CHAPTER I INTRODUCTION

I.1 Background

Over the past decade, agriculture has entered a data-driven era that mirrors earlier transformations in finance and health care. Market analysts estimate that global expenditure on artificial-intelligence (AI) solutions for farming stood at roughly USD 1.5 billion in 2023 and will expand to about USD 10.2 billion by 2032, implying an average compound annual growth rate of 24.5 percent (Pangarkar, 2025). The largest share of that investment is projected for machine- and deep-learning engines, followed by predictive-analytics platforms and computer-vision systems. Figure I-1 illustrate both the commercial momentum behind agricultural AI and the growing expectation that digital tools can help agricultural systems meet rising global demand.

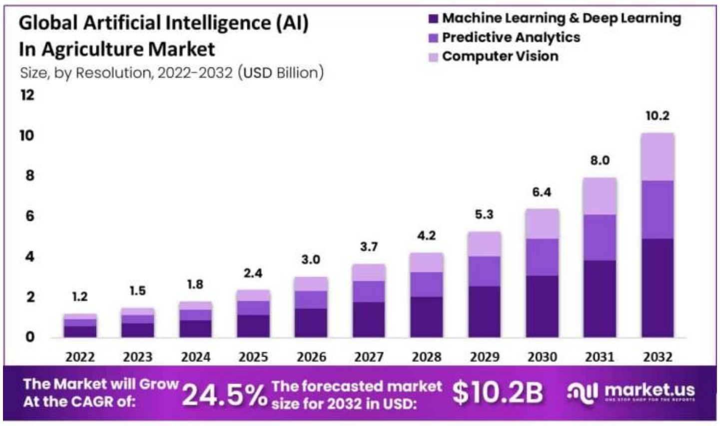

Figure I-1. AI in agriculture market size. (Source: https://scoop.market.us/ai-in-agriculture-statistics/)

Indonesia, however, shows a disconnect between these rapid diffusion of emerging technologies and day-to-day farm management practices. Badan Pusat Statistik or BPS, recently reported that 46.84 percent of the nation’s 28 million farmers now own modern machinery or digital devices, yet only 10.8 percent of rice farmers actually use the Internet to obtain agronomic information (Mardiyanto, 2023; Ruslan & Prasetyo, 2021). This discrepancy highlights that despite technological availability, many farmers still rely heavily on traditional knowledge and rarely benefit from online agricultural resources. These Traditional agricultural practices often rely on experience, local knowledge, and word-of-mouth recommendations passed down through generations (Carolan, 2018). While invaluable, these methods can be limited in scope and may not always account for factors such as climate change, market trends, or emerging agricultural techniques.

Parallel developments worldwide suggest what more comprehensive information pipelines could achieve. A recent Market.us survey of precision-agriculture activities found that farm-management platforms already account for 35 percent of IoT- and AI-enabled use cases, while weather-forecast decision tools and agricultural-learning systems contribute 20 percent and 15 percent, respectively (Pangarkar, 2025). These adoption patterns highlight a shift from single-function technologies toward integrated decision support. They also point to an opportunity for Indonesian stakeholders to jumpstart incremental solutions by focusing on inclusivity and ease of use.

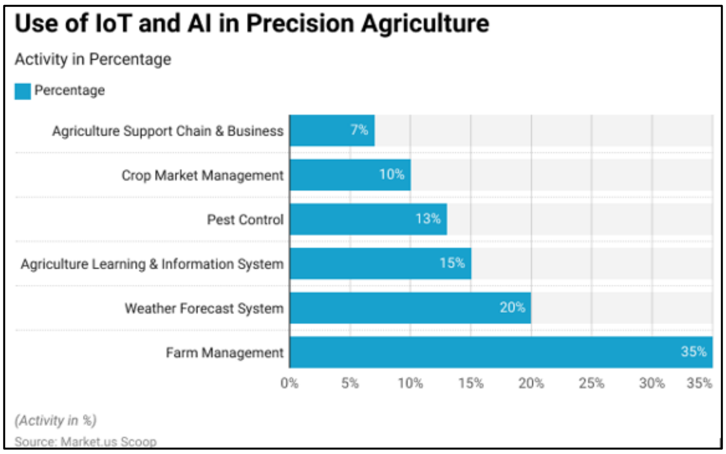

Figure I-2. Distribution of IoT and AI technologies in agriculture sector. (Source: https://scoop.market.us/ai-in-agriculture-statistics/)

Yet translating that broad "digital-age" promise into day-to-day practice hinges on the one segment that both owns the phones and still works the fields: millennial farmers (19-39 years) in Bandung and Bali. BPS tabulations released for the 2023 Agricultural Census show that this age group now accounts for about 17 % of West Java's farm workforce and only 15.18 % of Bali's 361 673 farmers, evidence of a widening regeneration gap (BPS-Statistics Indonesia Jawa Barat Province, 2024; Kurniawan et al., 2023). Paradoxically, independent baselines for the West Java Millennial Farmer program and a PRISMA youth study report smart-phone and daily-internet use above 80–90 % among these young farmers, nearly triple the rate observed in older groups, while a Kopernik field survey in Tabanan confirms “good internet access and strong digital literacy” even in hillside coffee plots (BEAM Exchange, 2021; Dwiarrahman, 2025). Focusing on this tech-savvy yet information-constrained group therefore offers the clearest near-term pathway to impact: a low-bandwidth, AI-powered mobile assistant can convert their connectivity advantage into timely, trustworthy guidance, while also making farming more attractive to the very generation whose continued exit would deepen Indonesia’s ageing-farmer crisis.

Prior studies illustrate steady advances in digital agriculture, yet they also expose several unresolved shortcomings. Kumar (2023) showed that farmers in six districts of Haryana increasingly rely on mobile apps such as Kisan Suvidha and WhatsApp to obtain price and production updates (Kumar, 2023). Nevertheless, respondents still cited “language difficulties and challenges in the mobile network” as persistent obstacles to deeper engagement with digital advisory services.

Building on simple information push, Bhuvaneswari et al. (2024) integrated Gaussian-Naïve-Bayes crop-recommendation logic with a VGG-16 transfer-learning module for disease detection inside an AI-driven chatbot (Bhuvaneswari et al., 2024). The prototype answered text queries accurately under laboratory conditions, yet it handled only a small set of crops and diseases with another limitation of only typed input, leaving open questions about inclusivity, multilingual support and accessibility for users with low literacy.

A different stream of work, exemplified by Rashmitha et al. (2022), tackles farmers’ capital constraints by enabling investor-farmer collaboration on a digital trust basis through blockchain-based crowdfunding platforms that record transactions, therby increasing financial transparency. While promising for finance, their systems does not rnish agronomic devcision support and farmers still have to look elsewhere for husbandry advices (Rashmitha et al., 2022).

Computer-vision related solutions also appear in the literature. Hasan et al. (2023) demonstrates the potential of using devices and mobile applications to analyze the types of diseases present in rice plants (Hasan et al., 2023). However, the research conducted by Hasan and their colleagues seems to be limited to one type of crop and require further tuning for additional criterias.

Collectively these studies demonstrate the value of mobile and AI technologies but stop short of delivering a voice-enabled, Bahasa Indonesia centric virtual assistant that can reason across multiple crops and run on low-cost Android handsets while using only modest data bandwidth. Verdant addresses precisely this gap: although it still requires an active internet connection, its Whisper-powered speech interface, GPT-4o multi-crop reasoning, and lightweight Flutter design lower the literacy barrier and streamline information retrieval for farmers operating under real-world connectivity constraints (Mushtaq et al., 2024; Rawas, 2024).

The present study seeks to close that gap through the development of Verdant, a mobile application that fuses three technologies: OpenAI's GPT-4o for context-aware agronomic reasoning in local languages, Whisper automatic-speech recognition for hands-free queries, and a Flutter front-end optimized for low-specification hardware. By uniting these components, Verdant aims to deliver real-time recommendations on nutrient management, pest diagnosis and market timing while preserving conversation histories for further review. In doing so, the application addresses the usability barriers identified by BPS and the functional limitations noted in prior studies.

I.2 Problem Statement

Despite the increasing availability of smartphones and internet access in rural areas, a large proportion of Indonesian farmers still struggle to obtain and apply reliable agricultural information due to barriers such as low digital literacy, language constraints, and the absence of user-friendly advisory systems. These conditions raise the following research questions :

1. How can farmers acquire agricultural information more easily and reliably through the use of digital technologies?
2. How to determine usability performance of the proposed solution?
3. What is the level of user acceptance and usability of the proposed system among its target users?

I.3 Research Objectives

To address the problems above, this research is conducted with the following objectives:

1. To design and develop a mobile-based recommendation system driven by AI that is easy to use and delivers reliable agricultural information for farmers.
2. By conducting usability testing of the developed system using methods such as the System Usability Scale (SUS), Single Ease Question (SEQ), User acceptance testing, and black box testing using postman.
3. To conduct user acceptance testing (UAT) to assess whether the target users are willing to adopt and use the developed application in practice.

I.4 Research Benefits

This research is expected to provide the following benefits:

1. For farmers and farming enthusiasts, especially those in rural and underdeveloped regions, the system offers a more accessible and affordable way to obtain reliable agricultural recommendations, helping them in increasing productivity, reduce losses, and make better-informed decisions without needing advanced digital skills or formal education.
2. For future researchers and developers, this study serves as a case example of implementing AI-based conversational systems (ChatGPT and Whisper) in agriculture, demonstrating their potential to bridge communication gaps and inspire further development of inclusive technologies.
3. For the academic and public sector, the prototype developed through this research can act as a foundation for policy-driven digital transformation programs in agriculture, helping governments and institutions target support where digital infrastructure exists but remains underutilized.

I.5 Final Project Scope and Assumptions

The scope of this research outlines the boundaries within which the study is conducted, including the conditions and assumptions established based on the problem formulation. The scope should neither be too broad nor too narrow to remain realistic and aligned with the actual research situation. Scope can include aspects such as the data used, problem characteristics (deterministic, probabilistic, or stochastic), budget constraints, time limitations, and other relevant factors. This scope defines the specific conditions under which the proposed solution or research findings are considered applicable. The scope of this study includes the following:

1. The respondents involved in this study are young farmers and farming enthusiasts (≈ 20–35 years old) living in the peri-urban agricultural zones of Bandung, West Java, and Denpasar, Bali, thereby tailoring the solution to the technological habits of this demographic.
2. The agricultural recommendations provided by the application are generalized and focus on commonly encountered issues in tropical farming.
3. The development and testing of the mobile application are limited to the time period of January-March 2025, within the scope of the final undergraduate project.
4. The mobile application is designed to run on Android devices only and does not yet support iOS or web-based platforms.
5. The study focuses on integrating speech-to-text and natural language processing for recommendation delivery, with some image-recognition capabilities provided by the OpenAI APIs.
6. The technical focus centres on Whisper speech-to-text and GPT-4o natural-language generation, with image-analysis calls included only as demonstrative features rather than fully tuned agronomic classifiers.

Assumptions are conditions or statements considered to be true for the purposes of simplifying the research and analysis process. They are used to manage the complexity of the system being developed and allow for more focused evaluation. This research is based on the following key assumptions :

1. All participants own Android 15 or above smartphones equipped with at least 4 GB RAM, and a stable 3G or better mobile-data connectivity.
2. Farmers are willing to use voice or text interfaces when interacting with the application.
3. Speech input from farmers using Whisper can be processed with acceptable accuracy, assuming clear pronunciation in standard Indonesian or common regional dialects.

4. Usability scores obtained through SEQ, SUS, and UAT instruments faithfully represent genuine user experience within laboratory and limited field conditions, even though those conditions only approximate the diversity of real-world environments.

Limitations are factors that set the boundaries of a study so its findings are read in the proper context. They are used to spell out the real-world conditions, such as time, place, and resources within which the work was carried out, and they help readers see where the results may or may not apply. Stating these limits is not a sign of weakness, rather, it clarifies the practical constraints guiding the project. This study is shaped by the following main limitations:

1. Because the sample is geographically bounded to Bandung and Denpasar, the behavioural insights and usability metrics chiefly represent young, smartphone-literate farmers in these hubs; regions with markedly different socio-technical profiles may yield divergent outcomes.
2. All evaluations presuppose continuous mobile-data connectivity of at least 3G quality; yet Indonesia is actively repurposing 3G spectrum for 4G/5G, and temporary service gaps or legacy-only areas could degrade performance outside the test locales.
3. The modest participant pool (n = 10 for SUS/SEQ and n = 5 for UAT) limits statistical power, so acceptance and usability figures should be interpreted as indicative rather than definitive.
4. All benchmarking was carried out on mid-range Android 15 devices that satisfy the 4 GB RAM baseline; responsiveness on lower-specification handsets remains unverified.

I.6 Final Project Report Schematics

This final project report is structured into six main chapters, each systematically developed to reflect the author's thought process in identifying the core problem, designing the proposed solution, and validating its implementation. The structure is designed to organize the logical flow of the research, from the initial problem formulation to the deployment of a functional solution.

Chapter I serves as the introduction, presenting the background and rationale for the research, which focuses on the information gap experienced by farmers—particularly in rural Indonesia—despite the increasing availability of digital technologies. The author articulates the problem clearly by highlighting barriers such as low digital literacy and language limitations that prevent farmers from utilizing existing digital agricultural tools effectively. This chapter also outlines the objectives, scope, benefits, and report structure, setting the foundation for the overall direction of the study.

Chapter II provides a literature review that delves into the specific technologies employed in the research. This includes the Flutter framework for front-end development, Flask for backend architecture, ChatGPT for natural language-based recommendations, and Whisper for speech-to-text input. Each subsection critically discusses not only the functionality of these tools but also their relevance and justification for use within an agricultural context. Furthermore, the chapter introduces usability testing methods (SUS, SEQ, and UAT) and prior related studies to identify the specific gaps this research aims to address.

Chapter III details the research methodology, which adopts a prototyping approach tailored to the exploratory nature of the system being developed. Each subchapter corresponds to a specific phase of the development cycle—initial requirements, design, prototyping, user evaluation, revision, implementation, and deployment. The use of prototyping allows for iterative feedback from stakeholders, particularly farmers and agricultural enthusiasts, ensuring that the system evolves in alignment with user needs and real-world limitations. The research also references the Hevner framework to structure the development process academically and methodologically.

Chapter IV focuses on the analysis and system design phase. It begins with the identification of specific user and system requirements, followed by a series of formal models such as use case diagrams, activity diagrams, sequence diagrams, and class diagrams. These models are not presented as generic artifacts but are developed based on actual user scenarios and anticipated interactions with the application. Through this design process, the author demonstrates how the system architecture was constructed to support accessibility, ease of use, and responsiveness for users with varying levels of digital proficiency.

Chapter V presents the results of the system development and evaluation. The author describes the actual implementation of the application, including user interface design, backend integration, and API interaction testing followed by a detailed analysis of the usability testing outcomes. The use of SEQ and SUS instruments provides empirical validation of the system's accessibility and user satisfaction. This chapter also reflects on user feedback gathered during controlled evaluations and discusses how these insights informed system refinements, particularly in improving speech input accuracy and simplifying recommendation outputs for agricultural users.

Chapter VI concludes the report by summarizing the key findings and proposing suggestions for future development. The conclusion emphasizes the relevance of AI-driven, voice-accessible systems in overcoming information accessibility barriers in agriculture. The suggestions address potential expansions of the system.