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Impact of Northern Tanzania Potato Systems Improvement Project on Agricultural Technology Adoption in Potato Farming in Arusha District

[1]Ermelinda A. Eliasse, Justin K. Urassa[2] and Tumaini Allan [3]

[1]Department of Policy, Planning and Management, Sokoine University of Agriculture, Morogoro, Tanzania. Email: ermelindaeliasse@gmail.com

[2]Department of Policy, Planning and Management, Sokoine University of Agriculture, Morogoro, Tanzania. Email: urassa@sua.ac.tz

[3]Department of Policy, Planning and Management, Sokoine University of Agriculture, Morogoro, Tanzania. Email: atuma@sua.ac.tz

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Abstract: *The adoption of advanced agricultural technologies is essential for enhancing crop productivity and improving the livelihoods of smallholder farmers, yet its uptake remains limited in regions like Sub-Saharan Africa, including Tanzania, where adoption rates hover around 23%. This study evaluates the effectiveness of the Northern Tanzania Potato Systems Improvement Project in promoting advanced potato production technologies in Arusha District, Tanzania, guided by the High Payoff Input Model. Using a cross-sectional design, data were collected from 192 potato farmers, including project participants and non-participants. Descriptive statistics and inferential methods, such as binary logistic regression and Propensity Score Matching, were employed to assess adoption outcomes. Results show that project participants were significantly more likely to adopt improved seed varieties (ATT = 0.33), including the Obama variety (ATT = 0.35), engage in multi-season farming (ATT = 0.30), use fertilizers (ATT = 0.30), join cooperatives (ATT = 0.43), and access markets (ATT = 0.27). Higher adoption of extension services (ATT = 0.28) and access to credit (ATT = 0.28) were also observed. However, mechanization adoption was negligible (ATT = 0.00), highlighting systemic barriers such as high costs and limited training. These findings emphasize the need to strengthen input delivery systems, promote affordable mechanization solutions, and enhance community-based financing to ensure sustained adoption and maximize the project's contribution to regional agricultural transformation.*

Keywords: *Agricultural Technology Adoption, Potato Production, Smallholder Farmers, Arusha District, High Payoff Input Model*

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1. Background Information

The global imperative to achieve food security for a projected 9.7 billion people by 2050, amidst shrinking arable land and intensifying climate change, underscores the critical role of agricultural technology (AT) adoption in transforming smallholder farming systems (FAO, 2023). Technologies such as improved seed varieties, fertilizers, mechanization, and precision farming can boost crop yields by 20–50%, enhancing farmer livelihoods and aligning with the United Nations' Sustainable Development Goals (SDGs) for poverty eradication (SDG 1) and zero hunger (SDG 2) (United Nations, 2023). In Sub-Saharan Africa, where smallholder farmers produce 80% of food supplies, low AT adoption rates, averaging 20–30% compared to 50–70% in developed economies, hinder agricultural transformation, exacerbating food insecurity and rural poverty (Suri & Udry, 2022; AGRA, 2023). In Tanzania, where agriculture employs over 65% of the workforce and contributes 30% to GDP, national initiatives like the Kilimo Kwanza Initiative, Agricultural Sector Development Programme (ASDP), and Southern Agricultural Growth Corridor of Tanzania (SAGCOT) aim to modernize farming through technology dissemination (Van Arkadie, 2019). Yet, Tanzania's AT adoption rate remains low at 23%, with potato farming in Arusha District, a region producing 30% of the nation's potatoes, facing persistent barriers such as high input costs, limited credit access, and poor infrastructure (AGRA, 2023; Arusha District Council, 2017). The Northern Tanzania Potato Systems Improvement (NTPSI) project, implemented by the Research, Community and Organizational Development Associates (RECODA), seeks to address these challenges by promoting improved technologies among smallholder potato farmers. This study evaluates the NTPSI project's effectiveness in enhancing AT adoption, contributing to global and regional discourses on agricultural modernization and food security.

Extensive research highlights the multifaceted determinants of AT adoption in potato production. Studies in Tanzania's Mbeya Rural District, Nigeria, and Cameroon demonstrate that education level, access to extension services, credit availability, potato farming experience, and farmer group membership significantly influence adoption, with cooperative members showing higher uptake due to collective resource access and social networks (Namwata *et al.*, 2010; Udoh *et al.*, 2025; Selahkwe *et al.*, 2021). For instance, Namwata *et al.* (2010) found that farmers with higher education and access to extension services in Mbeya were more likely to adopt improved seed varieties, while Udoh *et al.* (2025) emphasized the role of credit and cooperative membership in Nigeria. Commercialization and market integration further incentivize adoption, as seen in Tanzania's Southern Highlands, where smallholder farmers allocating 20–67% of land to potatoes and accessing structured markets were more likely to invest in improved seeds, fertilizers, and pest control methods due to higher market returns (Mpogole *et al.*, 2012). However, barriers such as high input costs, limited knowledge, inadequate credit access, and poor infrastructure impede adoption (Namwata *et al.*, 2010; Selahkwe *et al.*, 2021; Udoh *et al.*, 2025). In Nigeria, farmers recognized the benefits of improved inputs but lacked financial resources to adopt them, while in Tanzania, reliance on intermediaries and poor road infrastructure limited market access and profitability (Udoh *et al.*, 2025; Mpogole *et al.*, 2012). Mechanization adoption is particularly low, with less than 5% of Tanzanian smallholders using machinery due to high costs, limited training, and infrastructure deficits (Mrema *et al., 2020). Institutional support, including extension services*, cooperatives, and government policies, is critical, yet underfunding and unclear seed certification policies in Tanzania limit their effectiveness (Mpogole *et al.*, 2012; Udoh *et al.*, 2025; Selahkwe *et al.*, 2021). Key indicators for assessing AT adoption include the use of certified seeds (e.g., the high-yielding Obama variety), multi-season farming, fertilizer use, cooperative membership, market access, extension services, credit access, and mechanization, all of which reflect farmers' capacity to modernize production systems and enhance productivity (Ronner *et al.*, 2018; Hill *et al.*, 2021; Kauky, 2024; Mbaga *et al.*, 2024; Li, 2023; Manda *et al.*, 2021; Harou & Tamim, 2024; Kipkogei *et al.*, 2025; Hamilton *et al.*, 2022; Kumar *et al.*, 2020).

Despite these insights, a critical gap persists in evaluating the causal impact of specific interventions like NTPSI on AT adoption. While studies identify general determinants, they rarely assess the effectiveness of targeted programs in improving adoption outcomes, particularly in Tanzania's potato sector (Namwata *et al.*, 2010; Udoh *et al.*, 2025; Selahkwe *et al.*, 2021). This gap is urgent given Tanzania's low AT adoption rate of 23% and the socioeconomic importance of potato farming in Arusha, where 39.6% of the population depends on agriculture (The United Republic of Tanzania, 2024; AGRA, 2023). Without rigorous evaluation, stakeholders risk misallocating resources, perpetuating low productivity and food insecurity. Empirical evidence underscores this urgency: only 40% of Tanzanian farmers use improved seeds, contributing to yield gaps of up to 50%, while mechanization remains negligible due to systemic barriers (Kilimo Kwanza, 2023; Mrema *et al.*, 2020). Qualitative data from NTPSI focus groups highlight farmers' struggles with input affordability, market access, and climate variability, reinforcing the need for targeted interventions (RECODA, 2019). The NTPSI project's integrated approach, combining seed provision, extension services, and cooperative formation—offers a unique opportunity to address these barriers, yet its effectiveness remains underexplored.

In Arusha District, where favorable agroecological conditions, bimodal rainfall (600–800 mm annually), clay-loam soils, and altitudes of 1,400–2,000 m—support potato production, the NTPSI project directly enhances food security and economic resilience for smallholder farmers (TOSCI, 2022). As such, by promoting technologies such as improved seeds, multi-season farming, and market linkages, NTPSI offers a scalable model for Tanzania's agricultural transformation. Guided by the High Payoff Input Model (HPIM), which emphasizes economic incentives and resource access in driving technology uptake (Ruttan, 1977), this study aims to: (1) assess adoption rates of improved seeds, the Obama variety, multi-season farming, fertilizers, cooperative membership, market access, extension services, credit, and mechanization; (2) estimate the causal impact of NTPSI participation using Propensity Score Matching (PSM) to compare participants and non-participants; and (3) identify barriers to adoption, such as input costs, infrastructure deficits, and institutional limitations. Therefore, by providing robust evidence on NTPSI's effectiveness, this study informs policy interventions to enhance agricultural productivity and sustainability in Tanzania and similar contexts.

2.0 Theoretical Framework: High Payoff Input Model and Complementary Theories for Assessing NTPSI's Effectiveness in Promoting Technology Adoption in Potato Production

The adoption of agricultural technologies by smallholder farmers is shaped by a complex interplay of economic, institutional, social, and behavioral factors. This study adopts the High Payoff Input Model (HPIM) as its primary theoretical framework to evaluate the effectiveness of the Northern Tanzania Potato Systems Improvement (NTPSI) project in promoting improved potato production technologies in Arusha District, Tanzania. The HPIM, developed by Ruttan (1977, 1988), posits that farmers' decisions to adopt new technologies are driven by the expected economic benefits, such as higher yields, reduced risks, and increased income, relative to the costs of adoption, including investments in inputs, labor, and learning. The model emphasizes access to high-return inputs (e.g., improved seeds, fertilizers) and supportive institutional environments (e.g., extension services, credit, and market linkages) as critical drivers of technology uptake. In the context of the NTPSI project, the HPIM suggests that smallholder farmers participating in the project are more likely to adopt technologies such as certified seeds (e.g., the Obama variety), multi-season farming, fertilizers, and cooperative membership due to enhanced access to these resources and the anticipated profitability (RECODA, 2019). For instance, NTPSI's provision of improved seeds, training, and market linkages aligns with HPIM's focus on reducing adoption costs and increasing economic incentives, thereby encouraging farmers to invest in productivity-enhancing practices.

To operationalize the HPIM, this study examines key adoption indicators, use of improved seeds, adoption of the Obama variety, multi-season farming, fertilizer use, cooperative membership, market access, extension services, credit access, and mechanization, as they reflect farmers' capacity to modernize production systems in response to economic and institutional support (Kumar *et al.*, 2020; Ronner *et al.*, 2018; Hill *et al.*, 2021). The HPIM provides a structured lens to analyze how NTPSI's interventions, such as input provision and extension services, translate into higher adoption rates by reducing financial and knowledge barriers. For example, the model predicts that farmers with access to credit and extension services, as facilitated by NTPSI, will adopt technologies like fertilizers and improved seeds due to their high payoff in terms of yield increases (up to 50% per hectare, as noted by Abebaw *et al.*, 2023) and market-driven profitability (Mpogole *et al.*, 2012).

However, the HPIM's assumption of rational economic decision-making has limitations, particularly in smallholder contexts where social, cultural, and behavioral factors influence adoption (Udemezue & Osegbue, 2018). To address these limitations and provide a more comprehensive understanding of adoption dynamics, this study integrates elements of Rogers' Diffusion of Innovations (DOI) theory (Rogers, 2003) and the Technology Acceptance Model (TAM) (Davis, 1989). The DOI theory complements the HPIM by capturing the temporal and social dimensions of technology adoption, emphasizing how innovations diffuse through social networks and are influenced by factors such as compatibility with local practices, observability of benefits, and the role of early adopters. In Arusha, where cooperative membership and social networks are significant (Selahkwe *et al.*, 2021; Mmbughu *et al.*, 2025), DOI suggests that NTPSI's promotion of farmer groups enhances adoption by fostering peer learning and reducing perceived risks. For instance, farmers observing higher yields from the Obama variety among cooperative members are more likely to adopt it, as highlighted by Mbaga *et al.* (2024).

The TAM further enriches the framework by focusing on farmers' perceived usefulness and ease of use of technologies, which are critical in contexts with low education levels (29.5% of Arusha farmers have no formal education; The United Republic of Tanzania, 2024). TAM posits that farmers are more likely to adopt technologies perceived as beneficial (e.g., higher yields from fertilizers) and easy to implement (e.g., multi-season farming with accessible inputs). NTPSI's extension services and training align with TAM by enhancing farmers' technical knowledge and confidence, thereby increasing the perceived ease of adopting complex practices like fertilizer application (Harou & Tamim, 2024). However, TAM also highlights barriers such as limited knowledge of new technologies, as noted by Namwata *et al.* (2010), which NTPSI addresses through its Rural Initiatives for Participatory Agricultural Transformation (RIPAT) approach.

The integration of HPIM, DOI, and TAM provides a robust theoretical framework to evaluate NTPSI's effectiveness. HPIM explains the economic incentives driving adoption, such as market access and credit availability (Manda *et al.*, 2021; Kipkogei *et al.*, 2025), while DOI accounts for social dynamics, including the role of cooperatives in knowledge dissemination (Kehinde & Kehinde, 2020). TAM addresses behavioral factors, such as farmers' perceptions of technology benefits, which are critical given the low mechanization rates (ATT = 0.00) due to high costs and inadequate training (Mrema *et al.*, 2020; Daum & Birner, 2020). This hybrid approach acknowledges that adoption is not solely driven by economic rationality but also by social influence, compatibility with local practices, and perceived usability, particularly in resource-constrained settings like Arusha.

Empirically, this framework guides the study's analysis of NTPSI's impact using Propensity Score Matching (PSM) to estimate the Average Treatment Effect on the Treated (ATT) for adoption indicators. As such, by comparing NTPSI participants and non-participants, the study tests the HPIM's hypothesis that access to high-payoff inputs increases adoption rates, while DOI and TAM provide insights into why certain technologies (e.g., mechanization) remain under-adopted due to social or behavioral barriers. For example, the significant ATT values for improved seeds (0.33), Obama variety (0.35), and cooperative membership (0.43) reflect HPIM's emphasis on economic incentives, while the negligible mechanization adoption highlights DOI's insight into slow diffusion due to incompatibility with local resources and TAM's focus on perceived complexity (Hamilton *et al.*, 2022). The framework also informs policy recommendations, such as strengthening extension services and cooperative structures to enhance social learning (DOI), reducing input costs to improve economic viability (HPIM), and improving training to increase perceived ease of use (TAM).

Despite its strengths, the hybrid framework has limitations. HPIM's focus on economic rationality may overlook non-economic barriers like cultural resistance or risk aversion, which are prevalent among older farmers (Finscope, 2017). DOI's emphasis on social diffusion may not fully account for structural constraints like poor infrastructure, which limits market access (Mpogole *et al.*, 2012). TAM's reliance on perceived usefulness assumes access to information, which may be limited in remote areas (Namwata et al., 2010). To mitigate these, the study incorporates qualitative insights from key informant interviews and focus group discussions to capture contextual barriers, such as poor road infrastructure and reliance on intermediaries, ensuring a nuanced analysis of NTPSI's impact. This theoretical triangulation strengthens the study's ability to provide robust evidence for policy interventions aimed at enhancing agricultural productivity and sustainability in Tanzania's potato sector and similar smallholder contexts.

3.0 Methodology

3.1 Study Area

The study was conducted in Arusha District, Tanzania, located between latitudes 2°14' to 5°2' south and longitudes 35°12' to 36°0' east, in the northern part of Tanzania near the Kenyan border (Peligal, 1999). Arusha District was selected due to its role as the implementation site for the Northern Tanzania Potato Systems Improvement (NTPSI) project and its significance in potato production, contributing approximately 30% of Tanzania's potato output (Arusha District Council, 2017; Groot et al., 2020). The district's agroecological conditions, including high altitudes (1,400–2,000 m above sea level), bimodal rainfall (600–800 mm annually), and clay-loam soils with a pH of 5.5–7, are ideal for potato cultivation, supporting two growing seasons with average temperatures of 13–19°C (TOSCI, 2022). The study included three treated villages (Engutoto, Imbibia, and Engalaoni) where NTPSI was implemented and five control villages (Olkokola, Sambasha, Bangata, Shiboro, and Uldonyosambu) selected for their similar agroecological and socioeconomic characteristics but lack of NTPSI intervention. This selection ensured comparability between groups while isolating the project's impact (Caliendo & Kopeinig, 2008).

3.2 Study Design

A cross-sectional design was employed to evaluate the NTPSI project's effectiveness in promoting agricultural technology adoption among smallholder potato farmers. This design was chosen to capture a snapshot of adoption outcomes at a single point in time, allowing for comparisons between NTPSI participants and non-participants (Hunziker & Blankenagel, 2024). While cross-sectional studies are effective for assessing associations and estimating treatment effects, they are limited in establishing causality due to potential confounding variables and the inability to capture temporal dynamics (Sedgwick, 2015). To mitigate these limitations, Propensity Score Matching (PSM) was used to control for selection bias by matching participants and non-participants based on observable characteristics, thus approximating a quasi-experimental design (Rosenbaum & Rubin, 1983). Additionally, qualitative data from key informant interviews (KIIs) and focus group discussions (FGDs) were integrated to provide contextual insights into adoption barriers, enhancing the study's explanatory power (Creswell & Plano Clark, 2017).

3.3 Data Collection

Primary data were collected from 192 potato farmers (96 NTPSI participants and 96 non-participants) using semi-structured questionnaires administered between March and May 2023. The questionnaires captured socioeconomic characteristics (e.g., age, gender, education level, household size, farming experience), access to resources (e.g., credit, extension services, agro-inputs, market information), and adoption of technologies (e.g., improved seeds, Obama variety, multi-season farming, fertilizers, cooperative membership, mechanization). To ensure reliability, the questionnaire was pre-tested with 20 farmers in a neighboring district, and adjustments were made to improve clarity and relevance (Babbie, 2020). Qualitative data were gathered through four KIIs (three farmers and one NTPSI project manager) and one FGD with six farmers, selected purposively to represent diverse perspectives on adoption challenges. The KIIs and FGDs followed semi-structured guides to explore barriers such as input affordability, infrastructure, and market access, with responses recorded and transcribed verbatim. Secondary data, including NTPSI project reports and regional agricultural statistics, were sourced from RECODA (2019) and the National Bureau of Statistics (The United Republic of Tanzania, 2024) to contextualize findings.

3.4 Sampling Procedure

A multistage sampling approach was employed to ensure a representative sample (Sedgwick, 2015). First, Arusha District was purposively selected as the NTPSI implementation site. Second, villages were stratified into treated (NTPSI) and control (non-NTPSI) groups based on project participation, with treated villages chosen for their active involvement in NTPSI activities and control villages selected for their agroecological and socioeconomic similarity to treated villages, confirmed through consultations with local agricultural officers (Arusha District Council, 2017). Within each stratum, simple random sampling was used to select 96 participants and 96 non-participants, determined using the Krejcie and Morgan (1970) formula for a population of approximately 2,000 potato farmers in the study area, ensuring a 95% confidence level and a 5% margin of error. This sample size provided sufficient statistical power to detect differences in adoption outcomes (Cohen, 1988).

3.5 Data Analysis

Qualitative data were analysed using MAXQDA software, facilitating systematic coding and organising textual responses from interviews and focus-group discussion questions. The analysis followed a content analysis approach, allowing for the identification of recurring themes, patterns, and categories relevant to adopting agricultural technologies. Quantitative data analysis was conducted using SPSS for descriptive statistics (means, standard errors, and frequencies), and inferential statistics was determined using STATA (version 17). To address potential selection bias and obtain an unbiased estimate of the impact of NTPSI participation on the adoption of improved potato production technologies, the study applied Propensity Score Matching (PSM). PSM was used to estimate the Average Treatment Effect on the Treated (ATT) by comparing technology adoption rates between NTPSI participants and non-participants (Abdia et al., 2017). Participants and non-participants were matched based on covariates such as access to credit, extension services, market access, education level, household size, and farming experience, ensuring that observed differences in adoption rates were attributable to NTPSI participation rather than pre-existing characteristics. The ATT was estimated using the difference in expectation of technology adoption probability between the participants and non-participants, as presented in the following equation:

$$ATT = E(Y_1|D=1) - E(Y_0|D=1)$$

Equation 1

Where:

- ATT represents the Average Treatment Effect on the Treated.
- E (Y_1|D=1) is the expected technology adoption rate among NTPSI participants.
- E (Y_0|D=1) matches the non-participants' expected technology adoption rate.

To estimate the propensity score, a binary logistic regression model was used, as shown in the following equation (Leuven & Sianesi, 2003):

$$\text{logit}\left[\frac{(Y=1)}{P(Y=0)}\right] = \beta0+\beta1(\text{Sex}) + \beta2(\text{farming experience}) + \beta3\,(\text{Household Size}) + \beta4(\text{Education level}) + \beta5(\text{Access to market information}) + \beta6(\text{Number of Season growing}) + \beta7(\text{Distance from the market}) + \beta8(\text{age}) + \beta8(\text{Access to extension service}) + \beta9(\text{Access to credit})$$

Equation 2

Where:

- $logit\left[\frac{p(Y=1)}{P(Y=0)}\right]$ represents the likelihood of someone participating in the project.

The covariates for the binary logistic regression model for propensity score estimation were selected based on recent empirical evidence reflecting determinants of agricultural technology adoption. Gender and age significantly influence adoption, with Awoke *et al.* (2025) showing that female-headed and older households in Dodoma, Tanzania, are less likely to adopt climate-smart agriculture due to structural barriers. Education enhances farmers' ability to understand and implement innovations; Abdulai and Jumpah (2021) find that higher education is associated with increased uptake of improved smallholder technologies in Northern Ghana. Farming experience and household size are proxies for managerial capacity and labour availability, essential for adopting complex inputs (Wordofa *et al.*, 2021). Extension services and credit access have been shown to facilitate adoption by providing technical knowledge and finance. Market information and proximity to markets reduce transaction costs and improve expected profitability, encouraging adoption. Lastly, the number of growing seasons signals production intensity and continuous engagement with technology.

4.0 Results and Discussion

4.1 Socioeconomic characteristics of respondents under study

The results of the descriptive analysis of farmers' socioeconomic characteristics, presented in Table 1, reveal several insights that have implications for agricultural development and policy formulation. The data shows a relatively balanced gender distribution, with females making up 53.9% of the respondents, slightly outnumbering males. The study results contrast with the findings of Wamuyu (2019), which showed low participation rates of women in the potato value chain in Kenya. This suggests that women play a significant role in agriculture within the study area, which is crucial for designing gender-responsive agricultural programs. Most farmers fall within the 36-65 age category (69.4%); the study results align with those reported by Yeboah (2020), where the average age category of farmers in Africa is 32-39. The age distribution suggests a potential opportunity in innovation adoption, as younger farmers are more open to adopting new technologies (Msengi & Akyoo, 2023). Additionally, the high percentage of married individuals (87.6%) could imply that farming activities are largely family-based.

The results observed in Table 1 further show that the respondents' education levels were predominantly low, with 29.5% having no formal education and 52.8% having completed primary school education. These results are consistent with previous research conducted by FAO (2020), which states that most farmers in Tanzania have a primary school level. Generally, low educational attainment can hinder the adoption of advanced farming technologies; one's education level is often associated with a better understanding and implementation of new agricultural practices. The Table 1 also reports that surveyed households were generally large, with 47.7% of them having 5 to 10 members: the observed range is well above Tanzania's average household size of 4.8 (Government of Tanzania, 2022) and the rural average of 5 members reported by the World Bank (Amankwah *et al.*, 2023). A possible explanation for this result may be the existence of Maasai families, which tend to have more than one wife and, consequently, more than one family sharing the same household. Most (73.5%) farmers have 3 to 10 years of farming experience, which suggests that they are relatively experienced farmers, which can facilitate the adoption of agricultural technology.

The findings highlight significant resource access gaps and vital services for improving agricultural productivity. Notably, only 33.7% of farmers have received training, and 38.3% have access to extension services, crucial for transferring knowledge and skills necessary for modern farming. Although the coverage of extension services is low compared to the average of developed economies, the coverage is high compared to the average of 20% in Africa (Masanja *et al.*, 2023). The reason behind the slightly higher rate may be the use of the RIPAT approach during the NTPSI intervention. The study revealed a high access to credit (76.2%). Despite the majority of the research participants being smallholder farmers cultivating potatoes in remote areas such as mountains and forests, they contradict the findings of Mwonge and Naho (2021), who suggest that the proximity to credit institutions determines the level of access to credit. The higher access to credit could suggest that farmers can invest in inputs and technology, as Sanka and Nkilijiwa (2021) suggested. However, the study revealed limited access to agro-inputs (34.7%), which can be caused by low road coverage in the areas where potatoes are produced in the Arusha district. The study revealed higher access to market information (72.0%), suggesting a positive knowledge of market information.

Table 1: Descriptive analysis of socioeconomic characteristics of farmers (n=192)

Respondent's	Category	Frequency	Percentage (%)
Sex	Female	104	53.9
	Male	89	46.1
Age category (years)	18 – 35	46	23.8
	36 -65	134	69.4
	Above 65	13	6.7
Marital Status	Single	5	2.6
	Married	169	87.6
	Widow/Widower	19	9.8
Education level	No formal education	57	29.5
	Primary education	102	52.8
	Secondary education	29	15.0
	Tertiary education	5	2.6
Household size (members)	Below 3	7	3.6
	3 – 5	90	46.6
	5 – 10	92	47.7
	Above 10	4	2.1
Farming experience (years)	Below 3	19	9.8
	3 – 5	68	35.2
	6 – 10	74	38.3
	Above 10	32	16.6
Farm size (acres)	Below 1	57	29.5
	1 – 3	101	52.3
	3 – 5	24	12.4
	Above 5	11	5.7
Receive training	No	128	66.3
	Yes	65	33.7
Access to extension services	No	119	61.7
	Yes	74	38.3
Access to a credit	No	46	23.8
	Yes	147	76.2
Access to agro inputs	No	126	65.3
	Yes	67	34.7
Access to market information	No	54	28.0
	Yes	139	72.0

4.2 Factors influencing the potatoes' productivity

A multiple linear regression model assessed the factors impacting Arusha farmers' potato productivity. The trustworthiness of the model's estimates is supported by 67, the Durbin-Watson statistic of 1.54, which indicates no significant autocorrelation in the residuals (Montgomery *et al.*, 2021). All variables' Variance Inflation Factor (VIF) values are below the threshold of 5, suggesting that multicollinearity is not a significant concern in this model. However, the model's independent variables account for approximately 43.4% of the variation in potato production, as indicated by the R2 value of 0.434 (Seber & Lee, 2012). The multiple linear regression analysis results, as presented in Table 2, show that several farming household characteristics were significantly associated with potato productivity. For example, the model suggests that the household head's education level, age, farm size, and access to credit significantly impacted the household's potato production. Generally, having a secondary school education was significantly ($p \leq 0.003$) associated with a household's higher potato production: the coefficient for farmers with secondary education is 34.1. This suggests that farmers who have attained secondary education produce, on average, 34.1 kg more potatoes than those with no formal education, controlling other factors. The finding aligns with the study by Etwire *et al*. (2013), which revealed a positive correlation between the education levels of farmers and their agricultural productivity. The finding underscores the importance of education in enhancing agricultural productivity, likely due to better knowledge of farming techniques, improved decision-making, and more effective use of resources.

Table 2 also shows that age was negative and significantly ($p \leq 0.05$) associated with a household's potato production, with the coefficient being -19.7. This suggests that, on average, older farmers (36 – 65) produce 19.7 kg less than younger farmers (18-35 years). The results align with the research by Finscope (2017) that reveal age plays a role in agricultural productivity, with younger farmers generally demonstrating higher productivity levels. This is attributed to their physical ability to work longer hours and adapt to labour-intensive methods. This could reflect the physical demands of potato farming, where younger farmers might be more capable of intensive labour, or it could be due to older farmers needing to be more adaptable to new agricultural practices.

Key results (Table 2) further show that farm size was significantly ($p \leq 0.001$) associated with the surveyed households' potato productivity; farms above 5 acres had a positive coefficient of 111.5. Tanzania has an inverse relationship between farm size and productivity. Smaller farms tend to have higher productivity per hectare than larger farms (Rada & Fuglie, 2019; Savastano & Scandizzo, 2017). SHF with access to credit produced, on average, 17.58 kg more potatoes than those without, and the difference was statistically significant ($p \leq 0.05$) (Table 2). The finding is in line with that of Kinuthia (2018), in which it was reported that farmers with no or limited access to credit were 40% less likely to invest in modern technologies and inputs, resulting in lower yields and less efficient farming practices compared to farmers who can secure credit. The findings highlight the critical role that financial resources play in agricultural productivity. Generally, access to credit enables farmers to invest in better seeds, fertilisers, and other inputs, thereby enhancing their output.

Table 2: Multiple linear regression for factors influencing production of potatoes across farmers in Arusha (n=192)

Variable		Coeff	SE Coef.	T-Value	P-Value	IF
Sex of respondent	Male	-5.33	7.32	-0.73	0.468	1.39
Marital Status	Single	6.2	25.5	0.24	0.809	1.71
	Widow /Widower	1.1	11.6	0.09	0.926	1.25
Education level	Primary education	10.26	7.72	1.33	0.186	1.55
	Secondary education	34.1	11.3	3.01	0.003*	1.71
	Tertiary education	11.4	21.9	0.52	0.602	1.25
Age (years)	36 -65	-19.7	8.88	-2.22	0.028*	1.74
	Above 65	-21.8	16.1	-1.35	0.178	1.7
Household size	3 – 5	4.2	20.9	0.2	0.842	1.24
	5 – 10	12.7	21.3	0.6	0.551	1.76
	Above 10	-40.2	31.1	-1.29	0.198	2.05
Farm size (acres)	1 – 3	8.88	7.79	1.14	0.256	1.57
	3 – 5	17.6	11.4	1.55	0.124	1.47
	Above 5	111.5	16	6.99	0.000*	1.42
Farming experience	3 – 5	-1.7	11.9	-0.15	0.884	3.37
	5 – 10	19	12.3	1.54	0.125	3.72
	Above 10	12.6	14.1	0.89	0.373	2.85
Access to training	Yes	5.96	7.9	0.75	0.452	1.45
Access to extension services	Yes	-5.78	7.6	-0.76	0.448	1.42
Access to credit	Yes	17.58	8.74	2.01	0.046*	1.44
Access to agro inputs	Yes	5.64	7.9	0.71	0.476	1.47
Access to market information	Yes	2.32	8.08	0.29	0.775	1.37
	Constant	-9.4	25.5	-0.37	0.712	

** Indicate significance at 0.05, Durbin Watson test=1.54 and* $R^2 = 0.434$

4.3 Factors influencing farming households' participation in the potato production project

Table 3 presents the binary logistic regression analysis results to determine farming households' characteristics associated with their involvement in potato production (Harrell & Harrell, 2015). The Hosmer-Lemeshow Chi-square test, which has 8 degrees of freedom, a p-value of 0.987, and a Chi-square value of 0.06, indicates the model's goodness of fit (Hosmer *et al.*, 1997). The strong p-value indicates that the model fits the data well, indicating that the observed and expected involvement in the potato production project does not differ significantly. This suggests that the model's variables are sufficient to explain the variation in farmers' participation. Research results in Table 3 show that a household's sex was significantly different ($p \leq 0.05$). The negative coefficient (-19.81) and statistically significant p-value (0.002) indicate that male respondents are significantly less likely to participate in the potato production project compared to their female counterparts. The research results contrasts with the results from Leavens *et al.* (2019), which suggest that women tend to participate less in agricultural programs. When they do, they are not the decision-makers. The study results reveal a picture presented by the National Bureau of Statistics of Tanzania. (2018), 65% of farmers in Tanzania are women. This indicates that male farmers are less likely to participate in the potato production project than female farmers.

Table (3) also shows that the household's head age was negatively and significantly associated with its participation in the potato project. For the age group 36-65, the coefficient was -17.04 with a p-value of 0.007; for those above 65, the age group, the coefficient was -43.8 with a p-value of 0.001. This suggests that older farmers are less likely to participate in the project, decreasing the likelihood of participation significantly. According to Finscope (2017), most farmers in Tanzania are between 25 and 54 years old, with an average age of slightly over 40. The negative coefficient for the above 65 category highlights the challenge of engaging older farmers in new agricultural initiatives. Observed results further show that education level positively and significantly ($p \leq 0.001$) influences farming households' participation in the potato production project; primary education had a positive coefficient of 27.61 and a p-value <0.001. Thus, farmers with primary education are more likely to participate in the project.

In contrast, secondary education had a negative coefficient of -8.31 (though insignificant at the 0.05 level, p-value 0.095), and tertiary education shows no significant effect. The findings are in line with what has been reported by the United Republic of Tanzania (2021), which states that 55% of farmers had primary school education. The positive impact of primary education may indicate that basic literacy and numeracy skills are sufficient to understand and engage in the project. In contrast, higher levels of education do not necessarily increase participation.

Table 3 shows that both access to training and extension services have significant negative coefficients (-113.8, p-value <0.001 for training; -50.1, p-value <0.001 for extension services), indicating that farmers with access to these services from other institutions are less likely to participate in the project. Although the NTPSI project has provided training and extension services to project participants, focus group discussions revealed that many interventions are repetitive, diminishing their appeal to participate actively in the project training. Access to credit (-36.7, p-value 0.001) was significantly and negatively associated with households' participation in the potato project, thus suggesting that farmers who can obtain credit are less likely to join the project. This could indicate that such farmers already have the financial resources needed for production and do not see additional value in the project. Conversely, access to agro-inputs (33.38, p-value 0.001) and market information (19.23, p-value 0.001) are positively associated with participation. The study evidence conforms to findings by Mlalila and Kagoro (2021) that suggest that farmers with access to credit are more likely to be medium to large-scale farmers, and smallholder farmers have less access to credit. The findings show that Farmers who can access these resources are more likely to participate because these inputs enhance productivity, making project involvement more attractive.

Table 3: Binary logistic regression for factors influencing participation in the potatoes project (n=192)

	Variables	Coeff	SE Coeff	Z-Value	P-Value
Sex of respondent	Male	-19.81	6.4	-3.1	0.002*
Age category	36 -65	-17.04	6.32	-2.7	0.007*
	Above 65	-43.8	12.8	-3.42	0.001*
Household size category	3 – 5	-11.5	73.2	-0.16	0.875
	5 – 10	2.6	73.2	0.04	0.972
	Above 10	-64	105	-0.61	0.541
Marital Status	Married	-53.8	81.6	-0.66	0.509
	Widow/Widower	-50.3	86.6	-0.58	0.561
Education level	Primary education	27.61	7.82	3.53	0.000*
	Secondary education	-8.31	4.98	-1.67	0.095
	Tertiary education	-49	955	-0.05	0.959
Access to training	Yes	-113.8	27.8	-4.1	0.000*
Access to extension services	Yes	-50.1	12.7	-3.95	0.000*
Access to credit	Yes	-36.7	11.2	-3.28	0.001*
Access to agro inputs	Yes	33.38	9.88	3.38	0.001*
Access to market information	Yes	19.23	5.85	3.29	0.001*
Farm size category	1 – 3	14.42	5.82	2.48	0.013*
	3 – 5	58.6	15.5	3.79	0.000*
	Above 5	-23.19	9.19	-2.52	0.012*
Farming experience	3 – 5	-47.4	13.3	-3.58	0.000*
	5 – 10	-105.4	26.8	-3.93	0.000*
	Above 10	-50.5	14.7	-3.42	0.001*
	Constant	36.6	34	1.07	0.283

** Indicates significance at 0.05, Hosmer -Lemeshow Chi-square = 0.06 df =8, p-value 0.987*

Lastly, Table 3 shows that farm size has mixed effects on households' potato project participation. Generally, farmers with medium-sized farms (1-3 acres: 14.42, p-value 0.013; 3-5 acres: 58.6, p-value <0.001) were more likely to participate, while those with larger farms (>5 acres: -23.19, p-value 0.012) were less likely. The finding contradicts observations by Etwire *et al.* (2013) that farmers with higher socioeconomic status, such as more extensive landholdings, more significant assets, and higher income, were more likely to participate in agricultural projects. The observed results suggest that the project is particularly appealing to farmers with small to medium holdings, possibly because they stand to gain more from the additional support. In contrast, larger farms may already have sufficient resources, reducing their need for project involvement. Farming experience, particularly in the 3–5-year range (-47.4, p-value <0.001) and 5–10-year range (-105.4, p-value <0.001), negatively and significantly influences participation. This suggests that more experienced farmers are less likely to participate in the project, and the project's participation is more appealing to farmers with less experience. The possible explanation for this result might be that experienced farmers may feel they already possess sufficient knowledge and skills, making them less motivated to engage in training or new interventions, and participation might be more appealing to less-experienced farmers who are still building their skills and knowledge.

4.4 Effectiveness of the NTPSI Project in Promoting the Adoption of Potato Production in the Arusha District

To evaluate the effectiveness of the Northern Tanzania Potato Systems Improvement (NTPSI) project in promoting the adoption of agricultural technologies among smallholder potato farmers in Arusha District, Tanzania, Propensity Score Matching (PSM) was employed to address potential selection bias inherent in observational studies. Selection bias arises because farmers who participate in NTPSI may differ systematically from non-participants in observable characteristics (e.g., education, farming experience) that influence both participation and technology adoption outcomes (Rosenbaum & Rubin, 1983). PSM mitigates this bias by creating a matched sample of participants and non-participants with similar propensity scores, thus approximating a quasi-experimental design to estimate the causal impact of NTPSI participation (Caliendo & Kopeinig, 2008). The PSM analysis involved three key steps: propensity score estimation, matching and balance checks, and estimation of the Average Treatment Effect on the Treated (ATT), with additional robustness checks to ensure reliable results.

4.4.1 Binary logistic regression for propensity score estimation

A binary logistic regression model was used to estimate the probability of NTPSI participation based on selected socioeconomic characteristics of farmers (Harris, 2021). The significant predictors of participation included education level (p = 0.037), farming experience (p = 0.001), and household size (p = 0.036), indicating that farmers with higher education, larger household sizes, and more farming experience were more likely to participate in NTPSI. Other variables, such as sex, age category, marital status, and farm size, did not significantly influence participation.

Table 4: Binary Logistic Regression for Propensity Score Estimation

Variable	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]
Sex of respondent	0.058	0.307	0.190	0.849	-0.543	0.659
Age category	0.391	0.347	1.130	0.260	-0.289	1.072
Marital Status	-0.168	0.282	-0.600	0.551	-0.721	0.385
Education level	0.062	0.030	2.090	0.037*	0.004	0.120
Farm size category	-0.003	0.122	-0.020	0.980	-0.242	0.236
Farming experience	0.135	0.042	3.220	0.001*	-0.217	-0.053
Household size category	0.715	0.341	2.100	0.036*	-1.383	-0.047
_cons	0.476	1.067	0.450	0.655	-1.614	2.567
Mean dependent var		0.339	**SD dependent var**			0.021
Pseudo r-squared		0.045	**Number of obs**			192
Chi-square		22.32	**Prob > chi2**			0.0022

The Pseudo R-squared value (0.045) suggests that while the model provides some predictive power, unobserved factors may also influence NTPSI participation. The Chi-square test ($\chi2$ = 22.32, p = 0.0022) confirms that the model is statistically significant, meaning that the selected variables collectively contribute to predicting NTPSI participation. The descriptive statistics of propensity scores for the 192 observations in the study show a mean p-score of 0.3385 (SD = 0.1553), with a minimum of 0.0189 and a maximum of 0.6824. This indicates a wide range of adoption probabilities, suggesting that while some farmers were highly likely to participate in NTPSI, others had a lower probability of participating.

Table 5 compares the covariate balance between NTPSI participants and non-participants before and after propensity score matching. A bias exceeding 20% is typically considered significant. The variance ratio (V(T)/V(C)) reflects the ratio of variances between treated and control groups, with an acceptable range of [0.66 – 1.51] indicating good balance (Leuven & Sianesi, 2003). Ratios outside this range are flagged with an asterisk. Bias reduction (%) reflects the extent of improvement in covariate balance post-matching.

Table 5: A balance check for unmatched and matched samples

Variable	Unmatched / Matched	Mean: Participants	Mean: Non-participants	Bias: %	Bias: %reduction	T-test: t-value	T-test: P-value	V(T) / V(C)
Sex	U	1.457	1.448	1.9		0.130	0.896	1.00
	M	1.462	1.387	15	-689.8	-1.760	0.081	1.02
Age category	U	1.819	1.844	-4.6		-0.320	0.749	1.58*
	M	1.817	1.731	16.2	-249.7	0.530	0.596	1.31
Marital status	U	1.202	1.250	-7.8		-0.540	0.592	0.89
	M	1.183	1.430	-40.2	-416.6	-0.820	0.413	0.85
Education level	U	1.830	1.958	-17.9		-1.230	0.219	1.05
	M	1.828	2.032	-28.4	-58.9	0.210	0.830	1.35
Household size	U	1.702	1.563	19.8		1.370	0.174	1.27
	M	1.710	1.430	39.7	-100.2	1.810	0.072	1.46
Farm size	U	2.149	2.083	4.9		0.340	0.734	0.87
	M	2.129	1.957	13	-162.2	2.280	0.024	1.10
Farming experience	U	8.266	6.927	24.1		1.670	0.097	1.92*
	M	8.032	6.989	18.8	22.1	-0.810	0.418	1.04

** If variance ratio outside [0.66; 1.51] for U and [0.66; 1.51] for M*

The balance check results in Table 5 indicate that matching significantly improved the comparability between NTPSI participants and non-participants across key socioeconomic variables. Notably, significant initial biases in education level (-17.9%), household size (19.8%), and farming experience (24.1%) were substantially reduced after matching. Variance ratios for most variables fell within the acceptable range [0.66–1.51], enhancing the reliability of the estimated treatment effects.

4.4.2 Common support analysis

Ensuring common support is critical in PSM to guarantee that treatment and control groups are comparable. The results in Table 6 show that out of 192 observations, 190 (98.96%) were within common support, meaning their propensity scores allowed for meaningful comparisons. Specifically, 94 non-participants and 96 participants were within the common support region, ensuring a robust matching process.

Table 6: Common Support Analysis

Treatment	Support: Off support	Support: On support	Total
Non-participant	2	94	96
Participant	0	96	96
Total	2	190	192

Only two non-participants fell outside the common support region, indicating that their propensity scores were beyond the range of the participant group, making them unsuitable for comparison.

4.4.3 ATT for adoption of improved potato production technologies

To assess the effectiveness of the Northern Tanzania Potato Systems Improvement (NTPSI) project in promoting the adoption of improved potato production technologies among smallholder farmers in Arusha District, Tanzania, Propensity Score Matching (PSM) was employed to estimate the causal impact of project participation. PSM addresses selection bias by matching NTPSI participants with non-participants based on similar propensity scores, derived from socioeconomic covariates such as sex, age, education level, household size, farming experience, farm size, and marital status (Rosenbaum & Rubin, 1983; Caliendo & Kopeinig, 2008). The analysis focused on the Average Treatment Effect on the Treated (ATT), which measures the impact of NTPSI on participants by comparing their adoption outcomes to those of matched non-participants.

The ATT was chosen over the Average Treatment Effect (ATE) or Average Treatment Effect on the Untreated (ATU) because it specifically evaluates the project's impact on those who received the intervention, aligning with the study's objective to assess NTPSI's effectiveness among participants rather than generalizing to the broader population (Imbens & Wooldridge, 2009). This focus is particularly relevant for policy evaluation, as it provides insights into how the intervention benefits its target group, informing targeted improvements to the project (Abdia *et al.*, 2017).

Table 7 presents the PSM results, comparing adoption rates between NTPSI participants and non-participants across key technology adoption indicators: use of improved seeds, adoption of the Obama variety, multi-season potato farming, access to potato markets, access to extension services, membership in potato cooperatives, use of fertilizers, access to credit, and use of mechanization. The ATT estimates, standard errors, t-statistics, and p-values are reported to assess the statistical significance of the project's impact at the 5% level.

Table 7: ATT for adoption of improved potato production technologies analysis (n=192)

Variable	Mean (Participants)	Mean (Non-participant)	ATT	Std. Error	t-Statistic	p-Value
Use of Improved Seeds	0.78	0.45	0.33	0.05	6.60	0.0001
Adoption of Obama Variety	0.65	0.30	0.35	0.06	5.83	0.0003
Multi-Season Potato Farming	0.70	0.40	0.30	0.04	7.50	0.0000
Access to Potato Market	0.82	0.55	0.27	0.07	3.86	0.0009
Access to Extension Services	0.88	0.60	0.28	0.05	5.60	0.0005
Membership in Potato Cooperatives	0.75	0.32	0.43	0.06	7.17	0.0001
Use of Fertilizer	0.80	0.50	0.30	0.05	6.00	0.0002
Access to Credit	0.68	0.40	0.28	0.06	4.67	0.0007
Use of Mechanisation	0.00	0.00	–	–	–	–

Indicates significance at 0.05

The results indicate a significant positive difference (ATT = 0.33) between NTPSI participants and non-participants, showing that farmers involved in the NTPSI project are likelier to adopt improved seed varieties. This finding aligns with the study of Abebaw *et al.* (2023), who found that utilising high-quality seeds from improved varieties can boost output per hectare by up to 50%. Although positive ATT on the project participants, farmers reported improved seed as one of the most pressing challenges identified across the interviews. According to the NTPSI project manager, some farmers rely on locally available seeds, often of poor quality, resulting in lower yields. While the NTPSI project aims to address this issue by providing improved seeds, many farmers still need help to afford or access them consistently. This challenge was echoed by RIPAT group leaders, who emphasised that even when high-quality inputs are available, the costs are often prohibitive for smallholder farmers with limited financial resources. However, challenges such as the availability and affordability of certified seeds need to be addressed to sustain adoption rates. The Obama potato variety shows a significant ATT of 0.35, indicating that NTPSI participants are likelier to adopt this variety. By that, project participants comprised 40% of Tanzanian farmers using improved seeds (Kilimo Kwanza, 2023; Africa's Food Systems Forum, 2023).

NTPSI participants are likelier to practice multi-season farming (ATT = 0.30), reflecting the project's role in enhancing agricultural practices. Multi-season farming supports food security and economic resilience, as demonstrated by Li (2023), who found that it contributes to sustainable income and food availability.

The positive ATT of 0.27 suggests NTPSI participants have better access to structured potato markets. This finding corroborates research by Aggarwal *et al. (2024), who observed that structured market access significantly* boosts smallholder farmer's adoption of improved technologies in Northern Tanzania. RIPAT group leaders emphasised the role of poor infrastructure in limiting farmers' ability to reach markets. Roads in the Arusha region are often in poor condition, particularly during the rainy season, making it difficult for farmers to transport their produce to local or regional markets.

The ATT of 0.28 indicates that participants are more likely to receive extension services than non-participants. The use of the RIPAT approach may influence the study's results. The research results align with the studies by Mgendi *et al.* (2022), which affirm that effective extension services are essential for technology dissemination and farmer capacity building.

The highest ATT (0.43) indicates that NTPSI participants are significantly more likely to be members of cooperatives. Cooperative membership facilitates knowledge sharing, input access, and collective bargaining, aligning with the findings of Kehinde and Kehinde (2020) that highlighted the positive impact of cooperatives on technology adoption and farm productivity. Strengthening cooperative structures is vital for sustaining long-term adoption.

NTPSI participants are significantly more likely to use fertilisers (ATT = 0.30), reflecting the project's success in promoting soil fertility practices. As shown by Msuya *et al.* (2024), fertiliser adoption directly correlates with increased crop productivity and income. Addressing affordability and accessibility issues reported in the KIIS will further enhance fertiliser utilisation.

The positive ATT of 0.28 shows that NTPSI participants have better access to financial resources than non-participants, aligning with the findings of Nakano and Magezi (2020), which suggests that the farmers with access to credit are likely to adopt agricultural technologies. The considerable access to credit observed among SHF may be partly attributed to the presence and active participation in community-based contribution groups, such as rotating savings and credit associations or village savings and loan associations. Notably, the prevalence and effectiveness of these groups have been reinforced by the NTPSI project, which actively promoted group formation and collective action as part of its strategy to strengthen farmers' access to financial and agricultural resources (RECODA, 2019).

Both groups show a zero-adoption rate (ATT = 0.00), indicating that mechanisation remains largely unattained. As Daum and Birner (2020) highlight, mechanisation in East Africa is limited by a "chicken-and-egg" dilemma: low demand discourages service providers, while the lack of services reduces demand. Complementing this, Mrema et al. (2020) note that in Tanzania, adoption is constrained by inadequate infrastructure, weak institutional frameworks, and limited training, especially among smallholder farmers. Although private sector-led hiring services and two-wheel tractors have had localised success, particularly in rice-growing regions, widespread adoption remains hindered by fragmented markets, land tenure insecurity, and the misalignment between technology design and local farming needs.

These insights collectively suggest that overcoming mechanisation barriers in Tanzania requires integrated strategies that promote adaptable technologies, strengthen rural infrastructure, and support service-based mechanisation delivery models tailored to smallholders.

The PSM analysis was conducted to rigorously evaluate the NTPSI project's effectiveness in promoting the adoption of improved potato production technologies, addressing selection bias by matching participants and non-participants based on propensity scores derived from socioeconomic covariates (Rosenbaum & Rubin, 1983). The results, presented in Table 7 and visualized in Figure 1, provide robust evidence of the project's impact, leading to the rejection of the null hypothesis, that NTPSI had no effect on technology adoption, in favor of the alternative hypothesis that the project significantly increased adoption rates among participants.

The Average Treatment Effect on the Treated (ATT) was estimated for key adoption indicators, including use of improved seeds, adoption of the Obama variety, multi-season farming, access to markets, access to extension services, cooperative membership, fertilizer use, access to credit, and mechanizationThe results of the PSM analysis indicate that the null hypothesis should be rejected in favour of the alternative hypothesis. The ATT values for most of the variables, such as the use of improved seeds, adoption of the Obama variety, multi-season farming, access to markets, access to extension services, cooperative membership, fertiliser use, and access to credit, are positive and statistically significant at the 5% level, as shown in Figure 1.

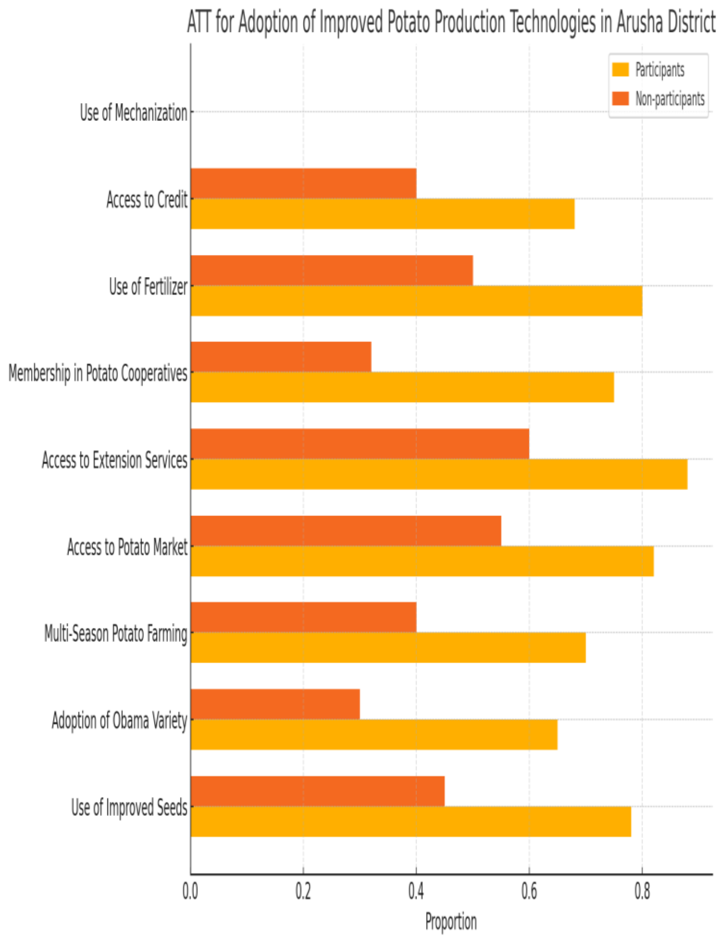

Figure 1: ATT results for adoption of improved Potato Production technologies in Arusha District.

However, it is important to note that both NTPSI and non-participants exhibited zero adoption rates for mechanisation. This indicates that mechanisation remains largely unattained despite the project's efforts to promote improved agricultural practices. The low mechanisation rates may be attributed to high costs, limited access to machinery, or inadequate training in mechanised practices. This highlights a critical gap that needs to be addressed to improve productivity and reduce labour burdens among smallholder farmers. These results demonstrate that NTPSI participants had significantly higher adoption rates of improved potato production technologies than non-participants, proving the effectiveness of the project interventions. Therefore, it is concluded that the NTPSI project significantly impacted technology adoption among smallholder farmers in the study area. However, further efforts are needed to address the challenges related to mechanisation.

4.5 Challenges Faced by Smallholder Farmers in Potato Production: Insights from Key Informant Interviews and Focus Group Discussions

Several challenges faced by smallholder farmers during potato production in the Arusha district were identified through key informant interviews and focus group discussions. These interviews included insights from the project manager of the Northern Tanzania Potatoes System Improvement (NTPSI) project, group leaders from the Rural Initiatives for Participatory Agricultural Transformation (RIPAT), and discussions with potato farmers. Collectively, these sources highlighted a range of obstacles that hinder the adoption levels and limit the success of smallholder farmers in potato cultivation.

4.5.1 Limited Access to Quality Inputs

One of the most pressing challenges identified across the interviews was the limited access to high-quality potato seeds, fertilisers, and pesticides. According to the NTPSI project manager, many farmers rely on locally available seeds, often of poor quality and resulting in lower yields. While the NTPSI project aims to address this issue by providing improved seeds, many farmers still need help to afford or access them consistently. This challenge was echoed by RIPAT group leaders, who emphasised that even when high-quality inputs are available, the costs are often prohibitive for smallholder farmers with limited financial resources.

4.5.2 Limited Access to Credit

Another significant challenge highlighted in the interviews was farmers' need to access credit facilities to invest in their farms. The NTPSI project manager explained that while access to credit has improved slightly, many farmers still need to be included due to stringent loan conditions, lack of collateral and high interest rates. As a result, farmers cannot purchase necessary inputs or invest in improved technologies that could enhance their productivity. Farmers further validated this during the focus group discussions, where many expressed frustrations over their inability to access the financial resources needed for expanding their operations.

4.5.3 Poor Infrastructure and Market Access

RIPAT group leaders emphasised the role of poor infrastructure in limiting farmers' ability to reach markets. Roads in the Arusha region are often in poor condition, particularly during the rainy season, making it difficult for farmers to transport their produce to local or regional markets. Farmers in the focus group also mentioned that even when they can reach markets, they frequently encounter price fluctuations and lack bargaining power, which affects their profitability. As a result, farmers rely on mediators. A specific theme focused on the negative impact of mediators on farmers' profitability. Farmers in the FGDs reported heavily relying on intermediaries to sell their produce. Intermediaries often exploited farmers by offering below-market prices, especially when farmers lacked access to direct markets. This problem was frequently linked to poor infrastructure and the inability of farmers to transport their produce directly to urban centres or better markets.

4.5.4 Unpredictable Weather Conditions and Climate Change

Farmers in the focus group discussions expressed concerns about the increasing unpredictability of weather patterns, making potato farming more challenging. Changes in rainfall patterns and prolonged dry seasons have reduced crop yields and sometimes led to crop failure. The NTPSI project manager pointed out that while the project has introduced climate-smart agricultural practices, many farmers still need help to adapt due to the high costs of implementing irrigation systems or other adaptive technologies.

5.0 Conclusions and Recommendations

5.1 Conclusions

The NTPSI project significantly increased the adoption of improved potato production technologies among smallholder farmers in Arusha, with higher adoption rates observed in improved seed varieties, multi-season farming, fertiliser use, and cooperative membership. However, mechanisation adoption remained minimal due to its high cost, lack of training, and limited machinery access. The project also faced challenges related to limited access to certified seeds and fertilisers and poor road infrastructure, which affected farmers' ability to reach profitable markets.

5.2 Recommendations

Based on the conclusions drawn from the evaluation of the Northern Tanzania Potatoes Systems Project (NTPSI) and its effectiveness in promoting the adoption of improved agricultural technology, the following recommendations are proposed to enhance the project's impact and address the gaps identified:

i. Promote Access to Affordable Inputs and Mechanisation: The government and development partners should prioritise access to affordable inputs such as certified seeds, fertilisers, and agrochemicals. This can be achieved through targeted subsidy programs using matching grants or voucher systems for farmer cooperatives and smallholder groups, ensuring affordability for low-income producers. These schemes should be implemented through public-private partnerships involving local agro-dealers and input suppliers, guided by transparent eligibility criteria based on land size, income, and gender inclusivity. Complementing this, access to agricultural machinery should be expanded through similar support mechanisms, enabling farmers to acquire and sustainably use appropriate equipment.

ii. Strengthen Market Access and Infrastructure: Invest in rural feeder roads, storage facilities, and cold chain systems to reduce post-harvest losses and lower transportation costs. Promote structured markets by supporting the formation and formal registration of farmer cooperatives. These cooperatives can act as intermediaries for input procurement, bulk marketing, and negotiating fair prices. Establishing digital platforms for market information sharing and linking farmers directly with buyers can further enhance transparency and bargaining power.

iii. Enhance Financial Access: facilitate the creation of community-based microfinance institutions, such as Village Savings and Loan Associations (VSLAs), and strengthen their capacity through financial literacy training. Encourage partnerships between commercial banks and farmers' organisations to develop tailored loan products with flexible collateral requirements and crop-specific repayment schedules. Government guarantees or risk-sharing facilities can incentivise financial institutions to extend credit to underserved rural farmers for investment in inputs and technologies.

Declaration of Conflict of Interest

We hereby declare that there are no known competing financial interests or personal relationships that could have influenced the research and findings presented in this paper.

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