and agricultural inputs, including fertilizer and other inputs, than can those distant from the local market. This result is consistent with the study by Endeshaw (2019).

The impact of pearl millet technology adoption on food security

Before estimating the GPS, we conducted a goodness-of-fit test to assess the normality assumption of the adoption index, which is the treatment variable. The test confirmed that the normality assumption was statistically satisfied at the 0.05 level, with skewness (−2.423) and kurtosis (8.232) values indicating a good fit. To account for a potential nonlinear relationship between the adoption index and other variables, we included quadratic and cubic terms of the main covariates and the outcome variable (HDDS) and then estimated the GPS.

Test for covariate balance

After the generalized propensity score (GPS) was estimated, we performed a balancing test for each adoption interval to assess the covariate balancing property. The test provides a high level of confidence in our findings (Table 6). The test assessed the conditional mean of pretreatment variables or covariates, ensuring that the GPS does not differ significantly between households in different treatment groups. Suppose the test fails to reject the hypothesis that the two sets of households are statistically indistinguishable. In that case, it provides reassurance that the treated and control groups matched by the GPS are indeed balanced (Liu and Florax 2014). The balancing property of the GPS was assessed by dividing the distribution of the adoption index at the 30th and 70th percentiles (Hirano and Imbens 2004). The covariate distribution was then compared among three groups: group one (households with an adoption index of $\leq$ 20%), group two (households with an adoption index between 20% and 80%), and group three (households with an adoption index of $\geq$ 80%). After verifying the matching property, we estimate the conditional expectation value of the household dietary diversity score (HDDS) as a function of the adoption index, GPS, and their interaction effects. The results indicated a positive and significant association between HDDS and the adoption index at the 5% significance level (Table 7).

The final step in the GPS-based impact analysis involved estimating the average dose–response function (DRF) via causal inference methods. Specifically, we aimed to determine the average impact of pearl millet technology adoption on the household dietary diversity score (HDDS) across different levels of the adoption index. Following the methodology of Hirano and Imbens (2004), we calculated the average possible outcome on the basis of ten values of adoption intensity or dose (t), with the values bounded between zero and one with 0.1 increments. We then estimated the dose–response function at each adoption index level 't' as E[HDDS(t)] and plotted the results. This approach allowed us to plot the association between the adoption index and HDDS across the entire range of adoption intensities (Figure 8). The dose–response function was estimated within a 95% confidence interval through 1000 bootstrap replications. The bootstrap method was also utilized to estimate the GPS, ensuring the robustness of our results.

We found that farm households have different levels of adoption or doses of pearl millet technology packages, which might influence their diet diversity score differently. Thus, we applied continuous treatment effects estimation via STATA to visualize the impact of different levels of adoption intensities of pearl millet technology packages on the household diet diversity score. Figures 8A and 8B show the probability distributions of the

Table 6: Common support region.

Treatment interval with GPS estimate	Dosage group	Minimum GPS-1	Maximum
≤0.2	Adoption index ≤ 0.2	0.0981942	0.9996592
	Common support region [0, 0.1586199998]		
	0.2 < Adoption index ≤ 0.8	GPS-2	
0.2–0.8	Common support region [0.2224999964, 0.7913889289]	0.0408586	0.9996592
	Adoption index ≥ 0.8	GPS-3	
≥0.8	Common support region [0.8002575039, 0.9906333685]	0.02064597	0.9996592

Table 7: Estimated dose-response function for household food security.

HDDS	Coeff.	*t* value
Adoption index	4.5012	2.36**
Square of Adoption index	6.002	3.62***
GPS	−1.787	−1.16
Square of GPS	−0.409	−0.30
Adoption index*GPS	2.307	1.58
Intercept	5.601	10.43***
Adjusted *R*-squared =	0.4215	
Sample =	172	
F(5,166) =	25.92	
Prob > *F* =	0.000	

dose–response functions and the marginal derivatives of the household diet diversity score (HDDS), respectively. We found a positive linear relationship between the household diet diversity score and adoption intensity (Figure 8). This positive linear shape shows that the household diet diversity score increases when the adoption intensity of pearl millet technology packages increases. In other words, adopting pearl millet technology packages positively influences the household diet diversity score, increasing returns. Our findings differ from those of a previous study conducted by Gebre et al. (2021), who reported that the effects of adopting improved new maize varieties on maize yield exhibited diminishing returns in Tanzania.

Conclusions and policy implications

We analyzed the factors affecting the adoption of pearl millet technology packages and their effects on food security in 172 sample farmers in the Waghimra zone of Ethiopia. We employed double-hurdle and generalized propensity score models (dose–response regressions) to examine the factors influencing pearl millet technology adoption and its effect on the food security of farm households. We applied seven agronomic packages related to pearl millet technology to construct an adoption index. We find that the adoption index is bounded between 0 and 0.99, indicating that farmers have different levels or doses to adopt pearl millet technology packages.

The results of the double-hurdle model estimation show that age, gender, number of oxen, training, extension services, plot fragmentation, and distance from home to the local market significantly influence the likelihood of the adoption decision of pearl millet technology packages. In contrast, the level of education, age, extension service, participation in farm field demonstrations, and distance from home to the local market significantly impact the adoption intensity of pearl millet technology packages.

The findings from the generalized propensity score confirm a positive linear relationship between the household diet diversity score and the intensity of pearl millet technology adoption. Thus, the impact of the adoption of pearl millet technology on the food security of farm households has resulted in increasing returns to scale, which shows that the improvement in pearl millet technology adoption has led to an increase in food security that is more than proportional. As a result, we found that the adoption of pearl millet technology significantly increased the food security of farm households. This study highlights the importance of capturing the heterogeneous impact of pearl millet technology adoption on the food security of farm households. Therefore, this study provides empirical justification for policy planning and the implementation of pearl millet technology, which targets smallholder farm households suffering from food insecurity and living in extremely drought-prone areas.

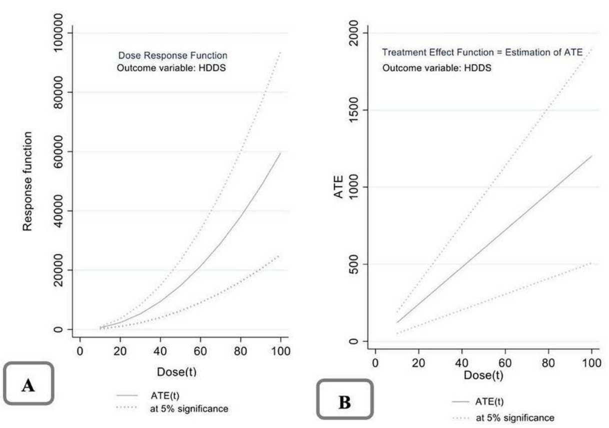

Figure 8: (A) Probability distributions of the dose-response functions. (B) Marginal derivatives of the household diet diversity score (HDDS).

Limitations of the study

Although this study has excellent policy implications, we employed a small sample size and area coverage. Thus, considering a large sample size across different regions of the country would reveal the overall impact of pearl millet technology on food security.

Notes

1. Tie ridges are moisture and soil conservation practices that involve constructing small rectangular basins within the furrow of farm fields. They mainly increase rainfall storage and allow more time for rainfall to infiltrate the soil, making them more suitable for drought-prone or low-rainfall distribution areas (Wiyo et al., 1999).
2. Injera is one of Ethiopia's national dishes. It is a sour fermented flatbread with a slightly spongy texture.
3. Porridge is a thick, sticky food made from pearl millet, oats, and other crops cooked in water or milk and eaten hot, especially for breakfast.
4. Tella is an alcoholic beverage which is locally prepared in Ethiopia.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement

The authors declare that they can provide the data upon the publisher's request. The datasets used and analyzed in this study are available from the authors upon reasonable request and are in STATA 14.0 format.

Author contributions

Asmiro Abeje Fikadu: Writing – original draft, Data curation cleaning, Formal analysis, Conceptualization, Writing – review & editing. **Girma Gezimu Gebre**: Writing – review & editing, Data curation cleaning, Formal analysis, Conceptualization, Supervision, Writing – review & editing. **Hisako Nomura**: Formal analysis, Conceptualization, Supervision, Writing – review & editing. **Bishaw Adamtie Takele**: Writing – original draft, Data curation cleaning, Conceptualization, Writing – review & editing. **Gedefaw Kindu Wubet**: Writing – original draft, Data curation cleaning, Formal analysis, Conceptualization, Writing – review & editing.

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