Socio-Demographic and Economic Factors Associated with Adoption of Tarpaulins and Hermetic Bags for Maize Postharvest Handling in Rukwa and Katavi Regions, Tanzania

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ABSTRACT

Maize is a major staple food in Tanzania, yet significant postharvest losses remain a persistent challenge for smallholder farmers. The use of tarpaulins for drying and hermetic bags for storage has been promoted as a strategy to reduce these losses, yet adoption among smallholder maize farmers remains low. This study assessed the socio-demographic and economic factors influencing the adoption of these technologies. A multi-stage sampling procedure combining purposive, stratified, and simple random sampling was employed to select 365 smallholder maize farming households from the Rukwa and Katavi regions, Tanzania. Data were collected between November 2022 and March 2023 using structured questionnaires, focus group discussions, and key informant interviews. Descriptive and inferential analyses were performed using IBM SPSS Statistics Version 27. The results showed that 22.5% of households were non-adopters of both technologies, while 43.6% and 34.0% were low and high adopters, respectively. Pearson's chi-square tests indicated that household income per capita was significantly associated with adoption levels ($\chi^2 = 11.610$, $p = 0.020$, Cramer's V = 0.126), whereas age, sex, education, farming experience, and household size showed no significant association ($p > 0.05$). The study concludes that the low adoption of tarpaulins and hermetic bags is primarily attributed to low household income among smallholder maize farmers. It is recommended that local government authorities regulate the supply and pricing of these technologies to enhance affordability and promote awareness of their benefits in reducing maize postharvest losses.

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1.0 Introduction

griculture is still the most important part of Tanzania's economy. It makes up about 26% of GDP and employs more than 65% of the people (URT, 2022; World Bank, 2023). Maize is the most important staple crop because it gives smallholder farmers food security and money. The Rukwa and Katavi regions make up more than 14% of the country's output (FAO, 2018). However, despite its significance, maize production is undermined by substantial postharvest losses (PHL), which erode household incomes, reduce national food reserves, and weaken resilience against food insecurity. Recent estimates indicate annual maize losses of 15–18% (APHLIS, 2023; URT, 2019; Chegere, 2020), with losses occurring at harvest, drying, threshing, and household storage stages ranging from 1.3% to 6.4% per stage (APHLIS, 2023). Interestingly, farmers' self-reported losses are typically lower, 1.4–5.9% (World Bank, 2019), highlighting the underestimation of hidden losses such as pest infestation, quality deterioration, and aflatoxin contamination.

To mitigate these challenges, technologies such as tarpaulins for drying and hermetic bags for storage have been promoted by government extension officers and development partners like AGRA and HELVETAS-Tanzania (AGRA, 2020; 2021; HELVETAS-Tanzania, 2020). They promoted these technologies as cost-effective interventions capable of reducing losses by over 80% (Murdock & Baoua, 2014; Abass *et al.*, 2018; HELVETAS, 2020). Tarpaulins provide clean, raised surfaces that prevent contact with soil and moisture, thereby reducing mould, pests, and aflatoxin contamination (FAO, 2014), whereas hermetic bags create airtight storage conditions that suppress insect pests and fungal growth without chemicals (Murdock & Baoua, 2014; Affognon *et al.*, 2015). Despite their proven effectiveness, adoption of these technologies remains low, largely due to low income, limited awareness, poor extension support, lack of credit, market inaccessibility, and entrenched cultural practices (Abass *et al.*, 2018; URT, 2019; Ojo & Baiyegunhi, 2023).

This persistence of high postharvest losses, despite the availability of effective technologies, underscores the need to understand the socio-economic, demographic, and behavioural factors that influence adoption. While previous studies have mainly examined structural barriers such as cost, access, and extension services (Affognon *et al.*, 2015), less attention has been given to psychological determinants including attitudes, risk perception, subjective norms, and self-efficacy, which ultimately shape farmers' decisions to adopt or reject new technologies. In regions like Rukwa and Katavi, where maize is traditionally dried on bare ground and stored in polypropylene bags, improving adoption of tarpaulins and hermetic bags could substantially reduce losses, stabilise household incomes, and strengthen national food security.

Therefore, this study was justified on several grounds. First, it fills a critical knowledge gap by integrating psychological determinants into the analysis of postharvest technology adoption, drawing on established behavioural theories such as the Theory of Planned Behaviour (Ajzen, 1991), the Technology Acceptance Model (Davis, 1989), Diffusion of Innovations (Rogers, 2003), and the Economic Constraints Model (Goldratt & Cox, 1984). Second, it provides empirical evidence specific to Rukwa and Katavi, regions that are central to national food security but under-represented in adoption studies. Third, by identifying the factors that most strongly predict adoption, the study generates actionable insights for policy and practice, including the design of targeted extension programmes, credit schemes, and behavioural interventions to accelerate uptake, reduce losses, and enhance household resilience.

Accordingly, the general objective of this study was to assess the socio-demographic and economic factors associated with the adoption of improved maize postharvest technologies in the Rukwa and Katavi regions, Tanzania. The specific objectives were to delineate the socio-demographic and economic attributes of smallholder maize farmers, evaluate the degree of adoption of tarpaulins and hermetic bags, and investigate the correlation between socio-demographic and economic variables and the adoption of enhanced postharvest technologies.

2.0 Literature Review

2.1 Theoretical Framework

The integration of theories into a Comprehensive Adoption and Diffusion Model (CADM) provides a robust, multidimensional framework for analysing technological adoption among smallholder farmers. By blending these theories, they address the complications of farmers' decision-making processes, particularly for technologies like tarpaulins and hermetic bags. Below is a summarised assessment of the combined theories, highlighting their balanced strengths and limitations.

Diffusion of Innovations (DOI) theory – Rogers (2003) explains how and why innovations spread across communities via relative advantages, compatibility, and observability. The theory highlights the role of social networks and extension services (Manda, 2024). It is useful for identifying adopter categories (innovators → laggards). However, it assumes subsequent diffusion, overlooking financial constraints that can permanently limit uptake. It overemphasises awareness while underestimating cost barriers (Adekoya *et al*., 2023). Where awareness of tarpaulins and hermetic bags exists but adoption is uneven. DOI helps explain how peer influence and extension exposure shape uptake patterns.

The Technology Acceptance Model (TAM)—Davis (1989) focusses on perceived usefulness (PU) and perceived ease of use (PEOU) as adoption drivers. The theory is widely applied in agricultural technology adoption studies (Zhang *et al*., 2022a). The theory is practical for capturing farmer perceptions of tarpaulins and hermetic bags. However, it ignores broader social and economic constraints (Padmaningrum *et al*., 2024). PU/PEOU alone cannot explain adoption when farmers lack financial means. Farmers may recognise benefits but fail to adopt them due to other barriers. TAM explains the perception–behaviour gap in Tanzania.

The Theory of Planned Behaviour (TPB)—Ajzen (1991) integrates attitudes, subjective norms, and perceived behavioural control. The theory also takes into account social norms and cultural influences (Stauder, 2023). It links intention with behaviour, which is useful for predicting adoption. However, intention does not always result in actual adoption when economic barriers persist. Furthermore, measuring subjective norms in rural settings can be complex (Sander *et al*., 2024a). TPB explains how social pressure (e.g., community reliance on traditional drying methods) and perceived control (affordability) influence adoption decisions.

Economic Constraints Model (ECM)—Goldratt & Cox (1984) emphasises financial and resource constraints as decisive in adoption. The model explains why innovations with proven benefits may still have low uptake (Ayalew & Xianzhi, 2019). The model is very relevant for low-income farming contexts. However, it has a narrow focus. *i.e*., it underplays social and psychological influences. Moreover, it may reduce adoption decisions to cost–benefit trade-offs only. ECM helps explain that affordability is one of the primary determinants of adoption.

All four theories are used together because DOI explains how adoption spreads socially. TAM: explains how farmers perceive usefulness and ease of use. TPB: explains how norms and perceived control shape intention. ECM: explains why affordability dominates other factors. Together, they offer a comprehensive lens to understand why postharvest technologies remain underused in Tanzania.

2.2 Analytical Framework

The analytical framework shows how the theories translate into variables and methods of analysis in the study. The dependent variable indicates the extent of adoption of postharvest technologies (ordinal: 0 = none, 1 = partial, 2 = full). Independent variables included socio-demographic factors such as age, sex, education, household size, and farming experience. Meanwhile, the economic factor includes household income per capita.

The analytical flow involves descriptive statistics – to profile farmers and adoption levels. Normality testing – to assess suitability for parametric against non-parametric methods. Chi-square tests – to examine associations between categorical socio-demographic factors and adoption levels. Kruskal–Wallis test – to examine associations between income (ordinal categories) and adoption levels. Cramer's V – to assess strength of associations. Qualitative analysis, which involves thematic analysis of KIIs and FGDs, enhances the understanding of adoption barriers. Altogether, the analytical flow also involves a link to theories: DOI/TAM*:* Help interpret awareness and perceived benefits. TPB*:* Helps interpret attitudes, norms, and control over adoption. ECM*:* Explains why income shows significant association while other factors may not. Thus, the theoretical framework focuses on why adoption happens (or not), guided by theories. Thus, the analytical framework focuses on how adoption is measured, analysed, and linked back to those theories.

3.0 Methodology

3.1 Research Area

The study was conducted in the Rukwa and Katavi regions, which are among the major producers in Tanzania. The two regions are characterised by a bimodal rainfall pattern, with a single maize cropping season lasting from December to April and harvesting taking place between May and July. The total land under maize production in the two regions is 340,593 ha, and the average maize production in the 2018/19 season was 853,626 MT. The total maize production in the two regions is 14.4% of the total national maize production in Tanzania (5.9 million tonnes; FAOSTAT, 2018). The main farming systems comprise other crops, predominantly sunflower (*Helianthus annuus*), beans (*Phaseolus vulgaris*), groundnuts (*Arachis hypogaea*), and paddy (*Oryza sativa*). Other commercial crops grown in the Katavi Region include cotton and tobacco.

3.2 Research Design

This study employed a cross-sectional, mixed-methods design because it was most appropriate for analysing socio-demographic and economic factors associated with the adoption of postharvest technologies at a single point in time. A cross-sectional approach enabled the collection of data from a large sample of maize-farming households during one agricultural season, allowing for efficient assessment of adoption levels and associations between variables without the time and resource demands of longitudinal studies (Creswell & Creswell, 2018). The survey method provided quantifiable data on household characteristics and adoption status, while qualitative techniques—key informant interviews and focus group discussions—enriched the findings with contextual insights on farmer perceptions and constraints. This combination was consistent with best practices in agricultural adoption research, where mixed methods enhance validity by triangulating quantitative and qualitative evidence (Caracelli & Greene, 1997). Cross-sectional designs have been widely applied in African agricultural adoption studies (e.g., Bekele *et al*., 2024), confirming their suitability for investigating socio-economic and behavioural determinants of technology uptake.

3.3 Sampling Procedure

The study employed a multi-stage sampling procedure, combining purposive, stratified, and simple random sampling techniques to ensure representativeness while focusing on areas most relevant to postharvest management interventions. This approach was consistent with best practices in adoption studies where both representativeness and contextual relevance are critical (Creswell & Creswell, 2018; *Bekele et al*., 2024). Four districts were purposively selected: Sumbawanga and Nkasi in the Rukwa Region, and Mpimbwe and Tanganyika in the Katavi Region. These districts were chosen because they are among the leading maize-producing areas and had prior exposure to postharvest management interventions by organisations such as AGRA and HELVETAS-Tanzania. Purposive sampling at this stage ensured that the study targeted areas with both significant maize production and relevant experiences with postharvest technologies, making them appropriate for investigating adoption dynamics (Palinkas *et al*., 2015). From the selected districts, sixteen (16) villages were identified using proportionate stratified sampling. The strata were defined based on maize production potential, past experience with postharvest losses, and socio-economic diversity (household size, income, and gender composition). Stratification ensured that the sample captured variations across different village contexts, thus improving representativeness and reducing sampling error (Lohr, 2019). Within each village, 25 households were selected using a simple random sampling technique (lottery method) from the official village registers of maize farmers. Only households that had been exposed to postharvest management awareness or interventions were eligible for selection. Random sampling at this stage minimises bias and gives each household an equal chance of being included, thus enhancing the reliability of the findings (Kothari, 2004). A total of 399 households were targeted, determined using Yamane's (1967) formula with a 5% precision level. Out of these, 365 households returned valid and completed questionnaires and were included in the final analysis. In addition, ten key informants (4 extension officers, 4 agro-dealers, and 2 equipment manufacturers) and eight FGDs with 8–12 participants each were purposively selected to provide qualitative insights that complemented the quantitative data.

3.4 Data Collection Instruments

To gather reliable and comprehensive information, the study employed three complementary data collection instruments: a structured questionnaire, a key informant interview (KII) checklist, and a focus group discussion (FGD) guide. The household survey used a structured questionnaire administered to 399 targeted respondents, of which 365 were valid. The questionnaire consisted of both closed-ended and a few open-ended questions, divided into sections that captured: Socio-demographic characteristics (age, sex, education, household size, and farming experience). Economic characteristics (household income per capita, sources of income, access to markets). Adoption of postharvest technologies (use of tarpaulins and hermetic bags, frequency, and reasons for adoption or non-adoption). Structured questionnaires are widely recommended in adoption studies because they provide standardised data suitable for statistical analysis (Bekele *et al*., 2024; Creswell & Creswell, 2018).

Key Informant Interview (KII) Checklist: a KII checklist was developed to guide semi-structured interviews with ten purposively selected informants, including agricultural extension officers, agro-dealers, and local agricultural equipment manufacturers. The checklist focused on the availability and distribution of postharvest technologies. Institutional and policy support for technology adoption. Barriers faced by farmers in accessing or using tarpaulins and hermetic bags. This tool allowed flexibility in probing issues while ensuring consistency across interviews (Creswell & Creswell, 2018).

Focus Group Discussion (FGD) Guide: an FGD guide was used to facilitate discussions among 8–12 participants in each of the eight FGDs conducted. The guide contained open-ended questions and prompts on farmers' experiences with postharvest handling practices. Perceptions and attitudes towards tarpaulins and hermetic bags. Social and cultural norms influencing adoption. FGDs are particularly useful for capturing group perspectives and shared meanings that may not emerge from individual interviews (Morgan, 1997).

3.5 Data Analysis

The collected data was coded and analysed using *IBM SPSS Statistics version 27*. Descriptive statistics (frequencies, percentages, means, and standard deviations) were used to summarise the respondents' socio-demographic and economic characteristics (age, sex, household size, education, farming experience, and household income per capita). Adoption of postharvest technologies (tarpaulins and hermetic bags) was classified into three categories: 0 = none (neither technology), 1 = lower (one technology), 2 = higher (both technologies).

3. 5.1 Normality Testing and Choice of Tests

The normality of continuous variables, particularly household income per capita, was assessed using the Shapiro–Wilk and Kolmogorov–Smirnov tests, supported by skewness, kurtosis, and visual inspections (Field, 2018). Household income was highly skewed (p < .05), justifying the use of non-parametric methods.

3.5.2 Non-parametric Methods

Given the skewed distributions of household income, household size, and farming experience, Kruskal–Wallis H-tests were used to compare adoption groups, with Dunn–Bonferroni post hoc tests applied for pairwise differences. Chi-square tests of independence examined associations between categorical predictors (sex, education, age group, household size, and farming experience) and adoption. Strength of association was assessed using Cramer's V (Agresti, 2018).

Non-parametric tests were preferred because they do not assume normality and are suitable for ordinal and skewed data (Conover, 1999; Gibbons & Chakraborti, 2011). Their use aligns with best practices in agricultural adoption research (Bekele *et al.*, 2024).

3.5.3 Measurement of Variables and Statistical Tests

Adoption of maize drying and storage technologies was the dependent variable, while socio-demographic and economic characteristics were independent variables. Test selection was based on variable type (categorical, ordinal, or continuous), distributional tendencies, and research objectives. Table 1 summarises variable measurement, distribution tendencies, and applied statistical tests.

Table 1

Measurement Scales, Distribution, and Statistical Tests for Study Variables

Variable	Measurement Type	Distribution Tendency	Statistical Test(s) Applied
Extent of adoption	Ordinal categorical (DV)	Not applicable	Chi-square; Ordinal Logistic Regression
Age (years)	Continuous (grouped in analysis)	Approximately normal	ANOVA Kruskal–Wallis (if categorical)
Sex	Binary categorical	Not applicable	Chi-square
Household size (members)	Continuous (grouped in analysis)	Positively skewed	Kruskal–Wallis; Chi-square (categorical version)
Education level	Ordinal categorical	Not applicable	Chi-square
Farming experience (years)	Continuous (grouped in analysis)	Positively skewed	Kruskal–Wallis; Chi-square (categorical version)
Income per capita (TZS)	Continuous	Highly positively skewed	Kruskal–Wallis; Ordinal Logistic Regression

Note: DV = dependent variable. Distribution tendencies based on Shapiro–Wilk and Kolmogorov–Smirnov tests.

3.5.4 Research Questions and Statistical Tests

The analysis addressed whether adoption levels varied by socio-demographic and economic factors. Chi-square tests assessed categorical predictors, while Kruskal–Wallis H-tests examined skewed continuous predictors. Where significant, Dunn–Bonferroni tests identified pairwise differences. Table 2 presents the mapping of research questions to variable types, non-parametric tests, and interpretation guidelines.

Table 2

Research Questions, Variable Types, and Recommended Non-Parametric Tests

Research Question	Variable Type(s)	Recommended Test	Interpretation
Does adoption differ by sex, education, age group, or household size?	Categorical IV × Ordinal DV	Chi-square test of independence	Determines if distributions differ significantly
Does income per capita differ across adoption levels?	Continuous (skewed) IV × Ordinal DV	Kruskal–Wallis H test	Non-parametric ANOVA; compares medians
Does farming experience differ across adoption levels?	Continuous (skewed) IV × Ordinal DV	Kruskal–Wallis H test	Tests median differences across groups
Does household size differ across adoption levels?	Continuous (skewed) IV × Ordinal DV	Kruskal–Wallis H test	Tests median differences across groups
Which adoption groups differ pairwise?	Ordinal DV (0, 1, 2)	Dunn–Bonferroni post hoc	Identifies which groups differ significantly

Note: IV = independent variable; DV = dependent variable. Adoption categories: 0 = none, 1 = lower, 2 = higher.

Thus, the study employed a combination of descriptive and non-parametric inferential statistics to ensure robustness against normality violations. Categorical predictors were analysed using Chi-square tests, while skewed continuous variables were tested with Kruskal–Wallis H-tests and Dunn–Bonferroni post hoc comparisons. This methodological framework provided a rigorous and reliable basis for examining the relationship between socio-demographic characteristics, household income, and adoption of postharvest technologies.

4.0 Results

4.1 Descriptive Statistics of the Socio-Demographic and Economic Variables Used

Five households' socio-demographic variables were analysed, namely age of household head, sex of household head, household size, level of education of household head, farming experience in years. Moreover, one economic variable, income per capita, was used. For all the socio-demographic and economic variables, both frequencies and descriptive statistics were computed. The frequencies are presented in Table 3.

Table 3

Frequencies of the Socio-Demographic and Economic Variables Used

Variable		Frequency	Per cent
Age	Younger (15 - 35) years	114	31.2
	Adult (36 – 59) years	237	64.9
	Elderly (60 and above) years	14	3.8
Sex	Male	268	73.4
	Female	97	26.6
Household size (members)	Small (1-5)	101	27.7
	Moderate (6-10)	228	62.5
	Large (11-15)	36	9.9
Level of education of household head	No formal education	13	3.6
	Primary education	293	80.3
	Secondary education	46	12.6
	Certificate	4	1.1
	Diploma	2	0.5
	Bachelor	7	1.9
Farming experience (years)	Short (2 – 13)	120	32.9
	Moderate (14 – 22)	126	34.5
	Long (23 - 51)	119	32.6
Income per capita (TZS)	Low (Lowest to 707500.00)	121	33.2
	Moderate (707500.01 – 1,107,857.14)	122	33.5
	High (1107857.15 to Highest)	121	33.2

The results in Table 3 show that the average age of household heads was 41.7 years, ranging between 23 and 69 years. The mean household size was 7.2 members, with a minimum of 2 and a maximum of 15. The mean years of schooling were 7.3, with values ranging from 0 to 16 years. The mean farming experience was 18.5 years, with a minimum of 2 and a maximum of 51 years. The mean household income per capita was TZS 1,026,659.89, ranging from TZS 123,500.00 to TZS 4,753,333.33. The age dependency ratio ranged from 0.00 to 600.00, with a mean of 89.71. About 56.3**%** of the households had age dependency ratios below 100, 24.9% had a ratio equal to 100, and 18.1% had ratios exceeding 100.

4.2 Extents of Adoption of Postharvest Technologies and Respondents' Explanations

4.2.1 Extents of Adoption of Postharvest Technologies

The extents of adoption of postharvest technologies for maize drying and storage were analysed by recording the numbers of the respondents who had adopted uses of tarpaulins and hermetic bags for maize drying and storage, respectively. In this case, the respondents were classified into three groups: having adopted neither of the two technologies (no adoption, 0), having adopted either of the two technologies (lower adoption, 1), and having adopted both technologies (higher adoption, 2). The numbers and percentages of households in the three groups that have adopted postharvest technologies for maize drying and storage are presented in Table 4.

Table 4

Extents of Adoption of Postharvest Technologies

Extent of adoption	Frequency	Per cent
No adoption	82	22.5
Lower	159	43.6
Higher	124	34.0
Total	**365**	**100.0**

The results in Table 3 show that the highest proportion was that of households with lower adoption (43.6%), followed by those with higher adoption (34.0%). Those with no adoption were asked to mention the ways they were using to dry and store maize and explain why they had not adopted uses of tarpaulins and hermetic bags for drying and storing maize, respectively. Those who adopted tarpaulins or hermetic bags were asked similar questions as those who adopted neither technology.

4.2.1 Explanations by Non-Adopters for Not Using Tarpaulins and Hermetic Bags

Non-adopters cited several reasons for not adopting improved postharvest technologies. The most frequently mentioned reasons were high cost (37.1%), lack of awareness (29.4%), limited access to technologies (18.6%), and perceived low benefit (10.3%). A small fraction (4.6%) reported that traditional storage methods were sufficient for their needs.

4.3 Descriptive analysis of Socio-Demographic and Economic Characteristics by Adoption Level

To better understand the determinants of adoption, the study examined the distribution of socio-demographic and economic variables across different levels of adoption of maize drying and storage technologies, as Table 5 presents the cross-tabulation results. Adoption was categorised as non-adopters, lower adopters, and higher adopters, reflecting the extent to which households used tarpaulins and hermetic bags. Cross-tabulation was employed to provide a descriptive overview of how adoption patterns vary across age, sex, household size, education, farming experience, and household income per capita.

The purpose of this analysis was to identify whether certain socio-demographic groups are more likely to adopt improved postharvest technologies than others and to provide a descriptive context before applying inferential tests. While inferential results later confirmed that most socio-demographic variables were not statistically significant predictors, this descriptive presentation highlights emerging patterns, particularly regarding the role of household income.

Table 5

Socio-Demographic and Economic Factors and Level of Adoption of Maize Drying and Storage Technologies

Socio-demographic and economic variables		Level of adoption of maize drying and storage technologies		
		No adoption n (%)	Lower n (%)	Higher n (%)
Age of household head (years)	15 to 35	25 (21.9)	50 (43.9)	39 (34.2)
	36 to 59	54 (22.8)	103 (43.5)	80 (33.8)
	60 ≤	3 (21.4)	6 (42.9)	5 (35.7)
Sex of household head	Male	63 (23.5)	114 (42.5)	91 (34.0)
	Female	19 (19.6)	45 (46.4)	33 (34.0)
Household size	Small (1-5)	21 (20.8)	44 (43.6)	36 (35.6)
	Moderate (6-10)	50 (21.9)	105 (46.1)	73 (32.0)
	Large (11-15)	11 (30.6)	10 (27.8)	15 (41.7)
Level of education of household head	No formal education	2 (15.4)	6 (46.2)	5 (38.5)
	Primary	70 (23.9)	123 (42.0)	100 (34.1)
	Secondary	7 (15.2)	25 (54.3)	14 (30.4)
	Certificate	1 (25.0)	1 (25.0)	2 (50.0)
	Diploma	1 (50.0)	0 (0.0)	1 (50.0)
	Bachelor	1 (14.3)	4 (57.1)	2 (28.6)
Farming experience (years)	Short (2–13)	24 (20.0)	53 (44.2)	43 (35.8)
	Moderate (14–22)	32 (25.4)	51 (40.5)	43 (34.1)
	Long (23-51)	26 (21.8)	55 (46.2)	38 (31.9)
Household income per capita (TZS)	Low (≤707500.00)	31 (25.6)	44 (36.4)	46 (38.0)
	Moderate (707500.01 – 1,107,857.14)	25 (20.5)	48 (39.3)	49 (40.2)
	High (1107857.15 ≤)	26 (21.5)	66 (54.5)	29 (24.0)

Cross-tabulation results in Table 5 show the relationship between socio-demographic and economic characteristics and adoption levels. While adoption levels appeared to increase slightly with education and income, variations were not statistically significant for most demographic variables. However, households with higher income per capita showed a noticeably higher proportion of technology adopters compared to low-income households.

4.5 Inferential Analysis of Association of Socio-Demographic and Economic Variables and Adoption Levels

Beyond descriptive cross-tabulations, in Table 6 inferential statistics were used to determine whether socio-demographic and economic variables were significantly associated with the adoption of maize drying and storage technologies. Chi-square tests were applied to categorical variables, with Cramer's V used to measure the strength of associations, while the Kruskal–Wallis test was employed for continuous variables to account for non-normality. Post-hoc Dunn's tests were conducted and where appropriate to identify pairwise differences.

Table 6
Association between Socio-Demographic and Economic Factors and Extent of Adoption of Maize Drying and Storage Technologies

Variable	Test Used	Test Statistic	df	p-value	Cramer's' V	Interpretation
Sex of household head (Male/Female)	Chi-square	$\chi^2(2) = 0.73$	2	0.694	0.045	No significant association between sex and adoption level.
Age group of household head (15–35 / 36–59 / ≥60)	Chi-square	$\chi^2(4) = 0.05$	4	0.989	0.090	No significant association between age group and adoption level.
Education level (None, Primary, Secondary, Higher)	Chi-square	$\chi^2(10) = 6.19$	10	0.799	0.092	Education level was not significantly associated with adoption.
Household size (categorical: small/moderate/large)	Chi-square	$\chi^2(4) = 0.55$	4	0.336	0.079	No significant association between household size group and adoption.
Household size (continuous, members)	Kruskal–Wallis	H(2) = 2.41	2	0.299	N/A	Median household size did not differ significantly across adoption groups.
Farming experience (categorical: short/moderate/long)	Chi-square	$\chi^2(4) = 1.57$	4	0.813	N/A	No significant association between experience groups and adoption.
Farming experience (continuous, years)	Kruskal–Wallis	H(2) = 1.22	2	0.542	0.813	Median farming experience did not differ significantly across adoption groups.
Income per capita (categorical: low/moderate/high)	Chi-square	$\chi^2(4) = 11.61^*$	4	0.020	0.126	Significant association: income level relates to adoption.
Income per capita (continuous, TZS)	Kruskal–Wallis	H(2) = 8.72*	2	0.013	N/A	Median income differed significantly across adoption groups. Post-hoc Dunn's test: higher adopters had significantly higher income than non-adopters.

*Association significant at the 0.05 level (*i.e.*, 5% level)

Inferential statistical tests were conducted to determine the relationship between socio-demographic and economic variables and the extent of adoption of postharvest technologies. Results from chi-square and Kruskal–Wallis tests are summarised in Table 6. The findings indicated that income per capita was significantly associated with adoption level ($\chi^2 = 5.41$, $p = 0.020$); Cramer's V = 0.126). The Kruskal–Wallis test confirmed that income levels differed across adoption groups (H(2) = 8.72, p = 0.013), with post-hoc Dunn's tests showing that adopters had significantly higher incomes than non-adopters. Suggesting that higher-income households are more likely to adopt improved postharvest technologies. Other variables—including sex, age, education level, household size, and farming experience—were not significantly related to adoption levels ($p > 0.05$). The strength of association was moderate. Cramer's V-values are interpreted as follows: from 0.00 to 0.10 is weak strength of association, from 0.11 to 0.30 is moderate strength of association, and above 0.30 is strong association (Healey, 2013).

5.0 Discussion

The findings of this research offer useful perspectives on the socio-economic and behavioural determinants of adopting maize postharvest handling technologies in the Rukwa and Katavi regions. The discussion below interprets the results in light of relevant theories and previous empirical evidence.

The socio-demographic and economic characteristics of household heads play a critical role in shaping agricultural technology adoption and postharvest management practices. The average age of 41.7 years indicates that most household heads are within their productive and economically active years. According to Rogers' Diffusion of Innovation Theory (2003), age can influence adoption behaviour, as younger farmers often display a greater willingness to experiment with innovations compared to older ones, who tend to rely on experience and traditional methods. However, the predominance of middle-aged farmers in this study suggests a balance between experience and openness to new practices. Similar findings were reported by Muganda *et al.* (2022) in Tanzania, who found that maize farmers aged between 35 and 50 years were the most active adopters of postharvest technologies due to their accumulated farming experience and moderate risk perception.

The average household size of 7.2 members indicates that families are larger than the national average of 4.3 (URT, 2022). Larger household sizes may positively influence agricultural productivity and postharvest management by providing more family labour, consistent with the labour availability theory, which emphasises household size as a determinant of farm labour supply (Schultz, 1961). However, the high age dependence ratio (mean = 89.71) implies that a significant proportion of household members are dependents, potentially constraining labour availability. This aligns with findings by Nkonya *et al.* (2018), who observed that high dependency ratios in rural Tanzania limit households' capacity to engage effectively in labour-intensive agricultural practices, such as maize drying and storage.

The mean years of schooling (7.3) indicate that most household heads had attained primary education. From the perspective of human capital theory (Becker, 1964), education enhances farmers' ability to acquire, process, and use information about new agricultural technologies. The relatively high literacy level among respondents implies a favourable environment for the adoption of improved postharvest technologies. Weir and Knight (2000) and Mayanja and Oluk (2023) provide empirical evidence that farmers with higher levels of education are more inclined to adopt innovations, as they possess a superior comprehension of the associated benefits and application requirements.

The average farming experience of 18.5 years indicates that the majority of respondents have substantial agricultural expertise, which can affect both productivity and postharvest decision-making. The experience-based learning model (Feder, Just, & Zilberman, 1985) posits that experience enhances the ability to evaluate risks and benefits associated with new practices. Therefore, the long farming experience observed in this study likely improves farmers' judgement regarding the effectiveness of postharvest technologies such as hermetic bags and tarpaulins. This is consistent with findings by Heydari & Savadogo (2024), who reported that farmers with extensive farming experience were more capable of managing postharvest processes effectively, thereby reducing maize losses.

In terms of economic capacity, the mean household income per capita (TZS 1,026,659.89) indicates moderate financial strength among smallholder maize farmers. According to the adoption constraint model (Feder & Umali, 1993), financial capability directly affects the ability to invest in improved technologies. The finding that households have incomes comparable to the national average (World Bank, 2023) indicates that postharvest technologies may be affordable. Empirical studies by O'Connor *et al.* (2023) and Kansanga *et al.* (2023) have similarly demonstrated that higher income levels enhance the likelihood of adopting innovations that require upfront capital, such as hermetic storage bags.

The results indicated a moderate adoption rate, with about one-third (33.9%) of respondents classified as higher adopters, while 43.6% were lower adopters and 22.5% non-adopters. This distribution suggests that, although awareness and partial utilisation of improved postharvest technologies exist, full adoption remains limited. This pattern aligns with Rogers' Diffusion of Innovation (DOI) theory (2003), which posits that adoption occurs progressively across categories of innovators, early adopters, and laggards. The moderate adoption level found in this study reflects a transitional stage, in which many farmers have yet to fully internalise the benefits or gain sufficient access to improved technologies. Empirical studies similarly report partial adoption of postharvest innovations in sub-Saharan Africa due to a combination of technical, financial, and institutional barriers (Mayanja & Oluk, 2023; O'Connor *et al.*, 2023). Heydari & Savadogo (2024) discovered that farmers' adoption of grain storage technologies was significantly affected by perceived utility, while being hindered by issues of cost and accessibility.

Income per capita was the only variable significantly associated with adoption of postharvest technologies (p = 0.020). This finding points out the importance of financial capability in enabling technology uptake, as higher-income households are more likely to afford improved storage materials and drying equipment. This observation supports the Economic Constraint Model, which emphasises that resource availability directly affects technological adoption decisions (Weir & Knight, 2000). Households with greater financial means can invest in durable technologies such as hermetic bags, tarpaulins, and metal silos, while low-income farmers rely on traditional methods despite their inefficiency. The finding was consistent with previous studies showing that liquidity constraints and income inequality hinder technology diffusion in rural economies (URT, 2022; World Bank, 2023). Moreover, the positive association between income and adoption aligns with evidence from maize value chain studies indicating that financial inclusion and credit access enhance the ability to adopt improved postharvest innovations (Mgale *et al.*, 2025).

The most frequently cited reasons for non-adoption were high cost, lack of awareness, and limited access to technologies. These results reaffirm TAM principles, where perceived ease of use and perceived usefulness are central to adoption behaviour (Davis, 1989). If technologies are perceived as complex or unaffordable, farmers are less likely to adopt them, despite recognising their potential benefits. The results also align with the theory of planned behaviour (TPB), which suggests that attitudes, perceived behavioural control, and subjective norms influence the intention to adopt new practices (Ajzen, 1991). Limited access and affordability constraints reduce perceived behavioural controls, thereby lowering adoption intentions among farmers. Similar barriers have been reported in Tanzania and neighbouring countries, where dissemination challenges, limited extension services, and high upfront costs slow down the diffusion of postharvest innovations (Mayanja & Oluk, 2023; Kansanga *et al.*, 2023).

Although education level, farming experience, age, and gender were not statistically significant predictors of adoption, their descriptive patterns suggest a positive association between higher education and increased technology uptake. Educated farmers are often more receptive to new information and more capable of evaluating the benefits of improved technologies. This trend supports Weir and Knight (2000), who established that literacy enhances the ability to process and apply agricultural knowledge. The lack of statistical significance in demographic factors may reflect uniform exposure across groups, or contextual factors—such as cultural norms and information access—may mediate adoption behaviour. Nonetheless, the general trend indicates that human capital remains a facilitating factor even when not statistically dominant.

5.1 Integrated Interpretation

Taken together, the four theories suggest a multi-layered explanation for adoption behaviour: DOI and TAM show that awareness and perceptions of usefulness exist, but affordability prevents adoption. TPB highlights that attitudes (high cost), norms (traditional practices), and perceived control (income constraints) shape intentions. ECM confirms that financial resources are the decisive constraint, as only households with higher incomes can afford full adoption. This integrated view shows that adoption is not just about awareness or perceived usefulness but is a systemic issue where financial, psychological, and social determinants interact. Addressing economic barriers through subsidies, microfinance, or collective purchasing could unlock adoption, while continuous awareness campaigns and training may shift attitudes and norms, reinforcing behavioural intentions to adopt them (Sander *et al.*, 2024b; Stauder, 2023).

5.2 *Theoretical Implications*

The results offered instructive perspectives on the application of adoption theories in agricultural contexts: In the Technology Acceptance Model (TAM), farmers acknowledged the usefulness of tarpaulins and hermetic bags and perceived them as beneficial for reducing losses. However, financial barriers moderated the role of perceived ease of use and usefulness, limiting adoption despite positive perceptions (Davis, 1989).

The Theory of Planned Behaviour (TPB): The significant role of income reflects perceived behavioural control. Farmers with higher incomes felt more capable of adopting, while lower-income farmers expressed negative attitudes towards cost and remained influenced by traditional storage practices (Ajzen, 1991).

Diffusion of Innovations (DOI): Adoption patterns showed evidence of diffusion, with awareness created through extension and demonstrations. However, the process stalled at the decision and implementation stages because of affordability challenges. The distribution of adoption levels (22.5% none, 43.6% partial, 34.0% full) aligns with Rogers' (2003) model of early majority adoption, slowed by economic constraints.

Economic Constraints Model (ECM): The clearest explanation for the findings comes from ECM (Goldratt & Cox, 1984), which argues that financial capacity is the primary bottleneck for innovation uptake. Hermetic bags and tarpaulins cost several times more than conventional options, making them inaccessible to low-income households.

6.0 Conclusion and Recommendations

6.1 Conclusion

The study revealed uneven adoption of postharvest technologies, with over one-fifth of households not using either tarpaulins or hermetic bags, while about one-third had embraced both. Although awareness of these technologies exists, adoption remains constrained. Among the factors examined, income per capita was the only determinant significantly associated with the extent of adoption, emphasising the decisive role of financial capacity. Farmers with higher incomes were more likely to adopt both technologies, whereas lower-income households either adopted them partially or not at all. Other socio-demographic variables such as age, sex, education, household size, and farming experience showed no significant association. These findings suggest that economic constraints, rather than knowledge or demographic attributes, are the primary barrier to widespread adoption.

6.2 Recommendations

To accelerate adoption of tarpaulins and hermetic bags among smallholder farmers, interventions should simultaneously address financial, informational, and structural barriers. Government agencies, NGOs, and development partners should introduce targeted subsidies or credit schemes through microfinance, cooperatives, and village savings groups to ease liquidity constraints. These efforts must be complemented by strengthened extension services and practical farmer training that build confidence, demonstrate ease of use, and foster positive community norms. At the same time, strengthening local supply chains and promoting cooperative purchasing will reduce transaction costs, improve accessibility, and ensure affordability through innovations such as smaller product packages and local production. Finally, adoption strategies must be gender-inclusive, guaranteeing that women farmers have equitable access to credit, subsidies, and training opportunities. Together, these measures can enhance farmers' economic capacity, improve access and awareness, and create supportive social environments necessary for widespread and sustained use of improved postharvest technologies.

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9.0 Declaration of Conflicting Interests

The authors declare no conflict of interests.

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