Cold Chain Technology Adoption in Agriculture: Insights from the UTAUT Model on Vegetable Producers' Willingness

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Abstract

The UTAUT model has been extensively applied in fields like information technology and education, but its application in the agricultural sector, regarding cold chain technology adoption among vegetable producers, remains scarce. Despite its potential to reduce significant post-harvest losses and improve food security, the adoption of CCT remains limited in low-resource agricultural settings. Using data collected from 87 vegetable producers and analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM), the study examines the influence of performance expectancy, effort expectancy, social influence, and facilitating conditions on behavioral intention. Data from 87 vegetable producers who used the technology was collected to test the hypothesized model. The model explained 58.9% of the variance in adoption intention, with performance expectancy ($\beta = 0.491$, $p \leq 0.000$), social influence ($\beta = 0.211$, $p \leq 0.05$), and facilitating conditions ($\beta = 0.206$, $p \leq 0.05$) emerging as significant predictors. The Effort expectancy, while positively perceived, did not show a significant effect, suggesting that ease of use is secondary to perceived utility. The findings underscore the importance of performance-driven messaging, peer influence, and supportive infrastructure in scaling agro-technologies. In conclusion, Vegetable producers indicate willingness to accept, adopt and use the technology; it is recommended that the training on the operation of the technology should be taken into account. This research contributes to the technology adoption literature in agriculture and informs policy and practice aimed at enhancing food system resilience and achieving sustainable development outcomes.

Keywords: Vegetable producers; Cold chain technology; unified theory of acceptance and use of technology; adoption intention; Technology acceptance and use; Solar powered modular technology

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1.0 Introduction

1.1 Background and Justification

The National Bureau of Statistics (NBS) in 2021 reported that agriculture sector in Tanzania contributes 26.9% of the National GDP; with 15.4% of GDP contribution was from the crop subsector. Match Maker Associated (2017) argued that the horticulture industry of which is principally dominated by vegetable contributed 38% of the foreign income earned from the agricultural sectors in 2017. The vegetable production in Tanzania is conquered by smallholder farmers, accounting about 70% of vegetable production in the country (NBS, 2021).

Despite the fact that the horticulture industry in Tanzania has a prospective benefits in GDP contribution and improve smallholders vegetable and fruits producer livelihoods, the sector is faced by significant post-harvest losses ranging from 30 -50% (Ekka & Mjawa, 2020) hence the sector is limited to its full growth potential. Several intervention has been applied to reduce the post-harvest losses in the horticulture industry among the technologies are the application of reliable, eco-friendly cold chain structures with the view to reduce the freshness losses while maintain the quality and quantity of fruits and vegetables (Makule, Dimoso & Tassou, 2022). However, the uptake of such technologies by smallholder farmers in low-resource settings remains limited. Several barriers including high upfront costs, lack of technical know-how, unreliable infrastructure and limited access to financing which hampers widespread technology adoption. In response to these challenges, solar-powered, modular CCT solutions were introduced as more accessible and sustainable alternatives, particularly in rural settings with unreliable grid access.

While Cold Chain Technology (CCT) is vital for reducing post-harvest losses and preserving the quality of perishable vegetables, there is limited research on vegetable producers' willingness to adopt such technology, particularly in emerging markets. Most studies focus on cold chain implementation at the retailer or logistics level, rather than at the producer level, where factors like technology accessibility, perceived benefits, and financial constraints significantly influence adoption decisions. Despite the potential of CCT to transform the horticultural value chain, especially in reducing spoilage and enhancing marketability of produce, limited empirical research exists on smallholder farmers' willingness to adopt such innovations. Most technology adoption studies in agriculture focus on digital platforms rather than physical infrastructure like cold storage systems (Mwalupaso, Baiyegunhi, & Zulu, 2021; Nkandu & Phiri, 2022). In addition, most of the existing literature tends to emphasize supply chain actors at the aggregation or retail levels, neglecting the critical adoption decisions made at the producer level. Therefore understanding these grassroots dynamics is essential for scaling appropriate technologies and ensuring sustainable development outcomes.

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This study fills that gap by applying the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate the behavioral factors influencing vegetable producers' willingness to adopt CCT in Arusha Region, Tanzania. By focusing on performance expectancy, effort expectancy, social influence, and facilitating conditions. The study offers a strong framework for identifying drivers or hampers of technology adoption adoption in smallholder contexts. The findings are expected to inform policy, guide technology dissemination strategies, and support agricultural transformation initiatives aimed at improving food security, increasing farmer incomes, and reducing post-harvest losses in line with Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption and Production)

A number of theories have been proposed to explain consumers' acceptance, adoption of new technologies and the intention to use such technologies (Lai, 2017). Venkatesh, Thong & Xu (2012) and Venkatesh, Morris, Davis, & Davis (2003) argued that Unified Theory of Acceptance and Use of Technology (UTAUT) model is one of the most prominent in testing the technology acceptance and adoption field. The UTAUT integrates various models on technology acceptance and adoption (Williams et al., 2015) such as Motivational Model (Deci & Ryan, 1985), Technology Acceptance Model (TAM) (Davis, 1993), Innovation Diffusion Theory (Rogers, 1995) and Theory of Planned Behaviour (Fishbein & Ajzen, 1975).

The UTAUT model has been extensively applied in fields like information technology and education, but its application in the agricultural sector, specifically regarding cold chain technology adoption among vegetable producers, remains scarce. Cold chain technology needs substantial infrastructure, resources, and training, which may involve unique challenges for farmers, especially in developing countries where resources are limited. Research addressing how UTAUT factors like performance expectancy, effort expectancy, social influence, and facilitating conditions affect technology adoption in this context is immature, particularly in low-resource settings (Venkatesh et al., 2003; Taherdoost, 2018). Therefore, the UTAUT model was adopted to test the technology acceptance, adopt and use by vegetable producers in Tanzania specifically in Arusha region.

1.2 Research Objectives and Research Hypotheses

1.2.1 General Objective

To analyze the factors influencing vegetable producers' willingness to adopt Cold Chain Technology (CCT) based on the Unified Theory of Acceptance and Use of Technology (UTAUT).

1.2.2 Specific Objectives

i. To examine the influence of performance expectancy on vegetable producers' willingness to adopt Cold Chain Technology.

ii. To assess how effort expectancy influences vegetable producers' attitudes toward adopting Cold Chain Technology.

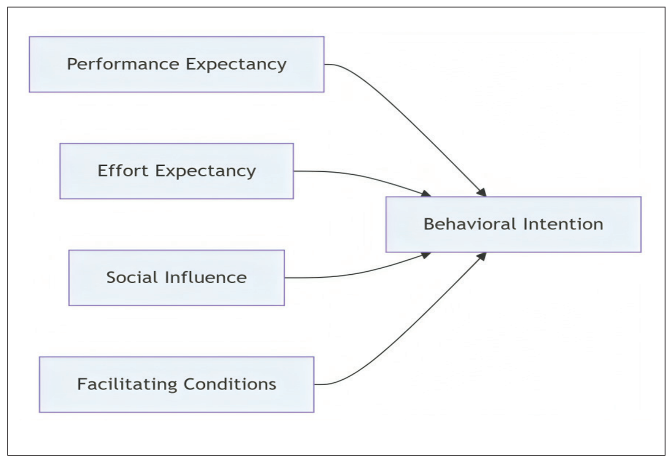
iii. To analyze the role of social influence in shaping vegetable producers' willingness to adopt Cold Chain Technology.

iv. To evaluate the effect of facilitating conditions on the adoption of Cold Chain Technology among vegetable producers

2.1 Research hypothesis formation

As argued by Agarwal and Prasad (1999), behavioral intention is used as a relevant substitute for behavior in for the use of technology by vegetable producers in Tanzania. Performance Expectancy (PE) as postulated by Venkatesh et al. (2003), it involves individual beliefs that using the technology will support the user to excel in production performance. Previous studies have suggested that performance expectancy is an important factor in accepting technology (Liu, Chen, Kittikowit, Hongsuchon & Chen, 2022). Therefore, it is postulated that there is positive correlation between the Performance Expectancy (PE) and Behavioral Intention (BI) of the vegetable producers to the technology (Eweoya et al., 2021 and Vankatesh et al., 2011). Recent studies by Xie et al. (2022) and Sharma et al. (2024) confirm that PE remains the strongest predictor of behavioral intention in technology adoption among farmers .This explanation leads to the first hypothesis: H1: *Technology performance expectancy has significant and positive influence on behavioral intention of vegetable producers on the technology acceptance, adoption and use* (**Figure 1**)

Figure 1: Conceptual Framework



Source: Author

Effort expectance (EE) is the individual belief that the utilizing of specific technology will be simple and easy (Cohen, 1988). Venkatesh and Morris (2000) and Vankatesh et al. (2011) claim that Effort Expectancy has a powerful effect over a sustained period of time for the user utilizing technology. However, findings on EE in agricultural contexts are mixed. While Eweoya et al. (2021) support its significance, others like Handoko et al. (2023) and Ky, (2025) find EE to be insignificant when performance gains outweigh usability challenges. Therefore, it is postulated that there is direct and positive relation between EE and BI the technology to the vegetable producers. This leads second hypothesis which says: H2: *Effort expectancy has significant and positive influence on the Behavioral intention of vegetable producers on the technology, acceptance, adoption and use.*

Eweonya et al. (2021) argued that Social Influence (SI) is the "extent to which an individual' ability is perceived by others to be able or expected to use the technology". As echoed by Venkatesh et al. (2003), social influence is the "degree to which important people have an impact on his or her decision to use the new technology". In the context

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of rural agriculture, this includes access to electricity, training, financial services, and maintenance support. Recent studies by Sharma et al. (2024) and Xie et al. (2022) affirms that facilitating conditions positively impact adoption, especially when technologies are resource-intensive like cold chain systems. Therefore the extrapolation of SI in relation to technology adoption leads to the third hypothesis which says: H3: *The social influence has significant and positive influence on the Behavioral intention of vegetable producers on the technology acceptance, adoption and use.*

According to Venkatesh et al. (2003) Facilitating conditions (FC) represent the degree to which an individual believes there are some conditions such as technical infrastructure to support using a Technology in organization. The same authors found FC has a direct impact on the behavioral intention to accept, adopt and use of the technology. In the case the technology, technical infrastructure such as solar power, batteries inventors are required for the adoption of the technology. H4*: The facilitating conditions have significant and positive influence on the Behavioral intention of vegetable producers on the technology acceptance, adoption and use.*

Identification of the Gap

While the UTAUT and its extended model UTAUT2 have been extensively applied in sectors such as information technology, education, and finance (Venkatesh et al., 2003; Venkatesh et al., 2012), the models application in agriculture especially in the context of Cold Chain Technology (CCT) adoption among smallholder vegetable producers remains underexplored. Most existing studies focus on digital tools such as mobile money (Mwalupaso et al., 2021) and ICT for advisory services (Nkandu & Phiri, 2022), leaving a critical gap in understanding how farmers engage with physical, infrastructure-dependent technologies like CCT. Cold chain technology needs substantial infrastructure, resources, and training, which may involve unique challenges for farmers, especially in developing countries where resources are limited. Research addressing how UTAUT factors like performance expectancy, effort expectancy, social influence, and facilitating conditions affect technology adoption in this context is immature, particularly in low-resource settings (Venkatesh et al., 2003; Taherdoost, 2018). In addition the study addresses this gap by applying the UTAUT model to a low-resource agricultural setting, thereby contributing empirical insights into the behavioral drivers and contextual barriers affecting adoption of climate-resilient, post-harvest technologies at the producer level.

2.0 Literature Review

The application of technology in agriculture is a major factor in promoting economic growth, improving farm production, and advancing food security on a global scale (Sharma et al,. 2024). Lescevica, Ginters & Mazza (2013) asserted that the UTAUT model has been applied by researchers when studying distinct technology acceptance and use across an array of situations such as diverse types of technologies. UTAUT has further been used in studies investigating technology acceptance in settings which are not in western countries (Chikoye, Gupta & Kandadi, 2018).

For example Xie et al. (2022) applied the Unified Theory of Acceptance and Use of Technology (UTAUT) in the adoption of ecological agriculture technology, the study applied the partial least squares structural equation modeling (PLS-SEM), the study found that performance expectation has the greatest impact on behavioral intention to adopt the ecological agriculture technology. The study found that effort expectation, social influence and the facilitating factors had positive and significant effects on the behavioral intention.

The UTAUT model was used by Eweoya, Okuboyejo, Odetunmibi & Odusote (2021) for empirical analysis in the acceptance, adoption and use of E- agriculture in Nigeria. The authors found that performance expectancy, effort expectancy, social influence and habit have significant effect on the behavioral intention to use E-agriculture technology. The empirical testing and application of the UTAUT model was postulated by de Sena Abrahão, Moriguchi & Andrade (2016) in the evaluation of the intention of adopting a future mobile payment technology. The study found that 76% of behavioral intention to adopt the technology was explained by the performance expectation, effort expectation, social influence and perceived risk.

Nkandu and Phiri (2022) assessed the effect of ICTs on Agriculture Productivity Based on the UTAUT Model in Developing Countries focusing Southern Province in Zambia. The study incorporated performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants. Data from 450 farmers was analyzed using SmartPLS 4.0 for structural equation modeling (SEM). The study found that ICT adoption significantly increased agricultural productivity in Zambia's Southern Province, with mobile advisories and digital finance tools improving crop yields by 15-20% and reducing post-harvest losses. Performance expectancy ($\beta=0.42$, $p<0.01$) and facilitating conditions ($\beta=0.31$, $p<0.05$) were the strongest adoption drivers, while social influence played a critical role among women farmers while the effort expectancy showed marginal significance ($\beta=0.18$, $p<0.10$).

Ky (2025) examined mobile money's transformative role in Sub-Saharan African agriculture through an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) lens, incorporating trust, liquidity constraints, and social networks as key moderators. The study applied SmartPLS 4.0 for partial least squares structural equation modeling (PLS-SEM). The analysis revealed that performance expectancy ($\beta=0.41$, $p<0.01$) and social influence ($\beta=0.33$, $p<0.01$) were the strongest adoption drivers, while effort expectancy showed unexpected non-significance ($\beta=0.09$, ns) due to increasing smartphone familiarity. Empirically it was reveal that mobile money adoption increased smallholder farmers' access to inputs by 35% and reduced payment delays by 50%, with performance expectancy and social influence the being the strongest drivers ($p<0.05$).

For example Handoko et al (2023) explored farmers' adoption of agricultural applications through an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) framework, incorporating community behavior and user experience (UX) as critical moderators. The study applied SmartPLS 4.0 for partial least squares

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structural equation modeling (PLS-SEM) with data from smallholder farmers. The results found social influence (β=0.34, $p<0.01$) was a stronger predictors while effort expectancy became non-significant (β=0.07, ns) due to low digital literacy.

Sharma et al. (2024) examines fintech adoption in agrarian economies using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model, incorporating additional factors such as perceived risk, trust, and financial literacy alongside core UTAUT constructs like performance expectancy, effort expectancy, and social influence. The study found that that performance expectancy, social influence, facilitating conditions, and trust significantly influenced fintech adoption, while perceived risk acts as a barrier. Effort expectancy and hedonic motivation were found to be less influential, suggesting that farmers are looking for practicality and reliability over ease of use.

The study by Bajunaied et al. (2023) extends the Unified Theory of Acceptance and Use of Technology (UTAUT) model to analyze FinTech adoption in Saudi Arabia. The study found that performance expectancy; effort expectancy and facilitating conditions, significantly positively influence behavioral intention to adopt FinTech services. The study highlighted the importance of trust, ease of use, and robust technical infrastructure in driving FinTech adoption.

With regards to the study on vegetable producers' technology adoption, acceptance and use with the aim of developing sustainable business model for the Walk-in, Modular, and Solar Powered Cold Chain Unit technology, UTAUT model was applied to give an overview on whether vegetable producers might adopt, accept and use the technology. The psychological factors regarding technology performance expectation (PE), effort expectation (EE), social influence (SI), facilitating conditions (FC) was used to test the UTAUT model. Therefore the study hypothesized that if the vegetable producers perceive the technology to be useful and easy to use there is higher likelihood of acceptance, adoption, and use.

3.0 Methodology

3.1 Research Design

Mixed-methods approach, combining quantitative and qualitative data to gain a comprehensive understanding of adoption factors was applied in this study. The structural equation modeling (SEM) with the Partial Least Squares (PLS) approach was used in this research to create and test the conceptual framework and describe specifically on vegetable producers' intentions to use the technology in Arusha region (Meru District).

The study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) as the primary analytical method using SmartPLS 4.0. The selection of PLS-SEM over techniques such as Covariance-Based SEM (CB-SEM) was guided by both theoretical and empirical considerations. PLS-SEM is suited for exploratory research, complex models with multiple latent variables, and studies aimed at prediction of vegetable producers intention to adopt cold chain technology and rather than strict theory testing (Hair et al., 2021).

Given the formative and reflective constructs included in the model and the goal of examining how various constructs (performance expectancy, effort expectancy, facilitating conditions and social influence) influence behavioral intention in agricultural context PLS-SEM offered flexibility and strength. Additionally, PLS-SEM is less restrictive regarding data distribution assumptions and is appropriate when working with smaller sample sizes, making it ideal for this study's dataset (n = 87).

Unlike CB-SEM, which requires large sample sizes to achieve statistical power and assumes multivariate normality, PLS-SEM handles non-normal, skewed data and maintains estimation accuracy with smaller samples. Besides, PLS-SEM allows for the simultaneous assessment of the measurement model (construct reliability and validity) of which this study tested for the structural model both was essential to achieving the objectives of this study.

In order to address the limitation the study applied bootstrapping (5,000 resamples) to improve the robustness and reliability of the statistical estimates. Furthermore, the construct validity and reliability were assessed through the PLS-SEM approach. The results confirmed the internal consistency reliability; composite Reliability (CR) and Cronbach's Alpha as the values exceeded the 0.7 threshold for all constructs (Fig.2 and Table 3). The Discriminant validity was verified through both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio, indicating that constructs were empirically distinct (Table 4 and Table 5). In conclusion, the combination of a theoretically grounded, empirically validated instrument, together with the strength of PLS-SEM, positions this study to offer meaningful insights into technology adoption in the agricultural sector despite the sample size constraint

3.2 Sample

The intervention of the technology was done to Arusha region in Tanzania to vegetable producers to test the efficiency of the technology in terms of effort, performance and facilitating conditions which leads to the reduction of post-harvest losses by the provision of cold storage and transport to the market of vegetables and fruits. Before the intervention of the technology, vegetable producers were training on how to operate the technology. The training and testing of the technology were conducted to 87 smallholder farmers producing vegetable and fruits in Arusha region, specifically in Arumeru district.

Purposively smallholder vegetable producers in Arusha Region where the technology intervention was conducted were selected. Stratified random sampling to ensure representation across different producers demographics focusing on farm size, income level and access to market were applied to the target population. The sample size of 87 vegetable producers was determined based on the population size where the technology intervention was done.

3.3 Procedures:

The research structured questionnaires was developed based on established constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extended versions (UTAUT2). Items of measuring performance expectancy, effort expectancy, social influence,

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facilitating conditions, and behavioral intention were adapted from previous studies (e.g., Venkatesh et al., 2003; Mwalupaso et al., 2021; Nkandu & Phiri, 2022) and modified to suit the agricultural and rural context of the study.

The questionnaires were taken through a three stage development process; the initial draft of the questionnaire was evaluated by three domain experts in agricultural technology, rural sociology, and ICT adoption the process ensured content validity and contextual relevance. In addition, the pilot testing was conducted with a small sample (n = 15) of farmers to assess the clarity, comprehension, and applicability of the questions. Feedback from farmers led to minor revisions in language and response scale formatting to improve readability and cultural appropriateness.

The questionnaires were administered randomly to 87 vegetable producers who used the technology in the area where the technology intervention was tested. The first part of the questionnaire focused on the demographic information and willingness to pay on the technology. The second part included questions for data to test the model which comprises the four explanatory variable; performance expectance, effort expectance, social influence and facilitating conditions. The second part requested vegetable producers declare their opinions based on the Likert-scale of (5 (strongly agree) to 4 (agree) to 3(neutral) to 2 (disagree) and 1 (strongly disagree). Based on literature review, the questions was formulated to capture information and factors that have significant impact on the behavioral intention (BI) to accept, adopt and use the technology based on latent variables such as the performance expectancy (PE), effort expectancy (EE) social influence (SI) and facilitating Conditions (FC). There were 72 variables with main questions to test the model.

3.3 Data Analysis:

The Smart-PLS 4.0 software was used to model the structural equation and analyze the survey results from vegetable producers in Arusha region. Exploratory factor analysis was used to determine the reliability and validity of the research model and the fitting index. Confirmatory factor analysis was used to determine the relationships between variables and test the research hypotheses. Bootstrapping resampling was performed to test the significance of the path coefficients in the inner model.

4.0 Results

4.1 Sample characteristics

A total of 87 valid completed questionnaires were administered with males accounting for 54% and female 46% of responses and participants aged 19–59 years accounting for 96.6%. In terms of education, vegetable producers who completed primary education accounted for 79.3% and 1.1% were has college-level education or higher. This indicates that the vegetable producers have a certain level of knowledge. Furthermore, the demographic results confirmed that the technology intervention area represents groups of respondents who have the knowledge to accept and adopt the technology based on its usefulness and ease of use. In addition, having majority of the vegetable producers in the productive force indicates they are eager to learn and adopt new technologies that reduced post-harvest losses. **Table 1** gives the demographic characteristics of the sample.

Table 1: Socioeconomic Demographic Characteristics (***N*** = 87)

Characteristics		Responses	
		Frequency	Percentage (%)
Gender	Male	40	46.0
	Female	47	54.0
Marital status	Single	6	6.9
	Married	78	89.7
	Divorced	0	0
	Widowed	3	3.4
Age	Less than or equal to 19	2	2.3
	20 – 29 Years	11	12.6
	30 – 39 Years	22	25.3
	40 -49 Years	36	41.4
	50 – 59 Years	13	14.9
	60 Year and Above	3	3.4
Main source of income	Vegetable production	83	95.4
	Livestock keeper	1	1.1
	Employed	0	0.0
	Businessman/woman	3	3.4
	Artisan	0	0.0
Education Level of participants	Never attended School	3	3.4
	Completed Primary School	69	79.3
	Didn't Complete Secondary School	4	4.6
	Completed Secondary School	9	10.3
	Didn't Complete College	1	1.1
	Completed College	1	1.1

Source: Author (Field data)

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4.2 Descriptive statistics

The descriptive statistics show that vegetable producers in Arusha Region exhibit a generally favorable outlook toward Cold Chain Technology (CCT), with high mean scores across all UTAUT constructs. Performance expectancy recorded the highest mean (M = 4.158, SD = 0.399) (Table 2), suggesting that most farmers believe the technology can improve the productivity and reduce post-harvest losses. This aligns with findings by Xie et al. (2022) and Eweoya et al. (2021), who reported that performance expectancy was the most influential factor in agricultural technology adoption. Behavioral intention also showed a strong average (M = 4.14, SD = 0.141), indicating a high willingness to adopt and use the technology. These insights affirm previous studies by Venkatesh et al. (2003) and Sharma et al. (2024) that performance-driven motivations were central to technology acceptance in agricultural settings, where tangible benefits were prioritized over convenience.

Table 2: Descriptive Statistics

Variables	Number of Items	Mean	Standard Deviation
Behavior Intention (BI)	3	4.14	0.141
Effort Expectancy (EE)	3	4.022	0.468
Facilitating Conditions	3	4.106	0.426
Performance Expectancy (PE)	4	4.158	0.399
Social Influence (SI)	2	4.117	0.390

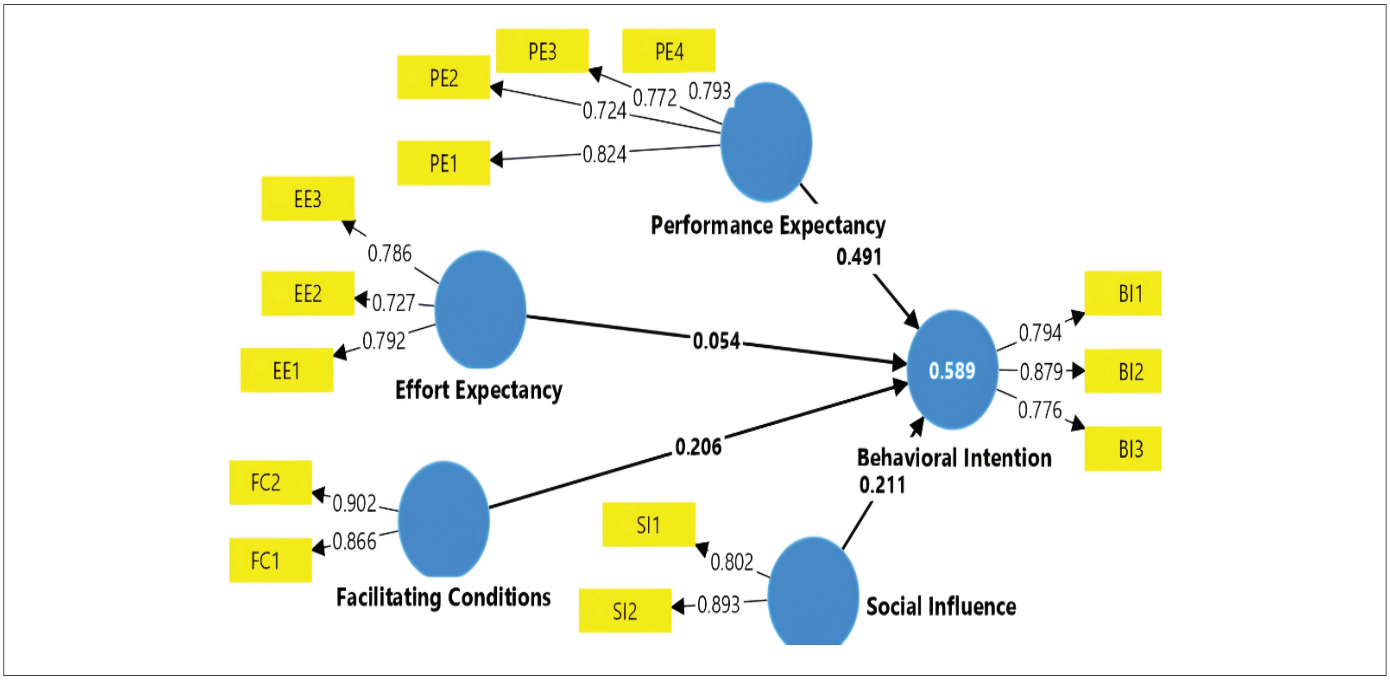
Source: Author (Field data)

Although effort expectancy was also rated positively (M = 4.022 SD = 0.468), it had the lowest mean among the constructs, suggesting that perceived complexity of CCT might pose a barrier to technology adoption to some users. Similar observations were made by Handoko et al. (2023), who noted that low digital literacy can limit the influence of effort expectancy. However, the relatively low standard deviations across all variables indicate strong consensus among producers, reinforcing the potential for well-targeted interventions to achieve broad-based technology adoption.

4.4 Evaluation of outer model

The PLS-SEM analysis involved the evaluation of the model. The purpose was to determine how sound the items load on the hypothetical-defined construct. The evaluation of the outer model confirmed the reliability and validity of the measurement constructs used to assess the adoption of Cold Chain Technology (CCT) among vegetable producers. All outer loadings exceeded the recommended threshold of 0.70, indicating strong indicator reliability (Hair et al., 2014).

Figure 2: Total Path Effect of the Model and R^2 (SmartPLS 4.0)



Source: Author (Field data)

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The evaluation of the outer model comprised the unidirectional predictive relationships between each of the latent construct that is linked with the observed indicator (Hair, Christian, Ringle &Sarstedt, 2011). Becker, Klein & Wetzels (2012), proposed two measures of indicators in PLS-SEM that are reflective and formative outer model which involved examining the reliabilities of the individual items (indicator reliability), reliability of each latent variables, internal consistency (Cronbach alpha and composite reliability), construct validity (loading and cross-loading), convergent validity (average variance extracted (AVE)) and discriminant validity by using Fornell-Larcker criterion, cross loading and HTMT criterion (Hair, Hult, Ringle & Sarstedt, 2014). The Evaluation of the model is presented in **Table 3**.

4.5 Construct validity and reliability

The model validity and reliability were examined using Composite reliability (CR), Cronbach's Alpha (CA), Average Variance Extracted (AVE) and Confirmatory Factor Analysis (CFA). Hair et al. (2014) postulated that variables to be included in the model must have a minimum value of factor loading 0.70 to be retained in the model. Hair et al. (2014) said that composite reliability/Cronbach alpha between 0.60 - 0.70 are acceptable but the authors advised that for advanced stage the value have to be higher than 0.70. The Composite Reliability (CR) values ranged between 0.813 and 0.877, and Cronbach's Alpha values were all above the 0.70 benchmark, further confirming internal consistency of the constructs (Becker et al., 2012) **(Table 3 and Figure 2)**.

Table 3: Constructs Reliability and Validity

Variables	Items	CFA	AVE	Cronbach's alpha (α)	Composite Reliability	VIF
	BI1	0.794				1.419
Behavioral Intention	BI2	0.879	0.667	0.751	0.857	1.961
	BI3	0.776				1.583
Effort Expectation	EE2	0.792	0.593	0.761	0.813	1.644
	EE3	0.786				1.608
Facilitating Conditions	FC1	0.902				1.469
	FC2	0.866	0.782	0.722	0.877	1.469
	PE1	0.824				1.695
Performance Expectancy	PE2	0.724	0.607	0.787	0.860	1.864
	PE3	0.772				1.625
	PE4	0.793				1.962
Social Influence	SI1	0.802	0.721	0.760	0.837	1.252
	SI2	0.893				1.252

Source: Author (Field data)

The AVE values for all constructs were also above the recommended 0.50 level, which suggests good convergent validity, meaning that the items used to measure each latent variable share a high proportion of variance in common (Hair et al., 2013).The results prove that the internal consistency of the model was within the required standards. Hair *et al.* (2014) argued that the indicator reliability is the proposition of indicator variance that is explained by the latent variable and the values ranges from 0 to 1. The same authors proposed that the outer loadings values should be higher than 0.70. Hair *et al.* (2014) proposed convergent validity to be measured by the factors loading of the indicators, composite reliability (CR) and the average variance extracted (AVE). Henseler, Ringle & Sinkovics (2009) and Hair *et al.* (2014) and Henseler, Ringle & Sarstedt (2015) reported that the AVE values ranges from 0 to 1, and the values should exceed 0.5 for convergent validity. **Table 3** shows the convergent validity of the constructs that was applied to test the UTAUT model. The average variance extracted (AVE) was greater than 0.60 while the variance inflation factor. This indicates that the measurement model has good convergent validity (Xie *et al.,* 2022). Additionally, the Variance Inflation Factor (VIF) values were all below 2.0, suggesting no multicollinearity (Hair *et al.,* 2013) among indicators. These findings support the robustness of the measurement model and confirm that the data are suitable for further structural analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM).

4.6 Discriminant validity Testing

In addition to reliability and convergent validity, discriminant validity was also verified using both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT), as recommended by Henseler et al. (2015) **Table 4** and **Table 5**. Henseler *et al.* (2014) argued that HTMT values close to 1 indicates a lack of discriminant validity. Kline (2011) suggested the threshold of 0.85 while Gold et al. (2001) proposed a value of 0.9. In this study the HTMT values are within the suggested value by Hairl *et al.* (2014) and Henseler et al. (2014) which ranges from 0.428 to 0.841 (**Table 4**). The HTMT values were all below the conservative threshold of 0.85 (Kline, 2011), further affirming that there is no significant overlap between constructs.

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Table 4: Discriminant Validity (Heterotrait-monotrait ratio (HTMT) –Matrix)

Items	Behavioral Intention	Effort Expectation	Facilitating Conditions	Performance Expectancy	Social Influence
Behavioral Intention					
Effort Expectation	0.618				
Facilitating Conditions	0.649	0.679			
Performance Expectancy	0.841	0.612	0.513		
Social Influence	0.798	0.601	0.428	0.707	

Hairl *et al.* (2014) suggested that the square root of each construct's average variance extracted (AVE) should have a greater value than the correlations with other latent constructs. The square roots of the AVE values for each construct were greater than the correlations with other constructs, indicating that each latent variable was distinct from the others **Table 5.**

Table 5: PLS- SEM Fornell and Larcker Test for Discriminant Validity

Items	Behavioral Intention	Effort Expectation	Facilitating Conditions	Performance Expectancy	Social Influence
Behavioral Intention	**0.817**				
Effort Expectation	0.447	**0.769**			
Facilitating Conditions	0.486	0.449	**0.884**		
Performance Expectancy	0.709	0.440	0.394	**0.779**	
Social Influence	0.557	0.402	0.299	0.538	**0.849**

4.7 Hypothesis testing

The purpose of this study was to identify factors that support vegetable producer's willingness to accept and adopt and use the solar powered cold chain technology by using the UTAUT model. The hypothesis testing using Partial Least Squares Structural Equation Modeling (PLS-SEM) provided strong insights into the behavioral drivers influencing vegetable producers' willingness to adopt Cold Chain Technology (CCT). The factors tested were the PE, FC, EE and SI the impact directly on behavioral intention. By using PLS SEM to estimate the path relationship of research constructs for path relationships, it was revealed that three assumptions attained significance.

Bootstrapping resampling was performed to test the significance of the path coefficients in the inner model (number of iterations: 5000). **Figure 2** and **Table 4** indicate that the path coefficient had a positive value in the performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC) variables. A two-tailed t-test was conducted to determine whether the inner model's path coefficient was significant (T-statistics two-tailed). The path coefficient was acknowledged significant if the T-statistics was greater than 1.65 at a 10% significance level, more significant than 1.96 at a 5% significance level, and greater than 2.58 at a 1% significance level (Salsabil, Pratama & Wulansari, 2022).

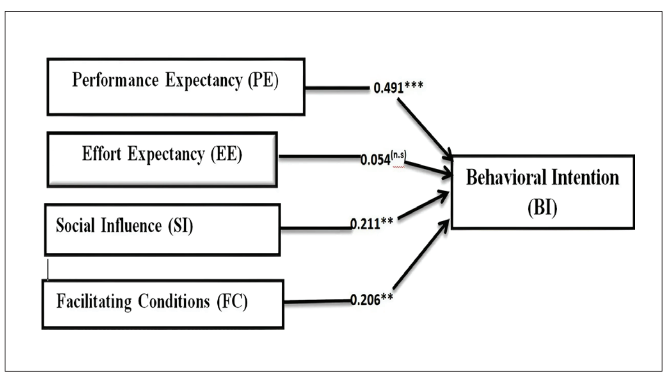
Table 6: Results of Hypothesis Testing Based on PLS-SEM Model

Hypothesis	Hypothesis Path	Path Coefficeint	T-Values	P-Value	Accepted or Rejected the significance
H_1	PE →BI	0.491	3.680	0.000	Accept***
H_2	EE → BI	0.054	0.393	0.347	Reject
H_3	FC → BI	0.206	1.957	0.035	Accept**
H_4	SI → BI	0.211	1.986	0.047	Accept**

Critical t-values for a two tailed test are:<1.96 (p >0.05*); 1.96 (p = 0.05**) and 2.58 (p = 0.001***)

According to Salsabil *et al.* (2022) the value of R^2 greater than 0.67 reflected "strong," and values between 0.33 and 0.67 was reflected "moderate," and a value between 0.19 and 0.33 was considered "weak" explanatory powers. The R^2 value obtained was 0.589, which was considered moderate (**Figure 3**). Each of the structural paths was significant except the effort expectancy thus tentatively confirming the three hypotheses (PE →BI, FC → BI and SI → BI) (**Table 6**). The most crucial factors that influence the behavioral intention (BI) were Technology performance expectancy (PE), facilitating conditions (FC) and social influence (SI).

Figure 3: Total Path Effect of the Model and P-Value (95% CI)



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5.0 Discussion

5.1 The Influence of performance expectancy on behavioral intention

The purpose of this study is to analyze the factors influencing vegetable producers' willingness to adopt Cold Chain Technology (CCT) based on the Unified Theory of Acceptance and Use of Technology (UTAUT). The model explained 58.9% of the variance in behavioral intention, which is considered a moderate-to-strong explanatory power (Hair et al., 2014), reinforcing the predictive relevance of UTAUT constructs in rural agricultural contexts. The analysis confirmed that performance expectancy (PE) had the strongest and most significant impact on behavioral intention ($\beta = 0.491$, $p \leq 0.000$), supporting Hypothesis 1 (H1) **Table 4** and **Figure 3**. This suggests that farmers are more likely to adopt technologies that are perceived offering practical benefits such as reducing post-harvest losses and improving product quality consistent with prior studies by Saparudin, Rahayu, Hurriyati, Sultan, & Ramdan, 2020; Eweoya *et al.*, (2021); Salsabil *et al.* (2022) and Xie *et al.*, (2022). Hence hypothesis (H_1) was accepted (**Table 4** and **Figure 3**).

5.2 Influence of effort expectancy on behavioral intention

On the other hand, effort expectancy (EE) was found to be statistically insignificant ($\beta = 0.054$, $p = 0.347$), leading to the rejection of Hypothesis 2 (H2). This finding indicates that the perceived ease of use of CCT is not a primary concern for most farmers, possibly because the perceived benefits outweigh any anticipated operational complexity. Similar trends were reported by Handoko et al. (2023) and Ky (2025), who found that smallholder farmers may overlook usability issues when the technology promises high returns (**Table 4** and **Figure 3**). When cold chain technology promises considerable value such as reducing post-harvest losses and extending shelf life producers may be willing to invest time and effort in learning how to use the technology, making effort expectancy a less critical determinant. This indicates that, in agricultural contexts, perceived utility can outweigh usability concerns, especially when technology is associated with improved productivity and profitability (Venkatesh et al., 2012). This also suggests the potential mitigating effect of prior training or community demonstrations, which may have alleviated concerns about difficulty. However, the results is contradicting with previous research conducted by Vankatesh *et al.* (2003), Eweoya *et al.*, (2021); Xie *et al.* (2022) and Salsabil *et al.* (2022) who found that the effort expectancy was positive and significantly affected behavioral intention. The positive influence indicated that some farmers perceive ease of use and operation of the technology while the majority perceived difficulties in the operation.

5.3 Social influence on behavioral intention

Social Influence significantly affected Behavioral Intention ($\beta = 0.211$, and $p \leq 0.005$) **Table 4** and **Figure 3**. The finding highlights the importance of peer dynamics the influence of community leaders and early adopters in driving technology acceptance among smallholders. The results tallies and is consistent with previous research by Eweoya *et al.* (2021) and Xie *et al.* (2022). This research finding supports previous research findings and demonstrated that social influence variables could be used in research for agriculture technology acceptance, adoption and use. The significance result demonstrated that the influence of vegetable producers on social environments, such as family and friends, encouraged them to use the technology in order to reduce the post-harvest losses as well as supply fresh products to the local and international market. In agricultural among smallholder farmers, decisions are influenced by the opinions and experiences of others in the community. Producers tend to value the experiences of other who have adopted new technologies, as farmers perceive firsthand testimonials trustworthy and relevant than information from external sources. The results lead to the acceptance of the third hypothesis $\mathbf{H_3}$.

5.4 Facilitator conditions on behavioral intention

Hypothesis testing using SmartPLS 4.0 software discovered that Facilitating Conditions significantly affected Behavioral Intention ($\beta = 0.206$, and $p \leq 0.005$) **Table 4** and **Figure 3.** The findings of this research were consistent with previous research (Xie et al., 2022 and Salsabil et al., 2022). The findings in this study strengthened previous research findings and demonstrated that the facilitating condition variable could be used in research on the acceptance, adoption and use of agriculture ecological friendly technology for reducing post-harvest losses of perishable crops. A positive and significant result validates that technology compatible with the environment in which the technology was being tested. This finding highlights the importance of infrastructure access that is solar power and storage units and suggests the acceptance of the fourth hypothesis H4.

6.0 Theoretical and Practical Implications:

The application of the Unified Theory of Acceptance and Use of Technology (UTAUT) to cold chain technology (CCT) adoption among Tanzanian vegetable producers yields critical theoretical contribution. The strong and significant influence of performance Expectance (PE) of $\beta = 0.491$, $p \leq 0.000$ aligns with prior UTAUT studies (Venkatesh et al., 2003; Xie et al., 2022; Bajunaied et al., 2023 and Sharma et al.,2024). However, the higher explanatory power (49.1%) in this agricultural context suggests that farmers prioritize tangible benefits like reduced post-harvest losses, extended shelf life over other factors. This emphasizes the economic rationality of smallholder farmers, where technology adoption is driven by perceived productivity gains rather than intellectual advantages.

The non-significant effect of effort expectancy (EE) ($\beta = 0.054$, $p = 0.347$) contrasts with classic UTAUT predictions but reflects findings in other agrarian studies like Handoko et al., (2023) and Ky, (2025). This divergence suggests that in low-resource settings, farmers might tolerate complexity if the technology's benefits outweigh usability challenges. The pre-intervention training might have mitigated initial usability concerns, shifting focus to long-term utility (PE) rather than ease of use (EE).

The strong prediction drivers of social influence (SI) ($\beta = 0.211$) and facilitating conditions (FC) ($\beta = 0.206$) indicates the socialist decision-making prevalent in agrarian communities. Unlike individualistic

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settings like fintech, farmers rely on peer validation (SI) and institutional support (FC), aligning with studies in Sub-Saharan Africa (Nkandu & Phiri, 2022; Mwalupaso et al., 2021).

This study extends UTAUT by revealing context-specific shades and proposes the introduction of "*Economic Vulnerability*" as a moderator this is due to the fact that smallholder farmers' technology adoption decision might be moderated by economic influence where by perceived risks like investment costs can outweigh effort expectance (EE). Future models could integrate this as a latent variable. The expansion of facilitating condition (FC) to include infrastructure reliability like solar power availability and maintenance access and not just technical support. Furthermore, effort expectance (EE) EE's insignificance may reflect measurement limitations for example farmers might confuse "ease of use" and "ease of outcomes" therefore refining EE indicators to capture practical skills could improve validity. Venkatesh et al. (2012) incorporates "habit" and "hedonic motivation" in UTAUT2, however these factors may be less useful in subsistence farming context but "*perceived necessity*" which is linked to food security could be a strong driver.

7.0 Limitations

Despite the suitability of PLS-SEM for small samples, a total sample of 87 respondents introduces limitations that should be acknowledged. First, the sample size might reduce the statistical power of the analysis, increasing the risk of Type II errors, where significant relationships might go undetected. Second, a small sample may affect the generalizability of findings, especially in heterogeneous populations like smallholder farmers who vary by geography, gender, age, land size, education, access to extension services and technology.

While the study provides valuable insights into the adoption of cold chain technology in a particular agricultural context, it may limit the generalizability of the findings to other types of agricultural producers. Factors influencing technology adoption varies significantly across regions with different climates, economic conditions, and agricultural practices. The study's cross-sectional design only provides a snapshot of vegetable producers' intentions at a single point in time. As such, it cannot capture changes in attitudes or adoption intentions over time. A longitudinal study would provide insights into how behavioral intentions evolve as producers become familiar with cold chain technology.

8.0 Future Recommendations

This study challenges effort expectancy (EE) of the UTAUT model construct in agrarian contexts, encouraging for a context-adapted framework where economic necessity and collective influence supersede ease of use. This study recommends that smallholder farmers training programs should focus on demonstrating tangible benefits like the performance expectancy (PE) than "ease of use" the effort expectancy (EE). In addition, there should be peer based advocacy where by the early technology adopters become community ambassador. The infrastructure investment is paramount in order to address the facilitating conditions (FC) gaps for example the solar energy access for adoption sustainability.

In order to comprehend how adoption intentions change and translate into actual usage, future research should consider longitudinal studies. Tracking vegetable producers can provide insights into how exposure to cold chain technology and changes in economic or environmental conditions affect the adoption decisions. This approach can assist in capturing the long-term effectiveness and sustainability of cold chain technology use. Future studies could incorporate contextual and cultural variables that may influence technology adoption. Integrating the factors could provide different perspective on how social, cultural, and environmental conditions impact technology adoption among smallholder farmers, offering tailored recommendations.

9.0 Conclusion

The findings of this study highlight that the Unified Theory of Acceptance and Use of Technology (UTAUT) is a relevant and robust framework for understanding technology adoption behavior among smallholder vegetable producers in Tanzania. Perhaps the striking finding was that performance expectancy explanatory power was 49.1% and it was significant at $p \leq 0.000$. The performance expectancy emerged as significant driver, indicating that vegetable producers are more likely to adopt Cold Chain Technology (CCT) when tangible benefits perceived such as reduced post-harvest losses and improved market access. This insight aligns with the economic rationality of smallholders who prioritize utility and productivity over other adoption considerations. These outcomes affirm the potential of CCT to play a transformative role in enhancing agricultural efficiency and resilience at the grassroots level. Critically, the study highlights the implications of Cold Chain Technology adoption for food security in Tanzania and in similar agrarian economies. For example the post-harvest losses in horticulture ranging from 30–50%, and the ability of CCT to extend the shelf life of perishable produce directly contributes to reducing food waste, increasing food availability, and stabilizing farmer incomes. By preserving crop quality and reducing spoilage, CCT enhances the capacity of farmers to supply both local and regional markets with consistent, high-quality produce.

Furthermore, the study contributes to Sustainable Development Goals (SDGs); particularly SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 12 (Responsible Consumption and Production). The adoption of solar-powered, modular CCT promotes environmentally sustainable practices and inclusive technological innovation tailored for underserved rural communities. Facilitating conditions such as access to training, reliable solar infrastructure, and local maintenance support were identified as essential to unlocking the full potential of such innovations. Addressing these infrastructure and knowledge gaps could accelerate the scaling of green technologies for climate-resilient agriculture.

The explanatory power of social influence was 21.5% and significant at $p \leq 0.05$ signifying that social factors has influence on the technology acceptance, adoption and usage. The influence of social factors reveals the importance of leveraging community structures in driving sustainable change. Social influence plays a pivotal role in building

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trust and reducing perceived risks, especially in rural societies. This finding suggests that peer-led advocacy, farmer cooperatives, and extension services can act as catalytic agents for wider adoption. In order to translate behavioral intentions into sustained usage, future programs should integrate cost-effectiveness evaluations, risk mitigation strategies, and long-term monitoring to ensure that technology adoption translates into real-world impact. Cold Chain Technology, if strategically supported, holds the potential to strengthen value chains, empower rural livelihoods, and strengthen Tanzania's food systems against climate and market shocks.

10.0 Relevance and Contribution

The study applied the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate the adoption of Cold Chain Technology (CCT) among smallholder vegetable producers in Tanzania, the research addresses a critical gap in agricultural technology adoption literature. The study goes beyond theoretical modeling by empirically demonstrating how performance expectancy, social influence, and facilitating conditions shape behavioral intentions in resource-constrained settings. These insights are important for policymakers, development partners, and agriculture technology innovators seeking to enhance adoption strategies and tailor interventions that resonate with the lived realities of smallholder farmers.

Critically the study is highly relevant to food security issues, particularly in regions where smallholder farmers are critical food producers. By examining factors influencing the adoption of cold chain technology among vegetable producers, this research addresses the significant challenge of post-harvest losses, which can lead to food shortages and reduced income for farmers. Findings from this study contribute to a better understanding of how technology adoption can mitigate these losses, making food systems more resilient and sustainable.

The relevance of this study extends to global development goals, particularly SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 12 (Responsible Consumption and Production). Post-harvest losses in horticulture industry remain a major barrier to food security and income stability among smallholders. Therefore by improving adoption of solar-powered cold chain technologies can contribute to reducing waste, enhancing food preservation, and improving nutrition. The study's findings support the design of inclusive, context-sensitive, and sustainable technology adoption by advocating for peer learning, targeted training, and infrastructure investment.

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