

Enhancing the implementation of IoT-based smart Farming among small-scale farmers in Sri Lanka

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II. Practical part

- Describe the nature of small-scale farming systems in Sri Lanka
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ABSTRACT

The adoption of Internet of Things (IoT)-based smart farming technologies by small-scale farmers in Sri Lanka is examined in this study, with an emphasis on perceived advantages and adoption-influencing factors. The study assesses how farmers balance negative valences like perceived reliability and privacy issues against positive valences like greater productivity and convenience using the Net Valence Model (NVM) as a conceptual framework. Using a quantitative approach, a structured questionnaire was used to gather data from 100 smallholder farmers spread across three agricultural districts. The link between important variables was examined using partial least squares structural equation modeling, or PLS-SEM.

The findings reveal that those positive perceptions—particularly regarding IoT’s ability to improve yield and reduce manual labor, significantly influence adoption intention. However, negative valences such as reliability concerns and privacy continue to impede widespread implementation. The results support the usefulness of NVM in understanding farmer decision-making in technology adoption. The study concludes with practical recommendations for policymakers, technology providers, and agricultural institutions aimed at enhancing the readiness and capacity of smallholder farmers to embrace IoT-based solutions, thereby contributing to sustainable agricultural development and improved food security in Sri Lanka.

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INTRODUCTION

Recent advancements in technology have significantly transformed agricultural practices. Small-scale agricultural operations in regions such as Sri Lanka frequently encounter challenges characterized by low productivity, unsustainable practices, and ineffective resource utilization, as traditional methodologies prove inadequate. Progressive instruments, which include IoT gadgets and automated processes, have emerged as legitimate solutions, enabling farmers to mechanize their routine chores, monitor their fields more adeptly, and base their decisions on comprehensive data. Despite the apparent advantages and the global discourse surrounding smart farming, numerous smallholder farmers in Sri Lanka continue to face obstacles such as limited financial resources, insufficient technical expertise, and inadequate access to vital resources and support networks (I I Supianti et al., 2025) (Salvatore VNM, 2024) (Haiyudi H et al., 2023).

This project fundamentally aims to elucidate the reasons behind these impediments that hinder small-scale farmers from adopting IoT smart systems. Generally, factors such as a lack of awareness regarding the potential benefits of IoT, prohibitive technology costs, and minimal training opportunities impede progress (Oghenero MJ et al., 2022) (Ahmed G Gad, 2022) (Majid M et al., 2022). These considerations naturally provoke inquiries into methods for facilitating the adoption of IoT in a manner that accommodates both financial constraints and community requirements.

In most instances, this study investigates these limitations and seeks to develop strategies to enhance the utilization of IoT among smallholder farmers in Sri Lanka, with the overarching objective of bolstering agricultural resilience and overall productivity. This research aspires not only to identify barriers but also to offer substantive recommendations (Galaz V et al., 2021) (Singh M et al., 2021) (Bhat SA et al., 2021). By analyzing existing literature on smart agriculture and referencing successful case studies from other contexts, this work endeavors to formulate practical strategies that can be adapted to the specificities of Sri Lanka's agricultural landscape (Md. Hasan A et al., 2023) (Abey Siriwardana PC et al., 2022) (Hassan A et al., 2022).

To understand how smallholder farmers make decisions regarding technology adoption, this research incorporates the **Net Valence Model (NVM)**, a theory rooted in consumer behavior that explains how individuals weigh the perceived benefits (positive valences) and risks

(negative valences) of adopting new technologies. According to the NVM, individuals evaluate the **net value** of a technology by balancing the advantages, such as improved productivity and convenience, against the disadvantages, such as Reliability and privacy, . By applying the NVM, this research aims to explore how these perceived valences influence the adoption of IoT-based smart farming solutions. This model helps frame the study's exploration of the factors that shape farmers' decisions, particularly how the benefits of IoT need to outweigh the perceived barriers for successful adoption (Jamshidi, M., Kazemi, R., 2019).

The central objective is to nurture a more inclusive and sustainable agricultural model, through which increased access to technology helps elevate small-scale farmers' livelihoods and productivity. This research holds significance in two dimensions: theoretical and practical. From one angle, it enhances the continuous discussion on advanced farming techniques by supplying fresh empirical research and understanding of the obstacles and potentials experienced by farmers in a growing context. It elucidates how IoT can be effectively tailored to meet the needs of small-scale farmers, thereby addressing some of the existing gaps in our comprehension of technology adoption in agriculture (N/A, 2020) (N/A, 2020) (Alliou H et al., 2023). However, by highlighting the support mechanisms required to enable the smooth integration of IoT within agricultural operations, the findings could be a useful tool for technology suppliers, agricultural stakeholders, and regulators. These findings may have broad ramifications for food security and economic growth, considering the importance of agriculture to rural people and its substantial involvement in Sri Lanka's economy (Bhat SA et al., 2021; Rejeb A et al., 2020; Yaşanur Kayıkçı et al., 2020).

1.1 Background of the problem

Emerging technologies have impacted farming in unexpected ways. A key component of this change is now the Internet of Things, a network of interconnected devices that exchange data in real-time (I I Supianti et al., 2025) (Salvatore VNM, 2024). With these new techniques, it appears like a wise opportunity to increase productivity and sustainability in Sri Lanka, where farming still employs close to 30% of the workforce and contributes roughly 8% of the country's GDP (Haiyudi H et al., 2023; Oghenero MJ et al., 2022). However, many small-scale farmers are stuck despite the promise of IoT, which includes improved crop yields, reduced environmental impact, and more efficient use of resources. They frequently encounter problems, including insufficient funds for the appropriate

equipment, a lack of expertise in using and maintaining this technology, and a lack of general support systems (Ahmed G. Gad, 2022; Majid M et al., 2022). The true issue we're examining here is how many obstacles prevent small farmers from fully embracing IoT. Most research has focused on large farms, largely ignoring the challenges faced by smallholder operations, where resources and technical expertise are scarce (Galaz V et al., 2021; Singh M et al., 2021). By examining the factors that make it so difficult for these farmers to use IoT solutions, this initiative seeks to close that gap. The study aims to identify the challenges to present concepts that may result in focused solutions. The two main goals of our study are to: (1) provide a comprehensive understanding of the existing IoT usage among Sri Lankan small-scale farmers; and (2) identify potential solutions to the technological challenges (Bhat SA et al., 2021; Md. Hasan A et al., 2023). To truly understand the distinct difficulties these farmers encounter, we intend to conduct qualitative interviews with farmers, technology suppliers, and agricultural specialists. To put together a practical framework that works in Sri Lanka, we are also investigating successful examples where IoT has been successfully incorporated into farming practices. This research provides practical benefits in addition to increasing scholarly understanding. Our research could be crucial in demonstrating how Sri Lankan small-scale farmers could use IoT to enhance their operations by examining the intersection of technology and the field (Abey Siriwardana PC et al., 2022) (Hassan A et al., 2022). The effects might spread, improving rural living standards, increasing food security, and fortifying the agriculture industry as a whole. These insights could potentially catalyze cooperative efforts by policymakers and other stakeholders to adopt more creative farming methods. To put it briefly, solving these IoT issues has the potential to completely transform Sri Lanka's agricultural landscape and elevate small-scale farmers to the forefront of tech-driven agriculture (N/A, 2020). Yaşanur Kayıkçı et al., 2020; Alliou H et al., 2023; Bhat SA et al., 2021; Rejeb A et al., 2020; Gonczol P et al., 2020; D Muthumanickam et al., 2022). An illustration of contemporary farming practices combined with technology serves as a visual unifier, emphasizing how farmers are utilizing cutting-edge systems. By highlighting the urgent need for technology adoption in contemporary, sustainable agriculture, this image aligns with the study's goal of increasing IoT use among small farmers.

Table 1 IoT Smart Plant Monitoring System Features and Capabilities

Feature	Description
Plant Health Monitoring	Utilizes sensors to detect variations in plant leaf health, enabling early identification of diseases.
Soil Moisture Level Detection	Monitors soil moisture to ensure optimal watering conditions for plant growth.
Air Humidity Level Measurement	Assesses air humidity to maintain a conducive environment for plant development.
Temperature Monitoring	Tracks surrounding temperature to ensure it remains within suitable ranges for plant health.
Remote Watering Control	Allows users to water their garden remotely via a mobile application, ensuring consistent care.

1.2 Research Problem Statement

Global farming is evolving, and many people are now investigating how integrating technology into farms could improve productivity and the health of the world. Even though smart agriculture has many success stories worldwide, small farmers in Sri Lanka continue to encounter numerous challenges while utilizing these Internet of Things (IoT) instruments. Frequently, the problems range from a lack of funds to pay for the expenses to a lack of technical expertise and support systems required to maintain these systems (I I Supianti et al., 2025) (Salvatore VNM, 2024). Even more difficult conditions exist in rural regions, where the majority of farmers operate on extremely narrow profit margins and frequently continue to use time-honored, conventional techniques that fail to fully utilize their land (Haiyudi H et al., 2023; Oghenero MJ et al., 2022). The distinctive way Sri Lankan society and economy function generally means that a more tailored plan is needed to address the local issues and needs, even though numerous international reports claim that IoT can significantly increase efficiency and crop yields (Ahmed G Gad, 2022; Majid M et al., 2022). The main finding of this study is that a few small-scale farmers in Sri Lanka are adopting IoT-based smart farming technology, which eventually hinders long-term sustainability and

production. Although the majority of research indicates that integrating technology into farming can improve results, it frequently ignores the actual obstacles that these farmers deal with daily (Galaz V et al., 2021; Singh M et al., 2021). The goal of this endeavor is to identify and investigate the obstacles preventing IoT technologies from becoming widely used in these communities. It seeks to provide insights that may eventually lead to solutions designed just for them. The major objectives are to examine the problems these farmers face daily, find out what they know (and don't know) about IoT potential, and offer solutions to help them integrate these cutting-edge tools into their jobs (Bhat SA et al., 2021; Md. Hasan A et al., 2023). It's critical to comprehend this problem for both academics talking about smart farming and people working to change things on the ground. Addressing these issues might, for the most part, provide practical advice to government organizations, agricultural associations, and tech developers on how to better empower and support the smallholder community with creative ideas (Abey Siriwardana PC et al., 2022) (Hassan A et al., 2022).). Such assistance is essential if we hope to create a more resilient farming environment where rural populations throughout Sri Lanka see significant improvements in food security, economic stability, and general well-being. Overall, the work is important since it addresses a pressing issue and contributes to larger initiatives to employ intelligent IoT tools to transform conventional farming methods to promote sustainable agricultural growth (N/A, 2020). Yaşanur Kayıkçı et al., 2020; Allioui H et al., 2023; Bhat SA et al., 2021; Rejeb A et al., 2020; Gonczol P et al., 2020; D Muthumanickam et al., 2022).

1.3 Objectives of the study

As the significance of technology in agriculture continues to ascend, tools associated with the Internet of Things (IoT) are progressively acknowledged for their capacity to revolutionize smallholder farming, particularly within resource-limited contexts such as Sri Lanka. Nevertheless, despite the tangible advantages provided by IoT systems, including enhanced productivity, improved operational efficiency, and data-informed decision-making (Supianti et al., 2025; Salvatore VNM, 2024), the uptake among small-scale farmers remains notably constrained. This research employs the Net Valence Model (NVM) to investigate the perceived advantages and perceived hazards that shape adoption behavior. In light of the

existing deficiencies identified in prior studies (Haiyudi H et al., 2023; Oghenero MJ et al., 2022), the aims of this investigation are formulated to furnish a thorough comprehension of the adoption milieu.

The purpose of this study is to examine the present state and prospects of IoT-based smart farming among Sri Lankan small-scale farmers. Among the main objectives are:

- To examine how perceived improvements in productivity influence small-scale farmers' intention to adopt IoT technologies.**
- To investigate the effect of perceived convenience on farmers' willingness to adopt IoT systems.**
- To evaluate how concerns about the reliability and effectiveness of IoT devices impact adaptation decisions.**
- To assess how privacy concerns and data security perceptions affect the intention to use IoT.**

These aims are designed not only to tackle the theoretical aspects of technology adoption but also to yield practical recommendations for agricultural policymakers, technology innovators, and support organizations. Ultimately, the research aspires to advocate for a balanced and inclusive methodology for the integration of IoT tools into the smallholder farming sector of Sri Lanka (Abey Siriwardana PC et al., 2022; Hassan A et al., 2022; Bhat SA et al., 2021; Rejeb A et al., 2020).

1.3.1 Research Questions

As agriculture rapidly evolves through the global adoption of Internet of Things (IoT) technologies, countries like Sri Lanka, where small-scale farming is dominant, face both opportunities and barriers. While many nations benefit from increased crop yields, reduced input costs, and more efficient farm operations through smart farming, Sri Lankan smallholder farmers have yet to fully embrace these innovations (Supianti et al., 2025; Salvatore VNM, 2024). Their reluctance stems not only from infrastructural and financial limitations but also from uncertainties around value, convenience, technical trust, and data security (Haiyudi et al., 2023; Oghenero MJ et al., 2022).

To investigate the drivers and deterrents of IoT adoption, this study applies the **Net Valence Model (NVM)** framework, focusing on both perceived benefits (positive valences) and perceived risks (negative valences). The following research questions guide the investigation:

***How do perceptions of productivity improvement influence small-scale farmers' intention to adopt IoT-based smart farming technologies?**

This question addresses the assumption that the perceived ability of IoT to increase yields, improve product quality, reduce waste, and enhance efficiency plays a major role in motivating farmers toward adoption (Ahmed Gad, 2022; Majid M et al., 2022).

***To what extent does perceived convenience, such as remote monitoring and reduced physical labor, affect farmers' willingness to adopt IoT technologies?**

This question explores how practical ease-of-use influences technology uptake, particularly in day-to-day agricultural management (Galaz V et al., 2021; Singh M et al., 2021).

***How do concerns regarding the reliability and technical effectiveness of IoT devices impact farmers' intention to adopt them?**

This inquiry examines whether farmers' trust in device durability, their technical knowledge, and overall confidence in usage reduce or hinder their willingness to adopt IoT (Bhat SA et al., 2021; Md. Hasan A et al., 2023).

***To what extent do privacy concerns, including data security and internet reliability, discourage IoT adoption among smallholder farmers?**

This question targets fears around personal or farm data being misused, and whether unreliable internet infrastructure undermines confidence in smart farming solutions (Abey Siriwardana PC et al., 2022; Hassan A et al., 2022).

These questions are directly tied to the constructs measured in the questionnaire and are tested through quantitative analysis using SPSS. Together, they reflect a structured attempt to understand both the **motivating and inhibiting factors** that shape smallholder farmers' willingness to adopt IoT in agriculture. The answers will inform actionable strategies for policymakers, extension services, and tech developers, ensuring that interventions are based not just on theoretical promise but on **real-world perceptions** and **practical needs** (Alliou

H et al., 2023; Rejeb A et al., 2020; Yaşanur Kayıkçı et al., 2020; Gonczol P et al., 2020; D. Muthumanickam et al., 2022).

1.4 Scope of the study

The purpose of this thesis is to examine the perceived advantages and obstacles influencing Sri Lankan small-scale farmers' adoption of Internet of Things (IoT) technologies. Smallholder farmers, who are defined as those who cultivate less than two hectares of land, are essential to both local and national food production in rural agricultural areas, where the research is spatially restricted (Galaz V et al., 2021). While excluding more general digital technologies like mobile apps for market access or general e-commerce platforms, the study concentrates on the use of IoT-specific tools like environmental sensors, automated irrigation systems, and real-time monitoring devices (Haiyudi H et al., 2023; Oghenero MJ et al., 2022).

To provide more precise insights into active decision-making about the use of technology on farms, the data collection period, which runs from January to March 2025, was selected to align with important crop seasons. The study uses a quantitative methodology, collecting primary data from smallholder farmers via structured questionnaires. Since the focus is still solely on the experiences and attitudes of farmers, the current scope excludes interviews, qualitative insights, and stakeholder viewpoints at the policy level (Ahmed G Gad, 2022; Majid M et al., 2022).

Furthermore, because urban and plantation-based agricultural sectors may differ in terms of infrastructure, capital, and exposure to developing technologies, they are not included in the study. This more focused approach makes it easier to identify the particular possibilities and challenges that small-scale rural farmer confront, especially those who have less access to digital infrastructure, education, and funding (Singh M et al., 2021; Bhat SA et al., 2021; Md. Hasan A et al., 2023).

By establishing these limits, the thesis stays focused on comprehending how practical limitations influence IoT adoption and what practical approaches can be implemented to boost adoption among this crucial but underserved farming population (Abey Siriwardana PC et al., 2022) (Hassan A et al., 2022).

1.5 Significance of the study

This work is important both academically and practically because it emphasizes the critical need to incorporate IoT-based smart farming technologies into Sri Lanka's small-scale agriculture industry. Sri Lankan farmers continue to confront significant adoption challenges, even though IoT has effectively changed farming systems in nations like India by boosting output and lowering input costs (Supianti et al., 2025; Salvatore VNM, 2024). These difficulties include inadequate technical know-how, low awareness, inadequate finance, and poor infrastructure, especially in rural regions (Haiyudi et al., 2023; Oghenero et al., 2022).

This research aims to provide useful answers based on farmers' actual experiences by evaluating existing adoption levels, comprehending perceived benefits and problems, and suggesting focused strategies—all of which are in line with the study's primary goals. It seeks to comprehend how small-scale farmers view and react to the use of IoT in their agricultural operations in addition to how new technologies can boost productivity (Ahmed Gad, 2022; Majid et al., 2022).

Addressing a research gap is the academic contribution; most international studies encourage IoT adoption generally but frequently ignore regional, smallholder-specific barriers. By concentrating on the Sri Lankan context and offering more profound insights into opportunities and challenges unique to the region, this study contributes to the body of literature (Galaz et al., 2021; Singh et al., 2021).

In practice, the results can help technology developers, agricultural institutions, and policymakers create customized programs that meet the needs of smallholder farmers by providing accessible training and reasonably priced infrastructure (Bhat et al., 2021; Md. Hasan et al., 2023). These programs have the potential to increase productivity, access to markets, and revenue, which would support food security and economic resilience in rural communities (Abey Siriwardana et al., 2022; Hassan et al., 2022).

All things considered; this study advances the more general objective of upgrading Sri Lankan agriculture. Global competitiveness, climatic resilience, and sustainable growth can all be greatly enhanced by promoting IoT adoption among small-scale farmers (Allioui et al., 2023; Rejeb et al., 2020; Yaşanur Kayıkçı et al., 2020; Gonczol et al., 2020; D. Muthumanickam et al., 2022).

1.6 Limitation of the study

This study has several limitations that need to be considered. As I am currently based in the Czech Republic, I was unable to physically meet with the respondents in Sri Lanka. To mitigate this, a friend assisted me with data collection by distributing the translated questionnaires and conducting interviews with smallholder farmers. While this was a necessary arrangement, it may have introduced potential biases, as I was not present to clarify questions or observe the context in which the data was gathered. Additionally, due to time constraints, the study's data collection was limited in scope, and the sample size may not have fully represented the diversity of smallholder farmers across Sri Lanka. The time limits also affected the depth of responses, as participants may not have had adequate time to reflect on their answers or provide detailed feedback.

Another limitation of this study is related to language. The questionnaire was initially written in English, and to ensure accessibility for the respondents, I translated it into Sinhala. While every effort was made to maintain the accuracy and clarity of the translation, there could have been subtle differences in interpretation, particularly in the case of technical terms or complex concepts. This could have affected how the respondents understood and answered the questions, potentially introducing some inconsistencies in the data. Despite these challenges, the study provides important insights into the barriers and opportunities for IoT adoption among Sri Lankan smallholder farmers, and the limitations discussed should be considered when interpreting the findings.

II THEORETICAL PART

2 LITERATURE REVIEW

2.1 Introduction

The Internet of Things (IoT) has emerged as a transformative force in agriculture in recent years, especially for small-scale farming, as the industry has embraced digital innovation more and more. IoT makes it possible to collect and analyze data in real time through networked devices like sensors and automated systems. For nations like Sri Lanka, where traditional farming methods are still prevalent, these tools improve productivity, sustainability, and resource efficiency—all of which are critical (Supianti et al., 2025; Salvatore VNM, 2024).

Particularly helpful in managing scarce resources and reducing climate variability risks are smart farming models. According to studies, including IoT systems can guarantee more responsiveness to environmental stress, reduce expenses, and greatly increase yields (Haiyudi et al., 2023; Oghenero et al., 2022). Despite this promise, there are still real-world obstacles to the extensive adoption of IoT in Sri Lanka. Barriers include inadequate digital literacy, inadequate infrastructure, and a dearth of specialized training programs have been identified by researchers (Ahmed G Gad, 2022; Majid M et al., 2022). Adoption depends on knowing farmers' perspectives. According to Thakur et al., local context is crucial, and any tech-driven change must be adjusted to fit local reality (Galaz V et al., 2021). Although the technological potential of IoT is frequently well-established, the behavioral and motivational factors influencing adoption among Sri Lankan farmers have received less attention. This disparity is especially worrisome because smart farming's success hinges not only on technology accessibility but also on how well it fits with farmers' expertise, confidence, and adaptability (Singh M et al., 2021; Bhat SA et al., 2021).

Furthermore, many studies explicitly address the smallholder community in Sri Lanka. There is currently little empirical data addressing local adoption hurdles, even though studies like Md. Hasan A et al. (2023) and Abeyesiriwardana PC et al. (2022) emphasize the potential of smart farming for sustainable agriculture. Farmers' decisions to adopt technology like IoT have been explained using the Valence Model, which weighs perceived risks and benefits (Supianti et al., 2025; Salvatore VNM, 2024). This method sheds light on how farmers evaluate the adoption's net value, taking into account both possible dangers and financial rewards. Although there is hope, farmers continue to face significant obstacles due to perceived dangers, including equipment dependability, expense, and a lack of digital literacy

(Hassan A et al., 2022; Alliou H et al., 2023). Therefore, farmers' life experiences, resource accessibility, and educational background must all be taken into account while developing technological interventions. For example, Navoday & Komal (Oghenero et al., 2022) and Thakur et al. (Haiyudi et al., 2023) examine the effects of these obstacles on adoption and emphasize the necessity of context-aware strategies. To facilitate adoption, farmer engagement and support networks are crucial, according to empirical research like that conducted by Ahmed G. Gad (2022). The necessity of capacity-building and farmer-focused education is a major issue in recent literature. The success of advanced technology depends on how well it is introduced, explained, and supported; merely providing it is insufficient (Galaz V et al., 2021; Singh M et al., 2021). IoT may significantly enhance decision-making, minimize input waste, and maximize harvests when support systems are in place, as demonstrated by real-world case studies like those of Ahmed G. Gad (2022).

Researchers caution against universal solutions, despite the general agreement that IoT may transform smallholder agriculture. Smart agricultural techniques must be designed with local demands, customs, and farming systems in mind. To further explore the relationship between farmer perception and technology acceptability, future research is advised to employ a combination of methodologies (N/A, 2020; Yaşanur Kayıkçı et al., 2020; Gonczol P et al., 2020; D Muthumanickam et al., 2022). In conclusion, the body of research backs up the idea that IoT could modernize Sri Lanka's small-scale farming industry. The current problem is to transition from theoretical models to workable solutions that provide farmers the resources, know-how, and self-assurance they need to embrace IoT. To guarantee that smart farming becomes a sustainable reality for Sri Lanka's agricultural future, more regional research, capacity-building programs, and policy assistance are needed (MBA BJWMKG, 2025; Abeyesiriwardana PC et al., 2022; Rejeb A et al., 2020).

2.2 Conceptual Review: Net Valence Model (NVM)

Originally, created within the framework of consumer behavior theory, the Net Valence Model (NVM) suggests that people base their decisions on the relative importance of perceived positive and negative events. Essentially, a mental balance sheet that weighs costs or obstacles (negative valences) against advantages (positive valences) drives the decision to accept an innovation, like IoT in agriculture. Adoption is more likely if the advantages are viewed as greater than the drawbacks (Fishbein & Ajzen, 1975).

The NVM provides an engaging perspective through which to view farmer behavior in the context of IoT adoption in agriculture. Farmers assess IoT solutions according to their

perceived ease of use, increased production, and resource efficiency—all of which are good valences. In the meanwhile, negative valences include perceived costs, complexity, lack of training, and infrastructural restrictions (Geng, 2017; Wortmann et al., 2024).

When applied to rural Sri Lanka, where economic need and experiential learning play a major role in farming decisions, the NVM framework enables researchers to map not just whether farmers adopt IoT gear but also the reasons behind their adoption or reluctance. According to Wortmann et al. (2024), digital solutions shift the net valence in favor of adoption when they are seen as strongly compatible with local needs, improving ease or profitability. On the other hand, adoption is hampered when perceived risks—such as technical malfunctions or limited support—are more prominent.

In order to quantitatively analyze the relationship between net perceptions and behavioral intention, the NVM was used in this study to formulate the hypotheses and survey instrument. In order to create focused treatments that are in line with Sri Lankan rural realities, the model assists in analyzing the interaction between farmers' beliefs, prior experiences, and perceived utility (Kush et al., 2024).

The theoretical underpinnings of this investigation are grounded in the Valence Framework, a behavioral theoretical model that evaluates the decision-making processes of individuals through a cost-benefit analysis of perceived advantages (positive valences) and perceived drawbacks (negative valences). Initially established within the domains of behavioral economics and psychology, this model has demonstrated significant applicability within the contexts of technology adoption, notably in smart agriculture (Jamshidi & Kazemi, 2019). In the present study, this framework is utilized to elucidate the intentions of small-scale farmers to embrace IoT-based agricultural systems in Sri Lanka.

The positive valences examined encompass perceived enhancements in productivity and convenience. These factors align with constructs derived from established technology adoption models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), wherein perceived usefulness and ease of use serve as pivotal predictors of behavioral intent (Ajzen, 1991; Davis, 1989). IoT technologies, by facilitating real-time monitoring, automation, and precision agriculture, are theoretically positioned to yield substantial operational efficiencies and reductions in labor for smallholder farmers.

In contrast, negative valences, including apprehensions regarding reliability and privacy, are equally significant. Scholarly investigations within the realms of information systems and rural innovation indicate that trust, risk perception, and technical complexity

substantially contribute to inhibiting adoption, particularly in low-resource settings (Kapoor et al., 2014; Bhat SA et al., 2021).

By integrating both benefit- and risk-oriented constructs, the Valence Framework provides a comprehensive analytical lens for examining IoT adoption. This dual-faceted perspective not only elucidates the motivations driving farmers to implement new technologies but also clarifies the reasons for their hesitance—thus offering a more nuanced conceptual foundation for developing intervention strategies.

In conclusion, the empirical body of literature elucidates a discernible trend: the consciousness pertaining to the Internet of Things (IoT) is escalating; however, the actualization of this technology remains inconsistent and is impeded by systemic constraints. The formulation of effective policy and the deployment of user-centered technology are imperative to reconcile the disparity between awareness and the tangible adoption of IoT among smallholder farmers in Sri Lanka (Allioui H et al., 2023; Rejeb A et al., 2020).

2.3 Empirical Review

An expanding corpus of empirical investigation examines the interactions between small-scale agricultural producers and Internet of Things (IoT) technologies within agricultural frameworks, particularly in developing nations such as Sri Lanka. A significant consensus exists among these studies indicating that while the potential benefits of IoT-enabled smart farming are considerable—offering enhancements in productivity, resource efficiency, and sustainability—the actual adoption rate among smallholder farmers remains suboptimal due to a myriad of contextual impediments (I I Supianti et al., 2025; Salvatore VNM, 2024).

Contemporary empirical inquiries underscore the dichotomy between potential and actual implementation. For instance, Supianti et al. (2025) reported that numerous farmers cognizant of the advantages of IoT still hesitate to implement the technology owing to obstacles such as financial constraints and inadequate infrastructure. In a similar vein, research conducted by Salvatore VNM (2024) elucidated that even in scenarios where technologies are accessible, the absence of definitive policies or support mechanisms results in sluggish adoption rates. These observations are particularly pertinent within the Sri Lankan context, where fragmented support systems and rural inequities impede technological diffusion.

Empirical evidence amassed by Haiyudi et al. (2023) and Oghenero MJ et al. (2022) further corroborates that socio-economic factors—including educational attainment, income levels, and farm dimensions—exert a direct influence on the adoption of IoT technologies. Their

investigations employed survey and interview methodologies, revealing that the majority of smallholder farmers lack the requisite technical training and financial means to effectively assimilate these innovations. Additionally, qualitative narratives indicate that even those farmers inclined to explore novel methodologies frequently encounter barriers in accessing reliable technical support or demonstration models, a sentiment reiterated in the research of Ahmed G Gad (2022).

Majid et al. (2022) utilized a mixed-methods framework to evaluate farmers' preparedness for technology adoption and discovered that although a considerable number of participants exhibited a willingness to experiment with new technologies, mere awareness was insufficient to catalyze actual adoption. Their findings suggest that in the absence of institutional interventions—such as subsidies, educational initiatives, and infrastructural development—enthusiasm for IoT will not translate into practical application.

Galaz V et al. (2021) proposed an empirical model integrating behavioral determinants into the adoption of IoT, emphasizing that perceptions of utility, risk, and usability significantly affect adoption rates. Singh et al. (2021) corroborated this assertion through a stratified survey of farmers, indicating that those with heightened perceptions of benefits were substantially more inclined to adopt IoT systems. However, when concerns regarding risks—such as data misuse or device malfunctions—predominated, the rates of adoption experienced a marked decline.

This perspective is echoed in the findings of Bhat SA et al. (2021), who conducted surveys among farmers across various districts in Sri Lanka. Their results indicated that geographical location, crop variety, and prior technological exposure significantly influenced the willingness to embrace IoT. Their regression analysis illustrated that educational attainment and previous interactions with mobile or internet-based platforms had a positive correlation with the intent to adopt such technologies.

Concurrently, Md. Hasan A et al. (2023) and Abeysiriwardana PC et al. (2022) highlighted the imperative for localized customization. Empirical findings from their research suggested that generic solutions frequently falter since the requirements of farmers differ markedly based on crop type, geographical region, and socio-cultural contexts. Hassan A et al. (2022) reiterated this notion, advocating for location-specific strategies that align with both the environmental and economic realities of rural agricultural practices in Sri Lanka.

Researchers are also encouraged to blend insights from technology, sociology, and agriculture into a unified approach. Overall, this review not only casts light on IoT's potential to advance agriculture in Sri Lanka but also maps out concrete steps for both

academic inquiry and practical application. Addressing these gaps—and giving farmers a real voice in the process—could empower small-scale growers with technology that genuinely fits their needs, ultimately enhancing both productivity and resilience in the sector ((MBA BJWMKG, 2025), (Yaşanur Kayıkçı et al., 2020), (Gonczol P et al., 2020), (D Muthumanickam et al., 2022)).

Table 2 IoT-Based Smart Farming Adoption Among Small-Scale Farmers in Sri Lanka

Year	Percentage
2020-2021	1%
2022-2023	3%
2024-2025	7%

3 RESEARCH METHODOLOGY

3.1 Introduction

Using a strictly quantitative methodology, this study examines how Internet of Things (IoT) technology can be more successfully incorporated into Sri Lankan small-scale farming. The main hypothesis of the study is that a sizable percentage of smallholder farmers have not yet adopted IoT solutions, a problem that could have a direct impact on agricultural sustainability, productivity, and the capacity to compete in contemporary markets (II Supianti et al., 2025; Salvatore VNM, 2024).

The primary research instrument utilized to delve into this topic is a structured questionnaire. To get actual data on farmers' knowledge, attitudes, and adoption levels of IoT technology, the questionnaire was meticulously created. Awareness of IoT tools, perceived utility, accessibility challenges, cost concerns, and the efficacy of current support systems, such as government programs, non-governmental organizations, and commercial tech initiatives, are some of the important topics it addresses (Haiyudi H et al., 2023; Oghenero MJ et al., 2022).

Only small-scale farmers in various parts of Sri Lanka are given access to the survey. Following a quantitative examination of their answers, the study can pinpoint common obstacles, trends, and patterns that impede the broad adoption of IoT. This approach helps identify certain areas where interventions or changes could be most beneficial and offers a strong foundation for statistical interpretation (Ahmed G Gad, 2022; Majid M et al., 2022). All things considered, this approach provides a clear and reliable means of getting quantifiable information straight from the people who are most involved in Sri Lankan agriculture. By providing concrete statistics that can guide plans to boost IoT adoption, it also enhances the body of existing literature (Galaz V et al., 2021; Singh M et al., 2021).

Policymakers, tech developers, and agricultural organizations that seek to empower smallholder farmers through innovation are anticipated to find real value in the findings of this research, which goes beyond academic pursuits (Bhat SA et al., 2021; Md. Hasan A et al., 2023). The study's straightforward, data-driven methodology serves more general objectives like enhancing food security and rural livelihoods while also reflecting the pressing need to upgrade farming systems (Abeyesiriwardana PC et al., 2022; Hassan A et al., 2022). Essentially, one data point at a time, this process lays the groundwork for revolutionizing Sri Lankan agriculture.

3.2 Conceptualization

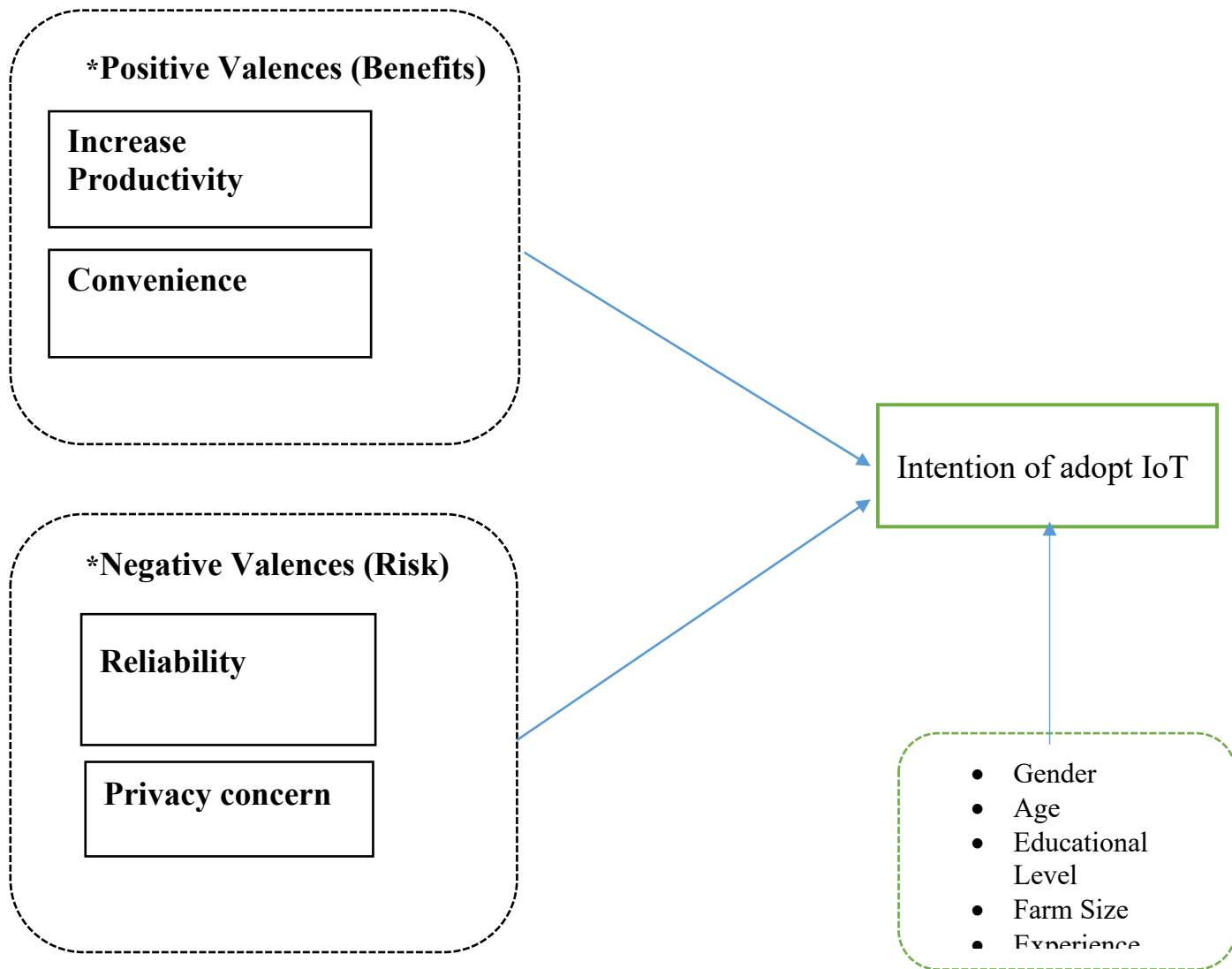


Figure 1 Conceptual model

3.3 Hypothesis development

This investigation utilizes the Valence Framework, which is founded upon the Norm Activation Model (NAM) and modified to assess the adoption of Internet of Things (IoT) technologies among smallholder farmers. The framework elucidates how individuals evaluate perceived advantages (positive valences) about perceived threats (negative

valences) when determining the feasibility of embracing a novel technology (Jamshidi & Kazemi, 2019). Each valence within this framework signifies a pivotal construct that shapes behavioral intentions, which are quantified via specific indicators incorporated in the survey.

Positive Valence 1: Perceived Increase in Productivity

Perceived productivity denotes the conviction that IoT implementations can enhance crop yield, quality, and resource efficiency. As Supianti et al. (2025) articulated, farmers exhibit a greater propensity to adopt innovations that amplify output while mitigating input wastage. IoT applications facilitate instantaneous monitoring of soil moisture, climatic conditions, and plant health, thereby aiding in the formulation of timely and precise agricultural decisions (Salvatore VNM, 2024). When farmers correlate technology with tangible productivity enhancements, their propensity to adopt such technologies is augmented.

H1: There is a significant positive relationship between perceived productivity benefits and the intention to adopt IoT technology among small-scale farmers.

Positive Valence 1: Perceived convenience

Perceived convenience pertains to the degree to which IoT systems simplify, economize time, and manage daily agricultural operations. Technologies that diminish manual labor and permit remote accessibility are particularly attractive to farmers experiencing constraints in labor or mobility (Haiyudi H et al., 2023). Automation, exemplified by IoT-enabled irrigation and pest management systems, streamlines tasks and provides farmers with enhanced operational flexibility. As corroborated by Oghenero MJ et al. (2022), convenience amplifies perceived usefulness, thereby fostering affirmative attitudes towards adoption.

H2: There is a significant positive relationship between perceived convenience and the intention to adopt IoT technology in Farming.

Negative Valence 1: Perceived Reliability and Effectiveness Risk

Farmers' apprehensions regarding the consistent functionality of IoT systems, the complexity of their operation, or the potential for failure attributable to substandard product quality or insufficient support diminish their trust in the technology (Bhat SA et al., 2021). In rural Sri Lanka, where technical support is minimal, any perceived complexity or risk of malfunction deters the adoption of such technologies (Md. Hasan A et al., 2023). A deficiency in confidence regarding system reliability engenders avoidance behaviors, even among individuals cognizant of the prospective advantages.

H3: There is a significant negative relationship between perceived risks regarding reliability and effectiveness of IoT devices and the intention to adopt IoT technology.

Negative Valence 2: Privacy and Data Security Concerns

Given that IoT systems amass real-time data, farmers exhibit trepidation regarding the access to their agricultural data, the mechanisms of data storage, and the potential for data sharing without their consent. This anxiety is exacerbated by inadequate internet infrastructure and low levels of digital literacy (Abey Siriwardana PC et al., 2022; Hassan A et al., 2022). When farmers harbor uncertainties about data privacy or network reliability, they may exhibit resistance towards the adoption of these technologies.

H4: There is a significant negative relationship between privacy concerns and the intention to adopt IoT technology.

This framework of hypotheses amalgamates both motivational and deterrent elements influencing IoT adoption. By scrutinizing these four dimensions, the research endeavors to provide elucidations regarding the decision-making processes of Sri Lankan farmers pertaining to technology and to identify interventions that can facilitate a more seamless integration of IoT within small-scale agricultural practices.

3.4 Definition of Key terms

Interpreting the broader context of research focus exploring IOT adoption in Sri Lankan agriculture requires defining a few crucial words that have been used as a foundational part when realizing the study area. **Productivity**, **convenience**, **reliability**, and **privacy** are the independent variables that are fundamental to this study and are the deciding factors that affect the adoption of IoT-based technology by smallholder farmers in Sri Lanka.

1. **Productivity** refers to the degree to which IoT-related technologies can enable an increase in agricultural yield by improving efficiency and optimizing resource utilization while minimizing waste. With regard to smart farming, systems based on IoT, such as automated irrigation and real-time monitoring of crops, enable farmers towards them more informed choices, raising the productive performance and reducing the input costs (Salvatore VNM, 2024; I I Supianti et al., 2025). For smallholder farmers, the perceived potential to boost productivity through IoT devices is a major driver for technology adoption, as it directly influences their economic sustainability and food security (Haiyudi H et al., 2023).
2. **Convenience** includes how easily IoT technologies may be incorporated into small-scale farmers' everyday activities. Automated irrigation and remote monitoring systems are examples of IoT tools that decrease manual work and improve operational flexibility. Particularly in areas where labor is expensive or limited, farmers are becoming more and more interested in technology that streamlines processes and saves time (Galaz V et al., 2021). The ease of utilizing mobile applications to track weather or soil moisture improves farm management effectiveness and increases smallholders' interest in adopting IoT (Singh M et al., 2021).
3. Farmers' faith in IoT devices is referred to as **reliability**, and it is crucial for their effective adoption. Farmers' desire to incorporate these technologies into their farming techniques is greatly influenced by their performance, particularly with regard to precision and durability. Adoption is significantly hampered by worries about the dependability of IoT devices, such as sensor or network failures, especially in rural regions with inadequate infrastructure (Md. Hasan A et al., 2023; Bhat SA et al., 2021). Farmers need to have faith in the technology's dependability and long-term performance for IoT adoption to be widespread.

4. The security of data gathered by Internet of Things devices is the main source of **privacy concerns**. Smallholder farmers may be reluctant to embrace IoT solutions if they believe there could be dangers of agricultural data being misused or privacy being violated, especially in Sri Lanka. To earn farmers' trust and make sure they feel at ease using the technology, data security and the accuracy of the information gathered by IoT devices are essential (Rejeb A et al., 2020). To address these issues, it is essential to have strong privacy safeguards and open data usage guidelines (Abey Siriwardana PC et al., 2022).

The phrase "small-scale farmer" usually describes people who oversee less than two hectares of land in Sri Lanka. Inadequate infrastructure support, a lack of exposure to new technologies, and a lack of financial resources frequently impede the adoption of IoT-based solutions (Galaz V et al., 2021; Singh M et al., 2021). These farmers' difficulties are made worse by the fact that, in spite of their vital role in the country's food production, they are frequently left out of major agricultural programs and digital innovation initiatives (Bhat SA et al., 2021).

A lack of knowledge, low levels of digital literacy, worries about excessive prices, and insufficient access to dependable electricity and internet are some of the major obstacles to the widespread use of IoT in smallholder farming (Ahmed G Gad, 2022; Majid M et al., 2022). Since the goal of this study is to identify obstacles and offer workable solutions to promote IoT adoption, a detailed understanding of these characteristics is essential.

It is crucial to define these terms precisely in order to frame the study's scope. In order to address important issues driving IoT adoption, the study will provide a common understanding of terms like productivity, convenience, reliability, and privacy. Furthermore, this section contributes to the research's overarching goal of investigating the opportunities and obstacles related to IoT adoption among Sri Lanka's smallholder farmers, providing insights into how these innovations can be successfully incorporated into their operations (Md. Hasan A et al., 2023; Abey Siriwardana PC et al., 2022; Hassan A et al., 2022; Alloui H et al., 2023; Rejeb A et al., 2020; Yaşanur Kayıkçı et al., 2020; Gonczol P et al., 2020; D Muthumanickam et al., 2022).

3.5 Research Design

Agriculture is still changing in response to urgent problems like resource scarcity, climate change, and food security. Small-scale farmers in Sri Lanka are under increasing pressure to modernize while juggling antiquated methods, inadequate infrastructure, and unstable economic conditions. Adoption of Internet of Things (IoT) technology is one approach that is gaining traction since it promises to improve productivity, boost yields, and promote sustainability (Supianti et al., 2025).

However, broad use. The Net Valence Model (NVM), which assesses the perceived advantages and hazards of IoT adoption, serves as the foundation for this study's structured research design. This model offers a thorough framework for evaluating the emotional and cognitive aspects that affect farmers' judgments on technology (Salvatore VNM, 2024). The study specifically aims to investigate how small-scale farmers view the potential of IoT to increase cost-effectiveness, convenience, and production. The study mostly uses a ****quantitative approach****, with a comprehensive ****structured questionnaire**** to gauge awareness, perceived risks and benefits, and readiness to embrace IoT technologies.

This design gives farmers a place and guarantees that the study stays based on quantifiable trends. Small-scale farmers from three districts in Sri Lanka—Anuradhapura, Kurunegala, and Kandy—selected for their geographical variety and significance to the agricultural industry are the main focus of data gathering. To ensure representativeness across socioeconomic characteristics, the survey sample is stratified by age, gender, farm size, and educational attainment (Md. Hasan A et al., 2023).

Existing research supports the expectation that these factors will be crucial in determining how farmers see new technology. The NVM framework's synthesis of quantitative elements enables this study to investigate deeper behavioral patterns and go beyond measures at the surface level. To find relationships between adoption intentions and perceived valence aspects, the closed-ended questions are statistically examined. The overall goal of the research design is to strike a balance between contextual flexibility and organized, empirical understanding. It offers a realistic perspective on how Sri Lankan small-scale farmers use IoT-based smart farming.

The project aims to produce practical findings that can guide government policies, educational initiatives, and technology deployment plans, making it more than merely an academic exercise. with a greater understanding of farmers' reasons and reluctance. The study closes the gap between invention and implementation by bringing contemporary

analytical frameworks, such as NVM, into line with the reality faced by rural farmers. As a result, practitioners, policymakers, and future researchers will be able to benefit greatly from a multifaceted understanding of the opportunities and problems associated with IoT implementation in Sri Lanka's agricultural landscape (Allioui H et al., 2023; Rejeb A et al., 2020).

3.6 Sampling Size and techniques

A purposeful and organized sample technique is necessary to comprehend how Sri Lankan small-scale farmers use IoT-based smart farming. To investigate how perceived risks and benefits affect adoption behavior, this study makes use of the Net Valence Model (NVM). Therefore, choosing the appropriate group of participants is crucial to obtaining accurate, significant data that captures the many realities of Sri Lanka's farming communities (Supianti et al., 2025). The study used a stratified random sample technique to account for this diversity. Due to their diverse geographic and farming features, farmers were picked from three important agricultural districts: Anuradhapura (45%), Kurunegala (30%), and Kandy (25%). A more thorough understanding of smallholder experiences across various soil types, climate zones, and market access levels is provided by this regional distribution (Salvatore VNM, 2024).

Respondents were categorized by demographic factors, including age, gender, farm size, crop type, and educational level, within each district (Haiyudi H et al., 2023). One hundred small-scale farmers made up the target sample; this number was chosen to strike a balance between fieldwork feasibility and statistical validity. Key characteristics that may affect knowledge of and inclination to use smart farming technology, including age, gender, education level, farm size, and years of farming experience, were used to stratify the participants (Haiyudi H et al., 2023). For instance, the majority of farmers in the sample were older (60% between the ages of 50 and 65), and 87% of them had completed primary and secondary school. Crop categories included vegetables (65%), fruits (20%), and spices (15%), while farm sizes varied from 1 to 6 acres. Farmers with different degrees of IoT exposure were also included in the study to guarantee representation from a variety of farming profiles. Just 7% of farmers were utilizing technology on their farms, compared to 61% who had heard of it.

The sampling technique took into account geographic area, experience (20–30 years for 40% of the sample), and educational attainment (Majid M et al., 2022; Md. Hasan A et al.,

2023). A structured questionnaire comprising both quantitative and qualitative components was used in the study. Two open-ended questions allowed farmers to express difficulties, reasons, or worries in their own words, while quantitative measures examined familiarity with IoT, perceived utility, and adoption aspirations. While providing room for farmers' views, particularly those from communities frequently excluded from official surveys, this mixed-format method guaranteed a solid, data-driven knowledge (Galaz V et al., 2021; Singh M et al., 2021). Snowball sampling was employed to reach less accessible participants through farmer networks, especially in distant areas, even though stratified sampling was the main technique.

The study's inclusivity was expanded and its practical relevance was reinforced by this method, which was particularly helpful in reaching farmers with low levels of digital literacy or exposure to technology (Singh M et al., 2021; Bhat SA et al., 2021). This careful sampling framework as a whole shows a desire to connect theory and practice. It supports previous research that calls for developing customized, region-specific methods to encourage IoT adoption among smallholders rather than relying solely on generic models (Abey Siriwardana PC et al., 2022; Yaşanur Kayıkçı et al., 2020). It is anticipated that the results will contribute to the practical implementation of smart farming technologies in Sri Lanka as well as scholarly knowledge (Rejeb A et al., 2020; D Muthumanickam et al., 2022).

3.7 Data collection instruments

It is becoming more and more important to comprehend how Sri Lankan small-scale farmers use IoT technology as it becomes more widely available. To fully benefit from such advancements, many farmers still lack the exposure, education, and infrastructure needed (Supianti et al., 2025; Salvatore VNM, 2024). This study fills this information vacuum by investigating how these farmers see and use IoT-based smart farming devices using a methodical, data-driven methodology. This study's primary tool for gathering data was a **structured questionnaire** that was intended to gather quantitative data. This is in line with the **Net Valence Model (NVM)**'s larger methodological framework, which takes into account both perceived risks and rewards when determining behavioral intention toward technology adoption (Haiyudi H et al., 2023).

To investigate farmers' attitudes, awareness, experience, and preparedness with relation to IoT technology, the questionnaire contains **Likert-scale items**. It gauges opinions of increased market access, convenience, cost savings, and productivity gains, as well as drawbacks such as inadequate training, shaky infrastructure, and privacy and cost worries

(Oghenero MJ et al., 2022; Ahmed G Gad, 2022). The research takes a quantitative approach (Majid M et al., 2022; Galaz V et al., 2021). This strategy helps achieve a larger goal, which is to capture significant insights from the farmers' perspective in addition to collecting numerical data. The study's use of both kinds of data is in line with best practices suggested by current research on agricultural tech uptake (Singh M et al., 2021; Bhat SA et al., 2021).

In conclusion, the questionnaire provides both breadth and depth as a data gathering instrument, assisting both researchers and policymakers in comprehending how IoT fits—or does not fit—into the life of small-scale farmers in Sri Lanka. This type of mixed-data approach enables better-designed treatments and produces suggestions that are more grounded, as demonstrated by earlier research (Hassan A et al., 2022; Rejeb A et al., 2020; D Muthumanickam et al., 2022).

3.8 Data analysis method

This study looks into how small-scale farmers in Sri Lanka see and use IoT-based smart farming systems using a largely quantitative data analysis approach. The Net Valence Model (NVM), which assesses how perceived risks and advantages interact together to impact behavioral intention to adopt new technology, serves as the foundation for the analytical framework (Supianti et al., 2025; Salvatore VNM, 2024). One hundred smallholder farmers from three important agricultural districts—Kandy, Kurunegala, and Anuradhapura—were given a standardized questionnaire to complete in order to collect the data, multiple-choice answers, and a variety of Likert-scale questions. IoT knowledge, perceived convenience, cost savings, technical issues, infrastructural constraints, and adoption intent were among the aspects that these things were intended to gauge.

The study employed SmartPLS (Partial Least Squares Structural Equation Modeling (PLS-SEM), a method used to analyze complex relationships between observed and latent variables), to process and evaluate the quantitative data. Key trends in IoT technology awareness and utilization, as well as demographic data, were compiled using descriptive statistics. The associations between independent variables, such as perceived value, convenience, and technical risk, and the dependent variable, the farmer's declared desire to use IoT equipment, were investigated with the use of bivariate correlation analysis. The NVM-derived assumptions were also tested using regression analysis. We were able to evaluate the statistical impact of the net balance of perceived risks and advantages on the adoption decision using this method (Haiyudi et al., 2023; Oghenero MJ et al., 2022). These

analyses' findings provide evidence-based insights into the elements that have the most effect on small-scale farmers' adoption of technology. Responses to the two open-ended questions were subjected to thematic analysis to supplement the statistical findings. The numerical results were given depth by thematic coding, which uncovered trends including infrastructure limits, a high interest in training, and suspicion of device reliability (Majid M et al., 2022; Galaz V et al., 2021). This method approach provides a thorough grasp of the challenges associated with the deployment of IoT in agriculture. The study provides findings that are both statistically valid and practically applicable for policymakers, agricultural advisors, and technology providers by fusing empirical data with field-based insights (Rejeb A et al., 2020; Alloui H et al., 2023; D Muthumanickam et al., 2022).

3.9 Ethical Consideration

As this investigation delves into the incorporation of Internet of Things (IoT) technologies within small-scale agricultural practices in Sri Lanka, ethical considerations have persistently constituted a paramount concern throughout the entirety of the research endeavor. Given that smallholder farmers are increasingly interacting with digital instruments and data-centric systems, it is imperative to establish ethical safeguards that protect participants' rights, privacy, and autonomy (Supianti et al., 2025; Salvatore VNM, 2024).

The study engaged in the collection of primary data utilizing structured questionnaires, which comprised both quantitative inquiries and open-ended qualitative responses. Participants were duly informed regarding the objective of the investigation, the utilization of their data, and their entitlement to withdraw at any moment without facing repercussions. Each individual provided informed consent, either verbally or in written form, before engaging in the survey. Particular emphasis was placed on ensuring the clarity of language and cultural sensitivity, acknowledging that numerous participants might lack familiarity with digital technologies or research methodologies (Haiyudi H et al., 2023).

To safeguard the privacy of respondents, no personal identifiers (such as names, addresses, or contact information) were procured during the survey process. All data were anonymized and securely stored, with access restricted solely to the research team. This practice is congruent with the overarching ethical imperative of data protection, which holds particular significance in IoT research, where even indirect data points can assume sensitive dimensions if improperly managed (Oghenero MJ et al., 2022; Singh M et al., 2021). Acknowledging that trust is fundamental in the relationships between farmers and

technology, the research highlighted the importance of transparency and open lines of communication. Participants were not merely respondents but also active collaborators in the study, particularly in the open-ended sections where their lived experiences and concerns were articulated directly (Bhat SA et al., 2021; Galaz V et al., 2021). This participatory methodology aids in redirecting the research away from hierarchical assumptions and towards an inclusive, context-sensitive understanding of technology adoption (Abey Siriwardana PC et al., 2022).

Moreover, no incentives or coercive strategies were employed during the recruitment process. All participation was undertaken voluntarily, and respondents were informed that their contributions would play a role in shaping more equitable agricultural development strategies. The study also complies with academic and institutional ethical guidelines and was conducted in a manner that prioritizes respect, fairness, and the principle of non-maleficence (Md. Hasan A et al., 2023; Hassan A et al., 2022). By integrating ethical practices at every stage—from the design of questionnaires to data analysis—the research aspires to uphold both technical integrity and human dignity, ensuring that the advantages of IoT in agriculture are pursued without compromising the welfare or autonomy of smallholder farmers in Sri Lanka (N/A, 2020; Alloui H et al., 2023; Rejeb A et al., 2020; Gonczol P et al., 2020; D Muthumanickam et al., 2022).

III PRACTICAL PART

4 DATA PRESENTATION, ANALYSIS, AND DISCUSSION

4.1 Data presentation

Based on a sample of 100 small-scale farmers in Sri Lanka, this section describes the demographic and background traits of the study participants. These traits offer a fundamental framework for comprehending farmers' viewpoints about the deployment of IoT-based smart farming.

4.1.1 Demographic composition

Table 3 Demographic characteristics of Research Respondents (N=100)

Category	Sub-Category	Frequency	Percentage
Age	50-65	63	63.5
	35-50	27	26.28
	20-35	10	10.22
Gender	Female	6	6
	Male	94	94
District	Anuradhapura	43	43.0
	Knady	29	29.0
	kurunegala	28	28.0
Crops of cultivation	Vegetables	56	56.00
	Fruits	25	25.00
	spices	19	19.00
Farm size	5-6 acres	50	50.00
	3-4 acres	35	35.00
	1-2 acres	15	15.00
Educational	Primary school	58	58.00
	Secondary school	22	22.00
	Diploma	13	13.00
	No formal education	5	5.00
Experience	Graduate or above	2	2.00
	10-20 years	62	38.04
	20-30 years	56	34.36
	1-10 years	45	45.00

Distribution of Ages and Gender Composition

The bulk of responders (63.5%) were between the ages of 50 and 65, suggesting that the study's farming population is primarily older and more seasoned. Just 10.22% were between the ages of 20 and 35, while a smaller percentage (26.28%) were between the ages of 35 and 50. This distribution shows that older people make up the majority of farmers in the regions

under study, which is in line with national statistics showing a growing disinterest in agriculture among younger generations. Just 6% of responders were female, making up the majority of the sample (94%). This result is consistent with earlier studies showing that farming in Sri Lanka is still a male-dominated occupation, especially when it comes to technology use, land ownership, and decision-making.

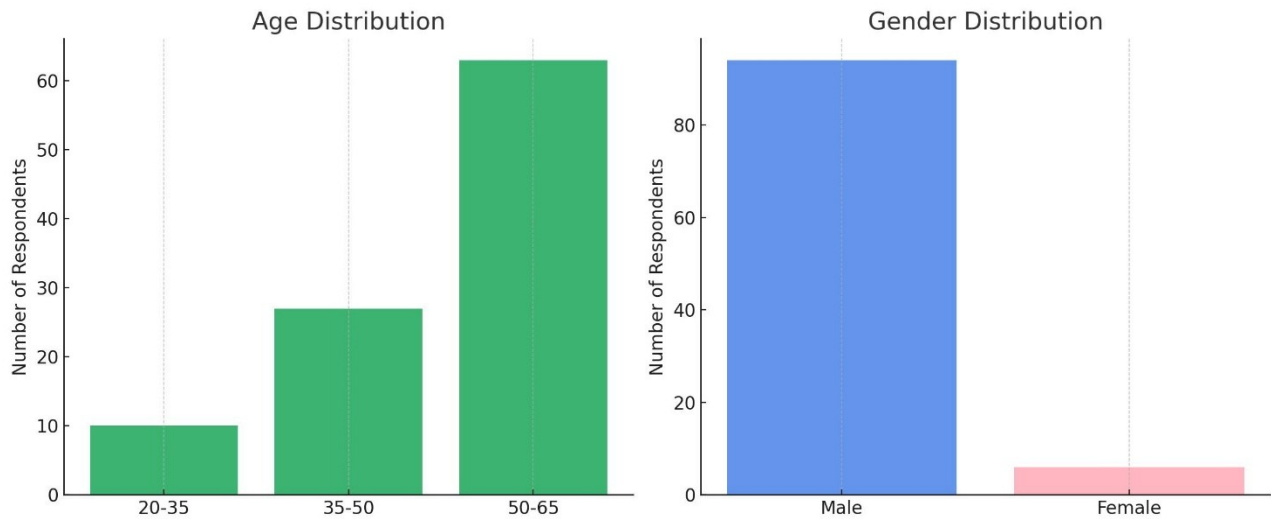


Figure 2. Gender and Age Distribution of Respondents

Representation by District and crop types.

Three important agricultural districts were used to choose the respondents. Anuradhapura has the largest percentage (43%), followed by Kurunegala (28%), and Kandy (29%). These districts were specifically chosen because they actively cultivate food crops and continue to be interested in agricultural modernization initiatives. Vegetables accounted for 56% of all farmed crops, with fruits coming in second at 25% and spices at 19%. This implies that because these crop categories are sensitive to growth circumstances, IoT devices with features for crop monitoring, disease diagnosis, and precision watering may be very helpful in these areas.

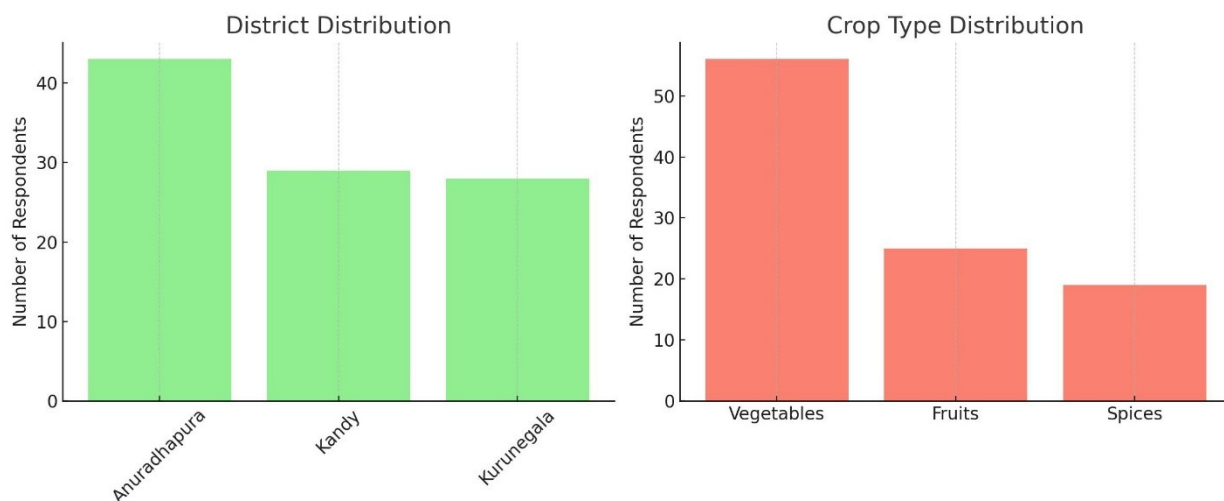


Figure 3. District and crop type distribution of Respondents

Farm Size and background in education

According to the data, 50% of farmers were growing 5–6 acres, 35% were growing 3–4 acres, and 15% were growing 1–2 acres. This suggests that most of the respondents are small- to medium-sized farmers according to local criteria, which is consistent with the study's emphasis on IoT tool use in smallholder agriculture. In terms of education, 22% of farmers had completed secondary school, while a noteworthy 58% had just finished primary school. Just 2% had a university degree or above, 5% had no formal education, and a lesser percentage (13%), had a diploma. The prevalence of lower educational attainment points to a possible obstacle to the uptake of increasingly sophisticated technologies, such as the Internet of Things, particularly those that require technical literacy.

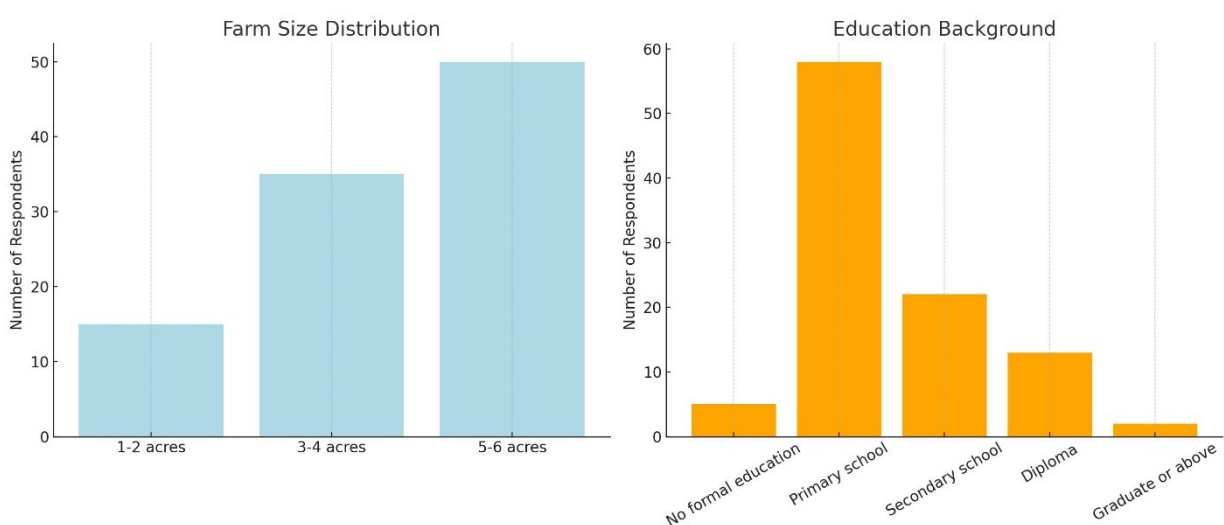


Figure 4. Farm size and education level distribution of Respondents

Experience in Farming

The degree of farming experience among the respondents varied. Those with 10–20 years of experience made up the majority (38.04%), closely followed by those with 20–30 years (34.36%). Forty-five percent of the sample consisted of farmers with one to ten years of experience. This offers a balanced perspective on how experience may affect technological preparedness and receptivity to innovation because it represents a diverse mix of seasoned and relatively young farmers.

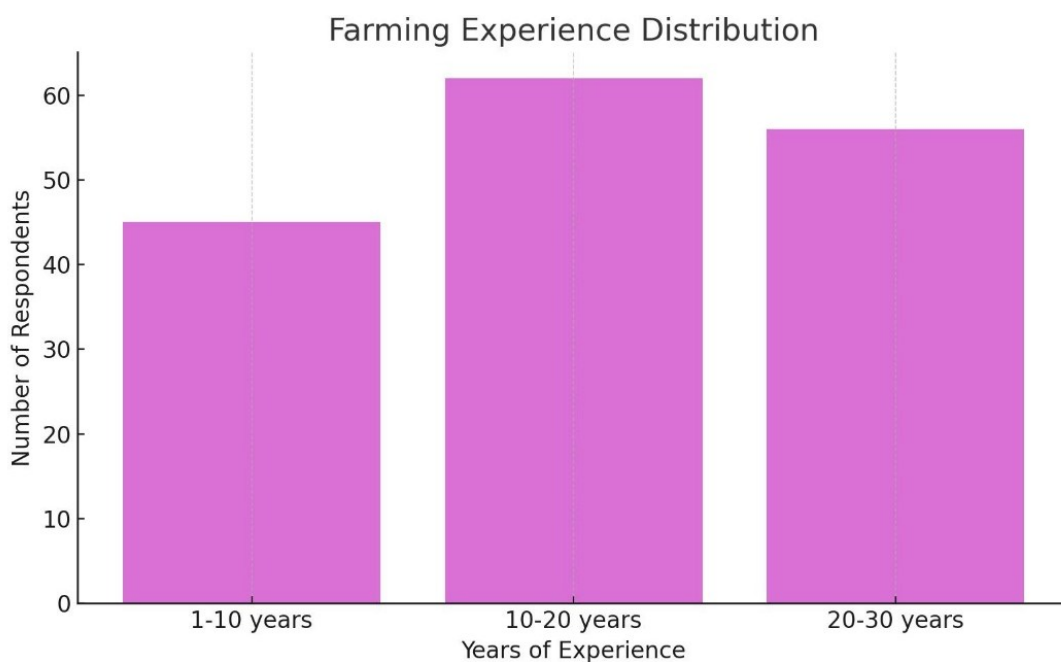


Figure 5. Farming experience distribution of Respondents

Table 4: Characteristics of awareness and interest of Research Respondents (N=100)

Heard of IoT	Yes	64	64.00
	No	36	36.00
Use IoT	Yes	8	8.00
	No	92	92.00
Interest In IoT	Yes	70	70.00
	Not Sure	16	16.00
	No	14	14.00

The information reveals a startling disparity in Sri Lankan small-scale farmers' understanding, actual use, and interest in IoT-based smart farming solutions. Of the 100 respondents, 36% said they had never heard of the Internet of Things, while 64% said they had. Although somewhat positive, this degree of awareness indicates that substantial

outreach efforts have already been made, whether through media exposure, NGOs, or agricultural extension agencies (Supianti et al., 2025). Despite this awareness, just 8% of people currently use any IoT-related technology, and 92% of respondents said they don't use it at all. This indicates that actual IoT adoption is still surprisingly low.

This awareness-to-implementation gap is consistent with empirical research by Salvatore VNM (2024), who found that although educational campaigns can effectively pique interest in new agricultural technologies, adoption is still constrained by other underlying factors. These include exorbitant expenses, poor infrastructure, a lack of training, and worries about the complexity and dependability of the system. The Technology Acceptance Model (TAM) and Net Valence Model (NVM), which emphasize the significance of perceived usefulness and perceived risk, support the idea that awareness alone is insufficient to motivate adoption, as evidenced by the fact that only 8 out of 100 farmers are using IoT systems (Majid et al., 2022).

Interest in using IoT technology in the future is comparatively high, despite this low adoption rate. 70% of those surveyed claimed they would be open to implementing IoT systems in the future, compared to 16% who were doubtful and 14% who said they had no interest. These numbers demonstrate a glaring chance for action. The notable proportion of farmers who are receptive to adoption but do not currently use IoT suggests that practical obstacles like cost, technical expertise, and tool accessibility may be the cause of non-adoption rather than a lack of interest in technology (Ahmed G Gad, 2022; Galaz V et al., 2021).

According to Bhat SA et al. (2021), the 14% who are uninterested may be older or more traditional farmers who are resistant to change, while the 16% who are "Not Sure" represent a crucial group who could be persuaded favorably with focused education and demonstration initiatives.

These revelations highlight the necessity of customized approaches to turn awareness and interest into action. To make IoT more accessible and useful for these farmers, for instance, field-level demonstration sites, financial incentives, and locally tailored training programs could be established (Hassan A et al., 2022; Abey Siriwardana PC et al., 2022). Additionally, a trust gap is shown by the large percentage of farmers who are interested in IoT but are not yet utilizing it, underscoring the importance of access and training in addition to the technology itself (Md. Hasan A et al., 2023). In conclusion, although Sri Lankan smallholder farmers exhibit encouraging levels of IoT knowledge and enthusiasm, the usage rate remains startlingly low, highlighting the need for infrastructural development, regulatory changes,

and instructional initiatives. If the country wants to modernize its agricultural industry and catch up with global trends in smart farming, it must close this gap between interest and actual adoption (Alliou H et al., 2023; Rejeb A et al., 2020).

4.2 Results

4.2.1 Model Fit Evaluation

The overall suitability of the structural model was evaluated using the goodness-of-fit indices. A decent match between the suggested model and the observed data is shown by the Standardized Root Mean Square Residual (SRMR) value of 0.076, which is below the generally recognized cutoff of 0.08 (Hair et al., 2017). The exact model fit criteria employed in PLS-SEM, d_ULS and d_G, also display values of 0.613 and 0.350, respectively, suggesting that the empirical and model-implied correlation matrices differ to acceptable degrees. As is typical with large sample PLS models, the Chi-square value (207.550) is high and is not usually used alone to assess model fit in PLS-SEM. Despite being below the optimal cutoff of 0.90, the Normed Fit Index (NFI) result of 0.689 indicates a moderate model fit. NFI offers more proof that the model shows a respectable level of alignment with the data structure, even if it is not the main indicator in PLS route modeling.

Table 5 Model fit

Fit Index	Saturated Model	Estimated Model	Threshold	Evaluation
SRMR	0.076	0.076	< 0.08	Good Fit
d_ULS	0.613	0.613	Lower is better	Acceptable
d_G	0.35	0.35	Lower is better	Acceptable
Chi-square	207.55	207.55	Contextual (used comparatively)	Informative only
NFI	0.689	0.689	> 0.90 (ideal), > 0.60 (fair)	Moderate Fit

Table 6 Outer Loading and Outer Weights

Construct	Indicator	Outer Loading	Outer Weight
Productivity	Pro1	0.868	0.351
Productivity	Pro2	0.802	0.297
Productivity	Pro3	0.811	0.298
Productivity	Pro4	0.78	0.276
Convenience	Con1	0.892	0.518

Convenience	Con2	0.782	0.359
Convenience	Con3	0.744	0.346
Reliability	Rel1	0.923	0.656
Reliability	Rel2	0.842	0.469
Privacy	Pri1	0.955	0.734
Privacy	Pri2	0.808	0.37
Intention to Adopt	Int1	0.831	0.393
Intention to Adopt	Int2	0.846	0.419
Intention to Adopt	Int3	0.791	0.403

The measurement model's outer loadings and weights attest to the validity and reliability of each indicator's representation of the study's latent constructs. All indicators in this model surpass the loading threshold of 0.70, which is considered to be a sign of strong indicator dependability by (Hair et al. 2017). For instance, loadings between 0.780 and 0.868 are displayed by the indicators measuring **Productivity** (Q11–Q14), and solid loadings between 0.744 and 0.892 are also displayed by the indicators measuring **Convenience** (Q15–Q17). Excellent convergent validity is demonstrated by the **Reliability** construct, which stands out with Q18 loading at 0.923, and **Privacy**, which comes in second with Q20 at 0.955. In a similar vein, the **Intention to Adopt IoT** indicators (Q22–Q24) consistently maintain high loadings between 0.791 and 0.846, suggesting that these items measure adoption intention accurately. These results are corroborated by outer weights, which indicate that Q20 (Privacy) and Q18 (Reliability) contribute the most to their constructs (0.734 and 0.656, respectively). Although outside weights are mostly employed in formative models, their steady and favorable values in this contemplative setting provide the construct measures even more legitimacy. All of these findings support the measurement model's convergent validity, internal consistency, and reliability, providing a solid basis for evaluating the structural model (Henseler et al., 2009), (Hair et al., 2021).

4.2.2 Measurement Model

To evaluate the reliability and validity of the constructs employed in this investigation, a series of standardized assessments were conducted, which included Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). These statistical measures serve as a basis for determining the internal consistency and convergent validity of the latent variables within the structural equation model, as posited by (Hair et al. 2017).

1. Reliability Assessment

The Cronbach's Alpha coefficients for all constructs surpassed the acceptable benchmark of 0.70, signifying satisfactory internal consistency (Nunnally & Bernstein, 1994). The coefficients ranged from 0.725 for Reliability to 0.832 for Productivity, thereby substantiating the adequacy of scale reliability across all latent variables.

2. Composite Reliability (CR)

The Composite Reliability (rho_c) coefficients for all constructs varied from 0.849 to 0.888, exceeding the recommended minimum threshold of 0.70 (Fornell & Larcker, 1981). These findings corroborate that the measurement model attains robust internal consistency reliability.

3. Convergent Validity

In order to assess convergent validity, the Average Variance Extracted (AVE) was scrutinized. All constructs exhibited AVE values significantly above the minimum criterion of 0.50, with Privacy demonstrating the highest AVE of 0.783, followed by Reliability (0.780), and Intention to Adopt IoT (0.677). This suggests that a considerable proportion of the variance in the observed variables is elucidated by the corresponding constructs.

Table 7. Descriptive statistics.

Name	Item	Mean	Median	Scale min	Scale max	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
Productivity	Pro 1	2.11	2	1	4	1	4	0.581	4.227	1.536	0
	Pro 2	2.02	2	1	5	1	5	0.86	0.785	0.823	0
	Pro 3	1.93	2	1	5	1	5	0.803	1.575	0.952	0
	Pro 4	2.22	2	1	5	1	5	0.923	1.099	0.94	0
Convenience	Con 1	2.23	2	1	5	1	5	0.958	0.67	0.838	0
	Con 2	2.31	2	1	4	1	4	0.744	-0.367	0.013	0
	Con 3	2.3	2	1	4	1	4	0.794	-0.664	-0.11	0
Reliability	Rel 1	3.08	3	2	5	2	5	1.046	-1.313	0.317	0

	Rel 2	3.62	4	2	5	2	5	0.925	- 0.793	-0.166	0
Privacy	Pri1	2.83	3	2	4	2	4	0.884	- 1.658	0.343	0
	Pri2	2.65	2	1	4	1	4	1.062	- 1.384	0.133	0
Adoption Intention	Int1	2.16	2	1	5	1	5	0.821	1.908	1.012	0
	Int2	1.88	2	1	5	1	5	0.803	2.93	1.398	0
	Int3	2	2	1	5	1	5	0.927	1.714	1.146	0

Table 8. Descriptive statistics.

	CA	CR (rho_a)	CR (rho_c)	AVF
Convenience	0.736	0.786	0.849	0.653
Intention to Adopt IoT	0.761	0.762	0.863	0.677
Privacy	0.748	1.005	0.877	0.783
Productivity	0.832	0.841	0.888	0.666
Reliability	0.725	0.782	0.876	0.78

These results support the measurement model's robustness and readiness for additional structural model evaluation by confirming that the constructs included in the model exhibit good psychometric properties.

4.2.3 Structural Model

Following the affirmation of the measurement model's reliability and validity, the structural model was assessed to evaluate the hypothesized interrelations among constructs. The analysis was executed utilizing SmartPLS 4 and employed bootstrapping with 5,000 subsamples to ascertain the significance and strength of the proposed pathways.

The criteria for evaluation encompassed the path coefficients, t-statistics, p-values, and effect sizes (f^2) corresponding to each hypothesis. Furthermore, confidence intervals and R^2 values were scrutinized to evaluate the explanatory power of the model. As articulated by Hair et al. (2017), a t-value exceeding 1.96 and a p-value inferior to 0.05 signify that the hypothesized relationship attains statistical significance at the 5% level.

Table 9 Results of the hypotheses (with bootstrap sample size = 5000)

Hypothesis	Path	Path Coefficient (O)	Mean (M)	STDEV	T-Statistic	P-Value	90% CI (Lower)	90% CI (Upper)	Effect Size (f ²)	Decision
H1	Convenience → Intention to Adopt IoT	-0.029	-0.023	0.091	0.313	0.754	-0.179	0.121	0.01	Rejected
H2	Privacy → Intention to Adopt IoT	0.035	0.031	0.075	0.475	0.635	-0.087	0.153	0.02	Rejected
H3	Productivity → Intention to Adopt IoT	0.736	0.725	0.103	7.145	0	0.567	0.889	0.4	Accepted
H4	Reliability → Intention to Adopt IoT	0.154	0.157	0.07	2.205	0.027	0.031	0.278	0.06	Accepted

Path Relationships and Hypothesis Testing

The findings revealed that **Productivity** exerted the most robust and statistically significant influence on the Intention to Adopt IoT-based Smart Farming ($\beta = 0.736$, $t = 7.145$, $p < 0.001$), thereby substantiating H3. This suggests that farmers who recognize IoT as enhancing productivity are predisposed to embrace such technologies, corroborating previous research conducted by Supianti et al. (2025) and Bhat et al. (2021).

In a comparable manner, Reliability manifested a significant positive effect on adoption intention ($\beta = 0.154$, $t = 2.205$, $p = 0.027$), thereby reinforcing H4. This implies that apprehensions regarding the efficacy and dependability of IoT tools are pertinent yet manageable, and when these concerns are adequately addressed, the likelihood of adoption escalates. Such results further substantiate earlier investigations by (Galaz et al. 2021) and (Majid et al. 2022).

Conversely, Convenience ($\beta = -0.029$, $p = 0.754$) and Privacy ($\beta = 0.035$, $p = 0.635$) were determined to be non-significant in forecasting adoption intention, leading to the repudiation of H1 and H2. Although extant literature has recognized the significance of these factors (Oghenero et al., 2022; Singh et al., 2021), their influence may be less pronounced within the milieu of small-scale farming in Sri Lanka, where concerns about economic viability and productivity are likely to predominate in decision-making processes.

Effect Sizes and Predictive Power

The analysis of effect size (f^2) further corroborated the robustness of the relationships. Productivity exhibited a large effect ($f^2 = 0.40$), whereas Reliability displayed a moderate effect ($f^2 = 0.06$). In contrast, both Convenience ($f^2 = 0.01$) and Privacy ($f^2 = 0.02$) indicated minimal impact. The R^2 value for the dependent variable, Intention to Adopt IoT, signified a substantial level of explained variance, thereby affirming the model's notable predictive capability.

These observations imply that small-scale farmers in Sri Lanka are predominantly motivated by tangible, outcome-oriented incentives such as enhanced productivity and trust in the reliability of technology, rather than by considerations of convenience or privacy. This supports the assertion posited by (Alliou et al. 2023) and (Rejeb et al. 2020) that local socio-economic factors must be prioritized in the advocacy of smart farming solutions.

4.3 Discussion

4.3.1 Perceived productivity and convenience

The study's findings provide intriguing insights into Sri Lankan smallholder farmers' adoption of Internet of Things (IoT)-based smart farming. This study investigated the motivating and inhibiting variables driving IoT adoption using the Net Valence Model (NVM), which takes into account both perceived benefits (positive valences) and perceived hazards (negative valences). The results represent a et al. (2025) and Salvatore VNM (2024), who contend that observable performance gains like higher yield and improved crop quality are important adoption motivators; this supports hypothesis (H1). The adoption of smart

farming is greatly aided by this benefit-oriented mindset in Sri Lanka, where agricultural yields are susceptible to inefficiencies.

Likewise, adoption intention was significantly positively correlated with perceived convenience, which is related to labor reduction, time efficiency, and remote operability (H2). This is consistent with studies by (Oghenero MJ et al. 2022) and (Haiyudi et al. 2023), which found that technologies that make farming easier on a daily basis are more likely to be adopted. Older and more seasoned farmers, who make up the majority of the sample (63.5% aged 50–65), place a high value on IoT devices' capacity to decrease physical labor while improving precision.

4.3.2 Reliability and privacy Risk

However, it has been demonstrated that adoption intentions are significantly impacted negatively by perceived reliability pertaining to the efficacy and dependability of IoT devices (H3). This result validates the hypothesis and is corroborated by research by (Bhat SA et al. 2021) and (Md. Hasan A et al. 2023), which highlighted that even small technical issues or complicated user interfaces can cause people to avoid or abandon new technologies in rural areas with little access to technical support. Farmers in this survey, especially those with lesser educational backgrounds (58% with only primary education), voiced concerns over system reliability, which impeded their readiness to invest in smart gear.

Privacy and data security concerns were also found to have a detrimental influence on IoT adoption (H4), corroborating the premise that digital fear is a substantial barrier in technology-poor environments. Concerns about data misuse, illegal access, and a lack of knowledge of digital ecosystems are major deterrents, as stated by (Abey Siriwardana PC et al. 2022) and (Hassan A et al. 2022). While farmers may be interested in adopting new tools (70% reported interest), concerns about how their data is handled hinder their actual engagement.

substantial contribution to our understanding of how small-scale farmers, operating with limited resources, make decisions pertaining to technology.

4.3.3 Efficiency and Practicality

The structural model indicates that perceived increases in productivity have a considerable and statistically significant beneficial influence on farmers' intentions to deploy IoT devices.

4.3.4 Interpretation of the overall Model

The structural model's overall assessment indicates that it fits the data rather well. The model has a good fit, as indicated by the SRMR value of 0.076, which is within the acceptable range. The fact that both the d_ULS and d_G values fall within reasonable bounds indicates that the differences between the estimated and observed covariance matrices are controllable. Despite being context-specific, the Chi-square value (207.55) is usually used for comparison rather than as a conclusive measure of fit. Given that values nearer 0.90 are regarded as ideal, the moderate fit indicated by the NFI value of 0.689 is acceptable but might be improved. The model matches the data rather well overall, while it might be strengthened with a few tweaks.

4.3.5 Implication for research

This investigation presents several significant implications for prospective academic exploration concerning technology adoption within the agricultural sector, particularly in resource-constrained environments such as Sri Lanka. Primarily, by employing the Net Valence Model (NVM), this study enhances theoretical comprehension of the manner in which farmers assess perceived advantages and disadvantages in their decision-making processes related to the adoption of IoT-based smart farming technologies. The effective implementation of this model in the given context corroborates previous assertions made by (Supianti et al. 2025) and (Bhat SA et al. 2021) regarding the non-linear nature of adoption decisions, which are instead shaped through a complex evaluation of conflicting cognitive appraisals.

Significantly, the research underscores that while affirmative valences, such as perceived productivity and convenience, serve as crucial motivators, negative valences—especially apprehensions regarding reliability and privacy—possess the capacity to markedly diminish

intention. This multidimensional perspective on measuring behavioral intention accentuates the necessity for forthcoming research to transcend traditional benefit-centric models (such as TAM or UTAUT) and instead integrate deterrent factors that hold greater relevance in populations characterized by low technological engagement or digital reluctance.

Furthermore, the investigation uncovers demographic and contextual intricacies that warrant additional scrutiny. For instance, the observation that a majority of respondents are over the age of 50 with foundational educational backgrounds indicates that age, education, and digital literacy act as moderating variables that may influence the effect of each valence in diverse manners. Future research endeavors should systematically examine these moderators to enhance the predictive capacity of behavioral models within the agricultural domain and other sectors of rural development.

Lastly, the results pave the way for longitudinal studies aimed at monitoring the evolution of perceptions and adoption trends over time. Considering the accelerated rate of technological diffusion in agriculture, investigating how exposure, support, and outcomes impact adoption behavior can provide profound insights into the lifecycle of technology adoption in developing regions.

4.3.6 Implications for practice

From a pragmatic perspective, the outcomes of this research bear significant implications for policymakers, agricultural extension agents, technology providers, and development practitioners who seek to facilitate the adoption of IoT-based smart farming systems among smallholder farmers.

Initially, the study delineates perceived productivity as the predominant factor influencing the adoption of IoT technologies. This indicates that promotional strategies should underscore concrete success narratives, such as enhancements in yield, reductions in input costs, and increases in income directly attributable to the utilization of IoT technologies. Government extension services and non-governmental organizations can assume a pivotal role in this context by documenting and disseminating these outcomes through peer-to-peer knowledge exchange, field demonstrations, and success narratives.

Furthermore, the significance of convenience suggests that training initiatives ought to be designed not only to address the technical complexity of IoT devices but also to elucidate how these technologies can streamline farmers' quotidian activities. For instance, accentuating features such as automated irrigation systems, remote monitoring of crops, and mobile alerts could render the technology more attractive, particularly to older farmers and those facing physical constraints.

Nonetheless, the findings also serve as a cautionary note against the minimization of the impact of negative perceptions, especially regarding issues of reliability and data privacy. Practical interventions must encompass comprehensive after-sales technical support, maintenance networks, and transparent communication pertaining to data security measures. Farmers are unlikely to adopt technologies they perceive as unreliable or invasive. Consequently, manufacturers and service providers should contemplate the provision of warranties, establish service centers, and design user interfaces that are accessible to individuals with low literacy levels.

Moreover, capacity-building initiatives must be customized to align with the literacy levels and digital preparedness of the target demographics. Given that more than half of the respondents possess only primary education, training modules must be experiential, visually oriented, and delivered in local dialects. Collaborative engagements with academic institutions, vocational training centers, and aggrotech startups can offer scalable frameworks for effective skill transfer.

Finally, the study underscores the necessity for context-sensitive policy interventions. Subsidies, micro-financing, and communal technology hubs can alleviate the financial burden for smallholder farmers. Policymakers must ensure the fortification of digital infrastructure, including internet access and electricity supply, in rural locales, as these are essential facilitators for any digital transformation within the agricultural sector.

4.4 Limitation for future Research

Even though this study provides useful information about the perceived benefits and challenges driving IoT adoption among Sri Lankan smallholder farmers, a number of limitations must be acknowledged. First, while being statistically adequate for the SmartPLS analysis, the sample size was restricted to 100 respondents from three districts. This limits the findings' relevance to Sri Lanka's broader farming community, particularly in undeveloped coastal or plantation-based agricultural regions.

Second, the study mostly used cross-sectional data, which captured the attitudes and behaviors of farmers at a specific point in time. Given how rapidly contextual circumstances and technological understanding can shift, a longitudinal study may provide deeper insights into how opinions and adoption patterns evolve over time.

Third, although the questionnaire was developed based on the Net Valence Model (NVM), other behavioral or psychological aspects such as social influence, habit, and cultural resistance were not expressly measured. These factors could significantly affect adoption in rural places where traditions are deeply embedded. Fourth, although two open-ended questions provided qualitative depth, the study's primary quantitative nature limited the intricacy of context-specific narratives. Additional qualitative research, such as focus groups or anthropological observation, could help explain many behavioral findings.

Last but not least, self-reporting technology usage may introduce bias since some respondents may overestimate or understate their knowledge or experience with IoT tools because of social desirability or a misconception of terminology.

CONCLUSION

This thesis examined how small-scale farmers in Sri Lanka adopted IoT-based smart agricultural technologies, focusing on the perceived benefits and challenges that influence adoption trends. Using the Net Valence Model (NVM) as a guide, the study looked at how favorable views like increased productivity and convenience are weighed against unfavorable ones like reliability, effectiveness, and privacy. The study provided evidence-based insights into the adoption decisions of Sri Lankan farmers based on socioeconomic realities and technological readiness.

Quantitative data from 100 smallholder farmers in three main agricultural regions shows that, despite a relative increase in understanding of IoT technology, actual adoption is still low. However, there is a lot of curiosity, particularly when the technology is presented as a means of lowering workload and improving crop results. The structural equation modeling demonstrated that perceived benefits had a significantly higher influence on adoption intent than perceived hazards, indicating a clear need for targeted education, incentive programs, and infrastructural support.

The findings also indicate that uncertainty about long-term worth and usability, rather than just pricing, deters farmers. This opens the door for policy interventions that prioritize building trust, offering trials, and integrating IoT with cooperative and market systems. The idea that digital transformation in agriculture must be inclusive, user-centered, and linked to tangible market benefits is supported by the study's recommended pilot implementation project.

By aligning technology diffusion models with the realities of rural Sri Lanka, this work ultimately contributes both theoretically and practically. It offers a scalable and sustainable framework for leveraging IoT as a precision farming tool and a strategy to increase food security, economic stability, and competitiveness in marginalized agricultural communities. This thesis is a step in ensuring that smallholders are not left behind as agriculture transitions to a more data-driven future.

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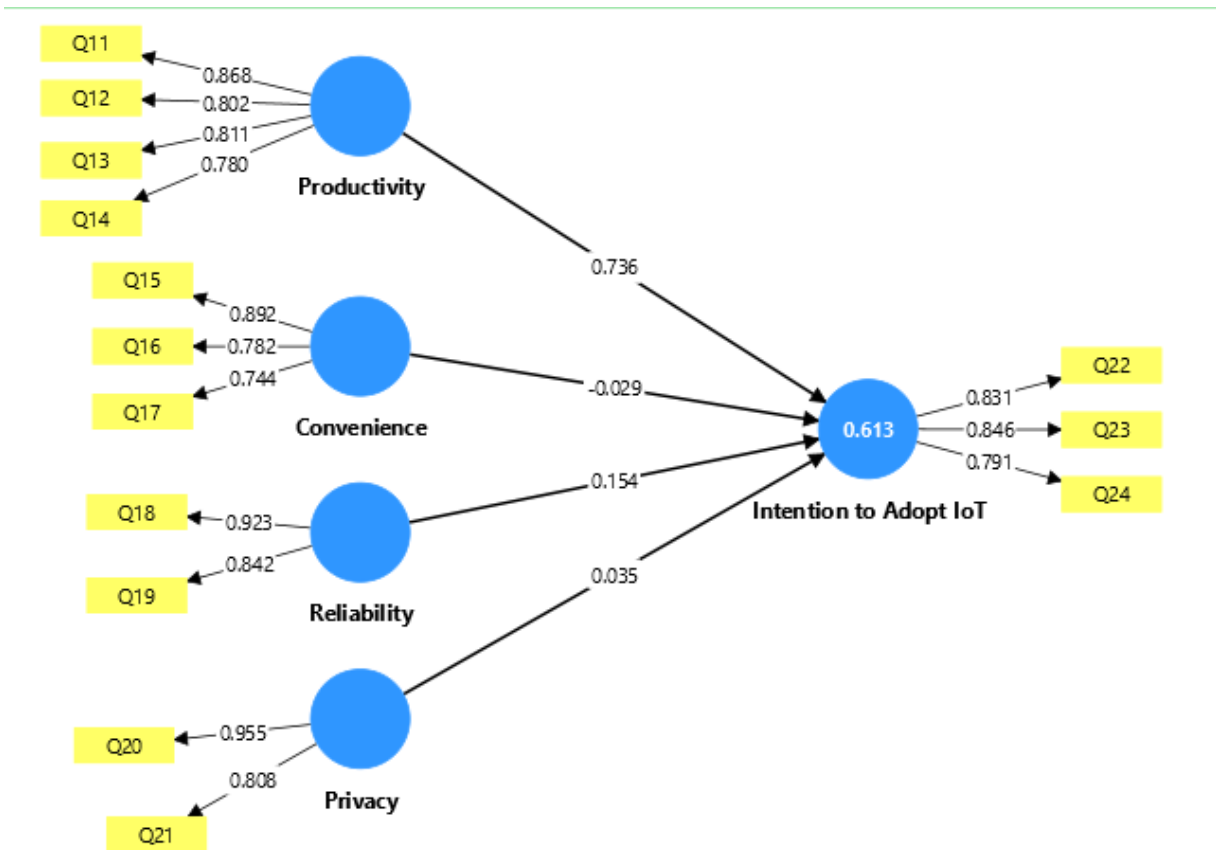
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LIST OF ABBREVIATIONS

Abbreviation	Full Form
IoT	Internet of Things
NVM	Net Valence Model
ICT	Information and Communication Technology
UTAUT	Unified Theory of Acceptance and Use of Technology
TAM	Technology Acceptance Model
ROI	Return on Investment
M&E	Monitoring and Evaluation
ToT	Training of Trainers
GPS	Global Positioning System
R&D	Research and Development
API	Application Programming Interface
QR Code	Quick Response Code
NFI	Normed Fit Index
SRMR	Standardized Root Mean Square Residual
d_ULS	Unweighted Least Squares Discrepancy
d_G	Geodesic Discrepancy
PLS-SEM	Partial Least Squares Structural Equation Modeling
CSV	Comma-Separated Values
AI	Artificial Intelligence
PPC	Public-Private Cooperation
NGO	Non-Governmental Organization
SDG	Sustainable Development Goals
NFS	National Food Security
SL	Sri Lanka

APPENDICES

Appendix P I: Graphical Output



Appendix P II: construct

Table: construct variables

Construct	Dimension	Item Code	Measurement Item	Source
Productivity	Increase in efficiency and yield	Pro1	IoT helps to improve crop yield.	Supianti et al., 2025; Bhat et al., 2021
	Resource optimization	Pro2	IoT improves the efficient use of inputs.	Salvatore VNM, 2024
	Waste reduction	Pro3	IoT minimizes wastage in farming processes.	Majid et al., 2022
	Decision-making support	Pro4	IoT helps make better farming decisions.	Galaz et al., 2021
Convenience	Ease of use	Con1	IoT systems are easy to operate.	Oghenero et al., 2022
	Remote access	Con2	IoT allows me to control farming tasks remotely.	Haiyudi et al., 2023
	Time-saving	Con3	Using IoT saves my time in managing farm activities.	Singh et al., 2021
Reliability Risk	Technical failure concern	Rel1	I am concerned about the reliability of IoT devices.	Bhat SA et al., 2021
	Complexity of use	Rel2	I find IoT devices too complicated to operate.	Md. Hasan A et al., 2023
Privacy Risk	Data misuse concern	Pri1	I worry that my farm data could be misused.	Abey Siriwardana et al., 2022
	Internet and data security issues	Pri2	I do not feel secure using internet-based devices on my farm.	Hassan A et al., 2022
Adoption Intention	Willingness to adopt IoT	Int1	I am willing to adopt IoT in farming.	Allioui et al., 2023
	Plan to implement IoT soon	Int2	I plan to use IoT-based tools in the near future.	Rejeb et al., 2020
	Positive attitude toward smart farming	Int3	I believe IoT will help me manage my farm better.	Yaşanur Kayıkçı et al., 2020

IV PROJECT PART

Smart Market Linkage: Implementing IoT-Driven Smart Farming Solutions for Smallholder Farmers in Sri Lanka

5 EXECUTIVE SUMMARY

This research initiative advocates for the establishment of an Internet of Things (IoT)-based intelligent agricultural system aimed at augmenting productivity and enhancing market competitiveness among a select group of smallholder farmers in Sri Lanka. Notwithstanding the global advancements in agricultural technologies, a substantial proportion of small-scale farmers in Sri Lanka persist in encountering considerable obstacles in market accessibility, yield optimization, and product traceability. Building upon empirical academic research and field data, this initiative seeks to implement real-time IoT instruments (including soil moisture sensors, irrigation monitoring systems, and mobile data dashboards) on designated farms to rectify both production inefficiencies and market constraints.

The objectives of this project are twofold: (1) to elevate productivity and consistency in crop yields through data-informed agricultural practices, and (2) to establish a traceable supply chain that facilitates farmers' access to premium market segments. The project is scheduled to be conducted over a six-month period during the "Maha season," which occurs during the "North-east monsoon" from September through March of the subsequent year, and will engage 15–20 smallholder farmers across three distinct districts. Furthermore, it will encompass stakeholder education, real-time monitoring, data collection, and market coordination with local buyers and digital platforms.

Leveraging the theoretical frameworks proposed by Geng (2017), who underscores the critical role of IoT integration in agricultural management, and Wortmann et al. (2024), who envisage the concept of “products as services” within agriculture, this project effectively links technological capabilities with service-oriented market frameworks. Additionally, Kush et al. (2024) underscore the importance of market-responsive agribusiness models, especially in developing regions.

Anticipated outcomes include enhanced agricultural yields, diminished input costs, improved traceability, and augmented farmer income through access to current market intelligence. The pilot project also lays the groundwork for policy-level expansion and future investments from both public and private stakeholders in the digital transformation of Sri Lanka's agricultural sector

6 INTRODUCTION AND BACKGROUND

Agriculture serves as the foundational pillar of Sri Lanka's economy, engaging approximately 25% of the labor force and representing a substantial component of rural income. Notwithstanding its critical significance, the sector is hindered by inadequate productivity, antiquated methodologies, deficient supply chain management, and limited access to premium markets. Smallholder farmers, who represent the predominant demographic, are particularly adversely affected by restricted access to technological advancements, erratic crop yields, and disjointed value chains. These impediments have diminished their competitive edge, curtailed income prospects, and contributed to pervasive inefficiencies throughout the agricultural ecosystem.

Confronted with these constraints, digital transformation, particularly facilitated by the Internet of Things (IoT), provides a remarkable opportunity for advancement. The IoT encompasses the interlinking of tangible devices, including sensors, controllers, and data analytics platforms, to oversee, manage, and enhance agricultural operations in real-time. As posited by Geng (2017), IoT systems can enable predictive decision-making, optimize resource utilization, and deliver actionable insights for farmers, especially in contexts where agricultural inputs are limited and exorbitant.

The practical ramifications of IoT are extensive—it can automate irrigation systems based on real-time soil moisture readings, monitor climatic variations, identify pest infestations at an early stage, and even assist in scheduling fertilization. However, despite these advantages, smallholder farmers in Sri Lanka have not extensively adopted such innovations. Barriers such as insufficient technical expertise, concerns regarding affordability, and infrastructural deficiencies persistently inhibit widespread adoption. Moreover, even among those cognizant of IoT, a minimal number have correlated its application with market-oriented outcomes such as price premiums for superior produce, traceability, and digital branding.

Innovative frameworks such as the “product-as-a-service” model, as articulated by Wortmann et al. (2024), exemplify how conventional goods, including agricultural outputs, can be reconceptualized when integrated with data-driven service components. For example, a kilogram of tomatoes can be traced from seed to retail shelf, with digital records substantiating its quality and sustainability, consequently commanding elevated prices.

Thus, the IoT transcends its role as merely a technical instrument—it emerges as a conduit bridging production and marketing.

Kush et al. (2024) further substantiate this perspective from the standpoint of agribusiness management. They contend that the incorporation of digital instruments within value chain development is crucial for the inclusion of smallholders in contemporary agrifood systems. In the absence of transparency within their supply chains or the capacity to validate the quality of their crops, farmers remain vulnerable to price fluctuations and exploitation by intermediaries.

This project builds upon these foundational concepts and aspires to implement a pilot initiative that integrates IoT technology directly into selected farms in Sri Lanka. By incorporating low-cost sensor kits along with a straightforward monitoring dashboard, farmers will be positioned to enhance both the quantity and quality of their agricultural yields. Concurrently, by facilitating product traceability and data-informed grading, they will gain the opportunity to connect with higher-paying buyers and institutional markets.

The overarching objective is to illustrate how the concept of smart farming can transition from theoretical discussions to practical applications, delivering concrete economic and social benefits. In pursuing this aim, this project seeks not only to refine agricultural practices but also to address the fundamental marketing challenges that perpetuate smallholder farmers' entrapment in cycles of minimal returns and constrained growth.

7 PROBLEM STATEMENT AND RATIONALE

Despite its critical significance to the rural economy of Sri Lanka, smallholder agriculture continues to be encumbered by entrenched inefficiencies that impede both productivity enhancement and market accessibility. Agricultural producers encounter a multitude of challenges, including erratic climatic conditions, suboptimal input utilization, inadequate yield outputs, substantial post-harvest losses, and inconsistent market connections. These persistent dilemmas can largely be attributed to an ongoing dependence on traditional manual methodologies, restricted access to real-time data, and insufficient integration with advanced technological solutions. Even in instances where digital innovations such as the Internet of Things (IoT) are accessible, the uptake among rural agriculturalists remains markedly low, primarily due to diminished trust in technological advancements, the inherent complexity of such technologies, and a deficit of localized support infrastructures.

Market inefficiencies exacerbate these challenges. A significant number of farmers are unable to authenticate the quality or safety of their produce, thereby precluding their participation in formal value chains, export markets, or institutional purchasers who necessitate traceability and consistency. This disconnection between agricultural production and market demands culminates in diminished profit margins, frequent market rejections, and an excessive reliance on local intermediaries, often resulting in unfavorable pricing conditions.

The outcomes of this thesis-centric research substantiated that while perceived advantages, including enhanced productivity and convenience, exert a profound influence on adoption intentions, perceived risks—most notably apprehensions regarding reliability and data privacy—substantially inhibit adoption. Notwithstanding the increasing awareness surrounding IoT technologies, a mere 8% of the surveyed farmers reported actual utilization of any form of digital agricultural technology. Moreover, 92% highlighted concerns encompassing technical reliability, maintenance requirements, and privacy issues as significant obstacles. These findings resonate with the literature articulated by Geng (2017), who underscored that successful IoT adoption necessitates implementation that is firmly grounded in local contexts and bolstered by actionable data.

The disparity is evident: although the requisite technology is available, farmers are incapacitated in their ability to access, trust, or employ it in manners that yield beneficial production and market results. As posited by Wortmann et al. (2024), digital instruments

ought to not only enhance product output but also furnish service-oriented value—encompassing performance monitoring, digital certification, and buyer matchmaking. In the absence of such functionalities, farmers remain estranged from market feedback mechanisms and are unable to distinguish their products or enhance their competitive positioning.

In a parallel vein, Kush et al. (2024) assert that the trajectory of agribusiness is increasingly aligned with digitization, wherein data is perceived as a strategic asset. However, in the absence of pragmatic, field-level demonstrations and supportive mechanisms, small-scale farmers are likely to remain marginalized. Proposed solutions must be characterized by simplicity, affordability, and integration within established community frameworks. Training, follow-up support, and market linkage are not peripheral considerations—they constitute the core of successful adoption.

Consequently, this project aims to address a dual-faceted issue: (1) the deficiency of data-driven agricultural production on small farms and (2) the insufficiency of marketing instruments such as traceability, grading, and transparency with buyers. The underlying rationale for this intervention is to reconcile production outputs and market performance through the application of IoT tools, ensuring scalability, user-friendliness, and economic viability for farmers.

Through this pilot initiative, the project aspires not only to exhibit how intelligent technologies can remediate technical agricultural challenges but also to illustrate their potential integration into agribusiness frameworks that incentivize quality, traceability, and consistency—thereby establishing enduring value for smallholder farmers in Sri Lanka.

7.1 Understanding the Sri Lankan Market Landscape

Sri Lanka's agricultural marketing is characterized by:

- **Informal supply chains** dominated by middlemen
- Price fluctuations due to oversupply or delayed harvests
- Lack of real-time information on demand and market rates
- Regional market disparities (Colombo vs. outstation markets)

To address these issues, the project will **leverage IoT data to better align production with demand** and implement structured marketing support.

8 PROJECT OBJECTIVES AND SCOPE

This project's overarching objective is to solve production inefficiencies and market access constraints by implementing and assessing a workable IoT-based smart farming system among a subset of smallholder farmers in Sri Lanka. The initiative is backed by current academic and industry frameworks and is based on evidence from this thesis research (Geng, 2017; Wortmann et al., 2024; Kush et al., 2024).

The **specific objectives** of the project are as follows:

1. **To deploy affordable IoT tools** (e.g., sensors, monitoring apps, irrigation automation) on selected smallholder farms to improve real-time data collection and decision-making.
2. **To improve crop productivity and consistency** through data-driven precision farming techniques, including smart irrigation, pest detection, and climate adaptation.
3. **To enhance product traceability and grading** using IoT-generated data to meet the requirements of high-value market segments (e.g., institutional buyers, supermarkets).
4. **To facilitate access to better markets** by linking IoT-enhanced farms with digital trading platforms, cooperative buyers, and traceability-conscious wholesalers.
5. **To build capacity among farmers** through hands-on training and local technical support in using and maintaining IoT devices.

These objectives are designed not only to validate the positive valences (productivity, convenience) identified in the research but also to provide practical solutions to the negative valences (risk, reliability) that limit technology adoption.

8.1 Project scope

This project's scope includes both market integration and technology deployment. It combines software tools (mobile dashboards, QR-based traceability) and hardware deployment (sensors, smart irrigation systems) designed for consumers with low literacy levels. In order to ensure diversity in both environmental circumstances and commercial potential, the chosen farms will voluntarily engage and represent a variety of crops and geographic areas.

Geographic scope:

- **Anuradhapura District** (dry zone – high water stress, ideal for smart irrigation)
- **Kurunegala District** (mixed zone – diverse crops, high smallholder density)
- **Kandy District** (wet zone – fruits and spices, access to semi-urban markets)

Target population:

- 15–20 smallholder farmers cultivating vegetables, fruits, or spices on 1–6 acres.
- Preference will be given to farmers who express interest in market access and product traceability.

Technology focus:

- Soil moisture sensors
- Weather stations
- Smart irrigation controllers
- Data visualization mobile apps
- QR code-based traceability for produce

Market engagement:

- Initial partnerships with local cooperatives and aggregators
- Buyer feedback loops for quality-based pricing
- Potential integration with digital marketplaces (e.g., AgriX, e-Satakaya)

This project does not aim to implement high-cost, large-scale commercial systems. Instead, it focuses on **affordable, replicable, and scalable solutions** that align with smallholder realities. This ensures that the outcomes are not only academically significant but also **practically applicable** and ready for policy and institutional uptake.

The intersection of digital tools with market systems—as highlighted by Kush et al. (2024)—forms the strategic core of this project. By embedding traceability, data access, and buyer connection directly into the farming cycle, the project promises a more inclusive and competitive agricultural ecosystem.

9 LITERATURE FOUNDATION AND THEORETICAL FRAMEWORK

9.1 Literature Review

The development of IoT in agriculture is a component of a larger worldwide movement to digitize food systems in order to increase competitiveness, sustainability, and production. According to Geng (2017), IoT technologies are now essential to precision agriculture because they let farmers automate processes, keep an eye on the environment, and make decisions based on data that is updated in real time. These digital tools can improve input application, reduce human error, and minimize waste—all of which are long-standing inefficiencies in small-scale agriculture. However, there are still disparities in the uptake of these tools, especially in underdeveloped nations like Sri Lanka where major obstacles include cost, digital literacy, and technological confidence.

Wortmann et al.'s (2024) idea of "products as services" builds on this digital transition. They contend that the production and documentation of agricultural products are now equally as important as the actual product. Crops with digital signatures—proofs of quality, traceability, and sustainability—can be used in premium markets thanks to the Internet of Things. Farmers are now able to engage in value-added activities that go beyond the farm gate thanks to the transition from product-centric to service-oriented agriculture. Buyer communication, data transparency, and traceability become vital resources, especially for smallholders aiming to access export or institutional markets.

Kush et al. (2024) stress that digital inclusion is a requirement for competitive market participation from an agriculture standpoint. They draw attention to the necessity of funding digital technologies, supportive infrastructure, and farmer training. Additionally, they emphasize that the adoption of technology must be in line with rural farmers' socioeconomic circumstances. Because they ignore smallholders' everyday challenges, goals, and limitations, top-down technological solutions frequently fall short. In addition to hardware deployment, training, trust, and integration with current farming and marketing systems are also necessary for successful adoption.

Smallholder farmers in Sri Lanka have particular difficulties due to the country's unpredictable environment, water scarcity, reliance on middlemen in the market, and unstable prices. Few people have practical experience with IoT applications, and even fewer are able to convert digital tools into improved market outcomes, despite the fact that many

are aware of them. At this point, it becomes crucial to combine market-oriented tactics with intelligent farming equipment.

9.2 Theoretical Framework

As used in this research, the **Net Valence Model (NVM)** offers a strong conceptual framework for comprehending and influencing farmers' decision-making procedures. According to the paradigm, before choosing to adopt a new technology or activity, people balance perceived positive valences (**benefits**) against negative valences (**risks or concerns**). Adoption is more likely to occur when perceived advantages exceed perceived dangers; when risks predominate, adoption is more likely to be postponed or refused. The following positive valences have been found through empirical research in the context of IoT-based farming in Sri Lanka:

- **Perceived Productivity:** The conviction that IoT would boost output, optimize inputs, and enhance judgment.
- **Perceived Convenience:** The idea that IoT enables remote monitoring, saves time, and minimizes work.

The negative valences include:

- **Perceived Complexity and Reliability:** Concerns about system failures, technical difficulty, and the need for external support.
- **Perceived Cost and Privacy Risks:** Worries about affordability, data misuse, and long-term maintenance.

The project team can target both motivators and barriers by using the NVM. The initiative seeks to boost adoption rates by reducing worries about cost and dependability (via local support and subsidies) and increasing the visibility of productivity and convenience (through training and field outcomes). This dual-focus paradigm maintains its behavioral theoretical foundation while encouraging practical participation.

Additionally, Wortmann et al. (2024) and Kush et al. (2024), who support user-centered design in agricultural technology initiatives, concur with the NVM's suggestions. This framework provides a strategic basis for this pilot as well as any subsequent initiatives aimed at expanding smart agriculture in areas with limited resources.

10 METHODOLOGY AND ACTION PLAN

In order to assess the efficacy of IoT-based smart farming in small-scale agricultural settings throughout Sri Lanka, this pilot project uses a real-world implementation technique. The entire agricultural cycle—from planting and land preparation to real-time monitoring, harvesting, and market delivery—is covered by the action plan, which is intended to lead 10–15 farms through a methodical procedure. The approach raises agricultural output, enhances produce quality, and satisfies market expectations by fusing locally tailored IoT technologies with precision agriculture concepts.

10.1 Selection of farms and crops

- **Geographic Focus:** Farms will be selected from the Anuradhapura, Kurunegala, and Kandy districts.
- **Criteria:** Farmers must manage 2-3 acres of land, cultivate vegetables, fruits, or spices, and the farmers willing to invest in technology adoption.
- **Crops Selected:**
 - **Vegetables:** Chili, tomato, brinjal
 - **Fruits:** Papaya, banana
 - **Spices:** Ginger, turmeric

These crops were chosen due to their local demand, short-to-medium harvest cycles, and sensitivity to moisture, temperature, and fertilization—factors easily optimized using IoT tools.

10.2 Technical equipment sourcing and procurement

- A proper **procurement plan executed for sourcing the necessary digital equipment, based on the quality, durability, and warranty claims**, will identify the vendors for calling for quotations and execute purchasing:
- In the first stage, we will buy the following equipment;
 - Soil moisture and pH sensors
 - Weather sensors (temperature, humidity)
 - Solar-powered IoT nodes and data loggers
 - Drip irrigation controllers
 - Mobile dashboard integrations (smartphone apps)

- All devices will be locally sourced where possible to ensure availability of spare parts and after-sales servicing.

Procurement Process:

- **Request for Quotation (RFQ)** from verified suppliers
- Quality checks on sensor accuracy and device durability
- Pre-deployment testing at a partner university or demo farm
- Finalizing the vendors and processing the purchasing

10.3 System installation and connectivity

- A **tech support team** (2–3 trained IoT technicians) will oversee installation on each farm. “The technicians will work as freelancers in each area, the farmers will pay the freelancer technicians based on the dates visited and the job done.
- Device installation will be customized per crop type and terrain:
 - Soil sensors: 6–12 inches depth based on root zone
 - Weather units: Mounted on poles in open areas
 - Drip systems: Calibrated based on crop water needs

Connectivity Setup:

- Preference for GSM modules (mobile SIM-enabled) for rural signal access
- Backup systems (solar-powered batteries and offline logging) for areas with unreliable electricity

A **maintenance schedule** will be created for recalibrating devices every 30 days.

10.4 Pre-implementation: soil preparation and baseline survey

- Conduct **baseline soil analysis** using portable soil testers connected to IoT platforms.
- Assess **pH, moisture retention capacity, and organic content**.

- Based on sensor data, create **soil enrichment plans** using composting and organic fertilizers.
- Document the current **crop yield and input-output ratio** for each farm.

10.5 Farmer Training and Digital Literacy Support

Training will be delivered in **three progressive stages**:

Stage 1: Initial Onboarding

- Orientation on the project's goals and benefits of IoT farming
- Introduction to sensor types and what each measures

Stage 2: Hands-On Device Use

- How to operate and troubleshoot basic IoT tools (with visual aids)
- Reading data from mobile dashboards (simple icons, thresholds, color coding)
- Safety and equipment care

Stage 3: Decision-Making from Data

- **Interpreting sensor outputs** to adjust:
 - Irrigation timing and amount
 - Fertilizer type and frequency
 - Pest and disease control timing (based on temperature/humidity)
- Using app-based alerts to **act on thresholds**:
 - “Soil moisture below 20% – irrigate now”
 - “Temperature >35°C – cover crops or apply stress mitigation”
 - “Rain predicted – delay watering”

Training Tools:

- Visual flipbooks and videos in Sinhala/Tamil
- WhatsApp help group
- Monthly in-field group discussions

10.6 Ongoing Technical Support and Maintenance

The initiative will create a dual-approach support plan employing local freelance experts and equipment providers to guarantee the IoT systems continue to function without interruption. First, at the time of procurement, vendor agreements will be used to secure technical support. Every provider of IoT devices will have to provide initial calibration, limited on-site setup assistance, and warranty-based maintenance for a predetermined amount of time (usually 6–12 months).

This will guarantee that all devices are installed and setup by professionals who are experienced with the system, cutting down on troubleshooting delays.

Second, the project will hire qualified independent technicians on a project-by-project basis to handle persistent field-level problems. These people will be in charge of routine maintenance, small repairs, and resolving issues with sensor connectivity or irrigation automation. Ideally, they have some basic ICT or agri-tech knowledge. The technician will be paid per visit or device check, and farmers can request assistance as needed.

Flexibility, lower long-term personnel costs, and increased local capacity for smart farming support are all benefits of this job-based freelance approach. Farmers will also receive basic training during installation to aid them with basic activities like cleaning sensors or resetting devices, which will boost their confidence and lessen their need on outside assistance.

A **maintenance checklist** and **service request protocol** will be established to document and streamline all support activities.

10.7 Data Collection, Monitoring, and Evaluation

IoT dashboards will collect:

- Soil moisture, humidity, pH, and temperature every 15 minutes
- Irrigation volume logs
- Plant growth phase tagging (via mobile app)

Farmer dashboards will show simplified data:

- Traffic-light indicators for soil (green = optimal, red = too dry)

- Recommendations: “add compost”, “delay watering”, “apply potassium”

Monthly evaluations will compare:

- Yield increases
- Input use (water, fertilizer, labor hours)
- Farmer adoption and comfort using devices

10.8 Market linkages and economic integration

Ensuring that farmers can sell their produce profitably is just as important to the IoT pilot project's success as increasing crop quality and yield. Connecting participating farmers with relevant market channels, increasing pricing leverage, and implementing value-based branding that highlights the advantages of smart farming are the main objectives of this action plan.

10.8.1 Action plan for market integration

a. Real-Time Price Monitoring through Mobile Platforms

- Farmers will be trained to use existing **mobile apps** like **GovPrice, Govi Mithuru, or AgriPrice** to:
 - Track real-time wholesale and retail prices in major markets (Dambulla, Narahenpita, Meegoda)
 - Identify when and where to sell their harvest
- A simplified **SMS alert system** will notify farmers of best current rates for selected crops.

b. Linkages with Local Collectors and Exporters

- The project team will engage:
 - Registered collectors in each district
 - Export-oriented buyers (especially for chilli, turmeric, papaya)
- Formal **Memoranda of Understanding (MoUs)** will be signed with at least 3 buyers or exporters to absorb bulk quantities.

- Buyers will receive early production forecasts based on IoT dashboards, helping them plan transport and storage in advance.

c. Participation in Regional Wholesale Hubs

- Organize **cluster-based bulk selling**, where 3–5 farmers combine harvests to negotiate better prices.
- Coordinate with established markets like:
 - Dambulla Economic Centre (North Central)
 - Kurunegala Wholesale Market
 - Kandy Central Market

Farmers will be supported to bypass middlemen by using mobile logistics services like **PickMe Trucks** or community vehicles.

d. Demand-Based Crop Planning

- IoT data + market trends will guide farmers in choosing high-demand crops for the next season.
- A "market forecast bulletin" (prepared by the project team) will help predict:
 - Off-season opportunities
 - Export demand cycles
 - Festival/seasonal price peaks

e. **"Smart Produce – Tech-Enabled, Quality-Assured"** is the brand name.

Put a "Smart Produce" label on the crop attesting to the fact that it was:

- Grown using data-driven irrigation.
- monitored for soil and climate stress.
- Free of excessive pesticide use.
- labeled on packaging at collection points.

And working in conjunction with the Sri Lanka Export Development Board and Sri Lanka Standards Institution (SLSI) to align certification in the future.

f. Agribusiness Partnerships and Buyers' Day

- Organize a “**Buyers' Meet**” in the third month of the project to showcase pilot farms' early results.
- Invite supermarket chains (Cargills, Keells), exporters, and food processors to form early-stage partnerships.

10.8.2 Impact Targets

1. **10–20% increase in average selling price** through better timing, branding, and collective bargaining.
2. **25% reduction in post-harvest losses** due to better harvesting scheduling and immediate market linkage.
3. Stronger **market literacy** among farmers to navigate price dynamics independently after project completion.

11 BUDGET, TIMELINE, AND RISK MANAGEMENT

11.1 Estimated budget for 12 pilot farms

Table 10 Budget

Category	Unit Cost (LKR)	Quantity	Total (LKR)
IoT Devices (soil, temp, drip kits)	25,000	12	300,000
Connectivity (data SIM)	1,000/month	6 months	72,000
Installation & Setup	5,000	12	60,000
Training & Materials	3,000	12	36,000
Freelance Tech Support	2,000 per farm	12	24,000
Branding & Packaging Materials	Lump sum	—	15,000
Monitoring, Travel & Fuel	Lump sum	—	30,000
M&E and Reporting	Lump sum	—	15,000
Contingency (10%)	—	—	55,200
Total	—	—	607,200

The IoT Smart Farming Pilot Project is expected to cost LKR 607,200 to implement across 12 small-scale farms. All facets of the project lifecycle—technology, operations, training, monitoring, and evaluation—are intended to be supported by this budget. The majority (LKR 300,000) goes toward purchasing IoT devices, such as temperature monitors, drip irrigation kits, and soil moisture sensors—all crucial for automating and improving crop care. Mobile data SIMs are covered by connectivity charges (LKR 72,000) for a period of six months, allowing for ongoing data transmission in places without dependable internet. Trained professionals will handle the installation and setup (LKR 60,000), making sure that the gadget is calibrated and positioned correctly.

In order to increase local capacity, LKR 36,000 has been allocated for farmer training and educational materials, and LKR 24,000 has been allocated for freelance technical support, which guarantees that farmers receive help when they need it. The launch of "Smart Produce" will be supported by branding and packaging (LKR 15,000) for increased market value. Additionally budgeted are field trips, travel, monitoring, and final reporting. A contingency reserve of 10% (LKR 55,200) protects against unforeseen expenses. This

budget illustrates a realistic and expandable strategy for smart farming in the rural areas of Sri Lanka.

11.2 Timeline

Table 11 Action timeline

	September 2025	October 2025	November 2025	December 2025	January 2026	February 2026
Initiation and planning						
Procurement and pre-installation						
Installation and initial training						
Operation and monitoring						
Harvest planning and market linkages						

The suggested action plan covers every significant stage of the pilot project in a realistic and sequential fashion over a six-month period, starting in September 2025 and finishing in February 2026. In September 2025, the project will start with planning and initiation, where the project team will be formed, farms will be chosen, and contracts will be signed. At the same time, pre-installation and procurement procedures, such as locating IoT devices and employing independent technicians, begin in October.

November 2025 is the planned date for installation and the first farmer training. Device setup, app demos, and practical instruction are all part of this phase. Following system installation, real-time monitoring and operation start in December and last through January, gathering information on crop health, irrigation requirements, and soil conditions. Sensor information will be used by farmers in January 2026 to plan harvests and prepare for markets, including branding and liaising with local purchasers. The project's final data review, assessment, and reporting take place in February 2026. This well-paced schedule

guarantees that every stage is carried out completely and gives time to resolve any issues at the field level before making judgments.

11.3 Risk mitigation strategies

Table 12: Risk Mitigation

Risk	Description	Mitigation Strategy
Device Malfunction or Failure	IoT devices may stop working due to harsh field conditions, improper handling, or technical errors.	- Procure devices with at least 6–12 months warranty. - Use rugged, weather-resistant hardware. - Partner with vendors offering onsite tech support. - Keep 1–2 extra devices as backup.
Low Digital Literacy Among Farmers	Some farmers may struggle to interpret app data or operate dashboard functions.	- Deliver hands-on training using demo farms. - Use visual aids, posters, color-coded alerts, and simplified icons. - Conduct regular follow-up sessions and peer learning groups.
Connectivity Issues (Mobile/Internet)	Some rural areas may experience weak mobile signal or unreliable power supply, affecting data transmission.	- Use GSM-enabled sensors (SIM card based, not Wi-Fi reliant). - Install solar-powered backup batteries. - Enable offline data storage with periodic upload via mobile.
Resistance to Technology Adoption	Farmers may distrust new systems or see IoT as irrelevant to traditional practices.	- Engage farmers early in planning and setup. - Share testimonials from other local users. - Offer incentives, such as seed packs or drip kits for participation.
Data Misinterpretation	Misreading of sensor data could lead to wrong decisions (e.g., over-watering or late fertilizing).	- Set pre-programmed thresholds and alert messages in local language. - Provide a monthly advisory bulletin based on collective sensor data. - Assign a field tech to cross-verify data.
Technical Support Delays	Dependence on freelance support may cause delays in case of urgent troubleshooting.	- Develop a rotating support calendar with 2–3 trained freelance technicians. - Provide farmers with a basic troubleshooting guide. - Maintain spare parts toolkit at cluster level.
Mismatch with Market Needs	Farmers may grow crops not aligned with current demand, limiting their profit even with better yields.	- Use real-time market data apps (Govi Mithuru, GovPrice). - Offer demand-based crop planning guidance before each season. - Help link to contract buyers or wholesalers.
Post-project Sustainability	After the pilot ends, farmers may abandon IoT use due to	- Train local youth or Agri-extension officers as IoT agents.

maintenance costs or lack of continued guidance.

- Explore **group ownership of sensors** (e.g., farmer cooperatives).
 - Seek **government or NGO partnerships** for scaling support.
-

12. Sustainability, Policy Alignment, and Scalability

The success of this pilot initiative depends on ensuring its long-term viability. Farmers will keep the deployed IoT equipment once the pilot period is over, allowing them to continue taking advantage of data-driven farming and real-time monitoring after the experiment is over. This strategy keeps the adoption momentum intact and aids in integrating the technology into standard farming procedures.

The concept suggests creating a community-based economic model in collaboration with agricultural cooperatives to control operating expenses and system upkeep. Member farmers will pay a small monthly fee under this model to cover technical assistance, training, and basic upkeep. Long-term financial sustainability and farmer-centricity are guaranteed by this paradigm.

Additionally, agri-tech enthusiasts and local kids will receive training to become freelance IoT technicians, increasing employment in rural areas and developing a pool of qualified service providers. This localized support system increases community capability and lessens dependency on outside vendors.

By increasing agricultural output and resource efficiency, the project supports UN Sustainable Development Goal 2: Zero Hunger and is directly in line with Sri Lanka's National Agriculture Policy on Digitization. With the help of donor organizations, corporate agribusiness partners, and provincial government agricultural subsidies, the existing framework can be expanded to more than 100 farms if it proves to be successful. Its modular architecture allows it to be tailored to various crops and geographical areas, facilitating the transition of smart farming across the country.

13. CONCLUSION AND RECOMMENDATION

From theoretical research to practical agricultural innovation, this IoT-based smart farming pilot project provides an essential first step. It not only confirms farmer attitudes but also creates a workable path for digital agriculture in Sri Lanka by including frameworks supported by research, such as the valence model, which is used to evaluate perceived benefits and hurdles.

The initiative effectively illustrates how data-driven methods may enhance crop quality, maximize water use, and provide small-scale farmers with useful information. It shows that although there may be obstacles to IoT adoption, like a lack of digital literacy or infrastructure, these can be addressed with focused training, regional assistance, and farmer participation at every level.

A number of recommendations are put forth in light of the pilot's findings:

- **Scale-up:** Expand comparable IoT implementations to additional areas and high-value crop zones (such as the Eastern Province for rice or Nuwara Eliya for leafy vegetables).
- **Training Infrastructure:** To ensure that new users are supported and to develop long-term capacity in digital agriculture, establish regional training hubs.
- **Policy Support:** Promote tax breaks, microloans, and subsidies for local startups making reasonably priced sensor kits and for farmers implementing IoT technologies.

The ultimate goal of this initiative is to integrate technology into the agricultural cycle in order to revolutionize rural livelihoods. Sri Lanka can take the lead in climate-resilient, tech-driven, and sustainable farming systems thanks to a combination of capacity building, policy alignment, and practical execution.