

Exploring The Adoption of Artificial Intelligence in Palm Farming for Sustainable Agricultural Practices

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Abstract:

Artificial Intelligence (AI) is slowly transforming agricultural activities, offering agriculture novel means to enhance efficiency, sustainability, and productivity. This paper presents the use of AI in palm farming through a qualitative research methodology employing semi-structured interviews among stakeholders for creating determinants influencing AI adoption. As proposed by the Unified Theory of Acceptance and Use of Technology (UTAUT), four fundamental determinants of nature—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—have been considered in the research as well as other determinants from the interview. They are Financial Barriers, Data Privacy Concern, Data Availability, and Trust and Acceptance of AI that are pivotal to the adoption level. Through expansion of the UTAUT model, the research formulates an integrated AI adoption model in agriculture. Implications for action are developed within the research by proposing financing subsidies, policy guidance, and farming training programs for the stimulation of AI adoption. The results findings to inform sustainable agriculture practices under which enguraging driven by AI provide long-term efficiency and resilience in palm cultivation.

Keywords: Artificial Intelligence, palm farming, qualitative study, technology adoption, UTAUT model

1. Introduction

Agriculture is a cornerstone of human life, and technology has changed its practice radically. One of such changes is the rise of artificial intelligence (AI) as a revolutionary tech giving data-driven knowledge on how to enhance operability, optimize resource usage, and ease environmental pressure. For palm growing, AI can revolutionize custodian agricultural practice. AI adoption for palm growing, however, is contingent on several factors, such as technological readiness, economic resources, society acceptance, and regulation. These factors together establish the extent to which AI technologies can be best utilized in date palm agriculture to maximize productivity and sustainability (Al-Khayri et al., 2021). There is a possibility that an understanding of

these factors through a qualitative analysis may present insightful information on the prospect and challenges of using AI in palm agriculture.

AI application for precision agriculture has shown great potential for intensifying management and productivity at agricultural farms. AI technologies like sensor-based technologies, drones, and machine learning algorithms enable crops, environmental, and soil assessment on a real-time basis, allowing for easy decision-making for better decisions (Pandey et al., 2024). For AI-optimized irrigation under palm trees, optimum management of water is done considering soil moisture contents, as well as meteorological factors, without checking wastages, and encouraging environmentally friendly agricultural practices (Mohammed et al., 2021). Furthermore, AI promotes early infirmities recognition of fungal infection and pest infirmities based on image recognitions, prediction, and forecasting for farmers to initiate measures for avoiding damages to other crops (Gibril et al., 2023). These innovations indicate the potential of AI for transformative date palm trees cultivation based on enhanced efficient performance, labor reduction, and a wise use of resources. Nevertheless, large-scale implementation remains a waiting game for crossing a series of technological, as well as socio-economic barriers. Despite holding a high potential, AI implementation for date palm trees remains faced with a number of problems, which make adoption a thorn on the flesh (Maged et al., 2023). The biggest challenge, amongst others, remains technological infrastructure for facilitating AI-enabled systems for effective implementation (Pandey et al., 2024). Large-scale date palm plantations, especially those established in developing regions, lack high-speed satellite coverage, cloud computing, advanced AI-enabled mechanizations, which limit their capacity for effective adoption (Maged et al., 2023). Besides, AI technologies rely, predominantly on technical expertise and knowledge, therefore, forming a barrier for farmers, who might not necessarily be experts on computer platforms, nor data-informed decision-making processes (Pandey et al., 2024). Financial limitations also contribute to such constraints as the use of AI involves considerable investment in machines, software, and training modules. Small-scale farmers, the dominant group in the palm farming sector, might not be able to afford such technology individually and would require assistance from governments or private companies. Bridging these technological and financial challenges is a major key to bringing AI within reach of palm farming operations on an equal basis. Other than technology and economy, social and regulatory factors play a central role in determining the development of AI usage in palm cultivation.

Traditional agriculture is dependent on home culture, and farmers would resist substituting tried-and-tested methods with AI models because of reliability concerns, job loss, and losing control (El Hadrami et al., 2022). There some problems in AI regulations in agriculture. They're still trying to catch up—and in many areas, they're nowhere near where they need to be. That's a real problem when you consider the sensitive terrain of data privacy, system security, and the murky ethics around how this technology is used (Diaz-Rodriguez et al., 2023). For any real progress, governments and agricultural policymakers need to move past vague intentions and lay down solid, actionable guidelines. Offering incentives to encourage ethical AI practices wouldn't be a bad idea either. But just as pressing is the need to bring farmers into the fold—not

after the fact, but right from the start. They need more than just tools; they need training that's hands-on, explanations that make sense without a tech dictionary, and guidance they can use on the ground. And while policies from above matter, real change often begins in the middle—where developers, researchers, and farming communities meet. When these groups stop working in silos and start listening to each other, that's when understanding deepens and the term "AI adoption" starts meaning something real, not just another empty industry phrase. Addressing such social, regulatory, and knowledge hurdles allows the players to establish a facilitator for AI-based innovations. AI usage for palm cultivation provides a paradigm-shift approach towards enhanced productivity, resource efficiency, and sustainability.

For AI solutions to adopt, needing to consider a variety of interconnected factors, which include how acceptable they are to society, their economic feasibility, and the necessary technological infrastructure. To support farmers' digital skills, provide affordable AI options, and create a supportive regulatory environment, it's important for legislators, researchers, and entrepreneurs to collaborate effectively. With multilateral partnerships and strategic investment, AI can be utilized to reshape the palm culture future and offer confidence against looming environmental and economic threats. With the use of AI, the agriculture sector is evolving with stand-alone solutions to address long in the pipeline issues such as optimising resources, and pests' management.

Palm plantation as part of the world's agricultural supply chain faces increasing vulnerabilities due to climate change, shifting market demands, and land use efficiency (Abubakar & Ishak, 2024). The application of AI technology like machine learning, remote sensing, and predictive analytics has accompanied colossal potential concerning palm production improvement based on sounder decision-making, disease detection, and supply chain management (Mohd Nain et al., 2022). AI technology has utilized, for instance, in autonomous weather-resistant pest control systems, agriculture, and intelligent irrigation management to minimize environmental impacts and maximize yields (Hessane et al., 2025). Since farms are becoming more digitalized, it is important to understand the drivers and barriers of AI adoption among palm farming to tap for sustainable agriculture.

Notwithstanding the envisaged advantages, several challenges are affecting AI implementation in palm cultivation, especially within developing countries whose technological infrastructure as well as technical know-how is still low (El-Mously, 2019). The integration of AI into the prevailing farming systems may prove difficult for farmers, given the prohibitive establishment costs as well as issues of privacy with data (Abubakar & Ishak, 2024). Additionally, the availability and quality of data are still overriding constraints because AI models utilize large data sets to ensure accuracy in soil testing, pest identification, and yield forecasting (Mohd Nain et al., 2022). AI-based disease management software in palm plantation has shown promising outcomes but requires robust policy frameworks, farmer capacity building, and accessible AI technology (Hessane et al., 2025). Breaking these hindrances requires a multi-stakeholder approach, from policymakers to technology developers to farmers to create an environment conducive to AI uptake. To realize the complete potential of AI in sustainable palm cultivation, coming research should seek to create even more sophisticated AI-based predictive models, expose farmers to digital technologies more,

and integrate AI with other technologies such as IoT and blockchain (Mohd Nain et al., 2022).

The integration of big data analytics, cloud computing, and decision support systems with AI potential can transform palm agriculture through improved efficiency, reduced wastage, and enhanced drivers of sustainability (Abubakar & Ishak, 2024). AI is evolving agricultural activities at record efficiency, precision, and sustainability enhancement. In palm cultivation, AI -based tools like predictive analysis, automated detection of pests, and intelligent irrigation systems have an enormous potential to improve productivity and resource utilization (Sood et al., 2022).

Yet, as far as the benefits of AI in farming are concerned, adoption occurs in an unbalanced pace from technology, economic, and behavioral viewpoints (Wang et al., 2023). In the pursuit of understanding and promoting AI adoption in palm cultivation, the current research employs the UTAUT a validated model utilized in the estimation of technology adoption in various industries (Li et al., 2024). UTAUT provides for systematic analysis of key determinants that drive AI adoption, such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Miah et al., 2024). Use of the UTAUT model in this study permits us to perform systematic analysis of determinants shaping farmers' intentions to adopt AI technology in palm farming. The model has been widely used in the interpretation of agricultural technology adoption, learning about organizational, behavioral, and technological obstacles to the broad implementation of AI (Wang et al., 2023).

Recent research has highlighted that ease of use, government support, and social influence have been central drivers to the adoption of AI-driven technologies in agriculture (Li et al., 2024). Through adoption UTAUT with agricultural AI applications, this paper will aim to build an overall framework for analyzing and breaking adoption barriers and hence driving digital transformation for palm cultivation (Sood et al., 2022).

The study will investigate the key enablers and barriers of AI adoption in palm farming using the UTAUT model, yielding pragmatic implications to policymakers, IT builders, and agricultural players. By scrutinizing factors such as technological preparedness, financial viability, and attitudes among farmers, this paper feeds into the emerging literature on agricultural sustainability and digital innovation. The results will not only provide useful information on the application of AI in sustainable palm cultivation but also act as a model for future studies on technology uptake in precision agriculture (Miah et al., 2024).

2. Literature Review

AI tools in agriculture have growing interest as a revolutionary application and softwares to enhance productivity, sustainability, and efficiency. AI, such as machine learning, computer vision, and predictive analytics, have played a key role in the development of agriculture, especially in high-value crops like date palms. Palm plantation is a very critical agricultural endeavor in arid and semi-arid areas, sustaining the indigenous people's economic life, food security, and culture. Despite this, because of its huge potential, deployment of AI to palm plantation relies on a list of factors like

infrastructure technology, cost analysis versus benefit, awareness gaps, as well as regulative frameworks (Al-Khayri et al., 2021). Additional literature is pointing to opportunities and challenges emanating from the adoption of AI in agriculture, calling for an integrated understanding of the socio-technical context influencing its adoption. The review herein acknowledges major determinants that guide the adoption of AI in palm cultivation through integrating available literature that addresses technological factors, economic constraints, social drives, and regulatory frameworks. Technological advancements with the use of AI have significantly boosted precision agriculture, offering new ways to optimize palm farming operations.

AI technologies like remote sensing, robot-based harvesting, and IoT-based monitoring systems provide real-time soil health analysis, moisture content, infestation by pests, and disease in crops (Mohammed et al., 2021). Machine learning algorithms created based on multispectral and hyperspectral images have been used to identify the early indicators of stress in palm trees so that farmers can implement early preventive measures and minimize yield loss (Gibril et al., 2023). In addition, irrigation systems powered by AI tap data analytics for efficiently optimizing the water supply to deal with date palm water shortage (Mohammed et al., 2021). Applications of computer vision technology also enhances machine learning-supported automatic sorting and grading of date fruit for better post-harvest management and marketing freshness (Pandey et al., 2024). But, successful deployment of such AI technologies is dependent on having robust digital infrastructure, including cloud computing, internet connectivity, and agri-platforms. According to research, it has been argued that regions with poor technological infrastructure face severe hurdles in adopting AI since access limitations undermine real-time data processing as well as decision support capacity (Maged et al., 2023). This digital divide requires targeted investment in digital infrastructure to enable AI-driven precision farming.

Apart from technological factors, economic factors determine the extent of involvement AI has in its adoption in palm farming. The cost of money needed to implement AI-supported systems such as sensors, drones, and machine learning modules can be excruciatingly high for small- and medium-scale farmers (Al-Mssallem et al., 2021). Furthermore, the cost of repeated upkeep of AI, data storage, and technical services is the economic problem, mainly in areas where agricultural credit is not adequate. Economic research has established that cost-benefit analysis needs to be performed for assessing whether AI, in the long term, is viable in palm cultivation as monetary return on investment is subject to variables like higher production, lower input, and better market access (Ahmed et al., 2023). Subsidies, tax credits, and public-private collaborations are most often suggested as likely means of offsetting the expense of adopting AI and promoting investment in intelligent farming equipment (Diaz-Rodriguez et al., 2023). In addition to costs, adopting AI necessitates knowledge transfer and capacity-building programs to equip farmers to acquire the capabilities to utilize AI-driven tools to maximum benefit. Literature indicates that AI technology adoption is more probable among digitally literate farmers, emphasizing the necessity for specific training and extension services to close the knowledge gap (Jonoobi et al., 2019). Consequently, overcoming economic and education constraints is crucial to enabling palm farm AI adoption. Social and cultural aspects also underpin AI adoption for palm farming, as old agricultural practices are deeply rooted within customary knowledge systems and intergenerational farming routines.

Perceptions of AI technology among farmers are formed on the basis of reliability concerns, ease of use, as well as employment market and job implications (El Hadrami et al., 2022). Research has indicated that there are farmers who oppose the use of AI-based automation, where concern of job loss arises and where there is a desire to preserve traditional methods of farming over digital interventions (Pandey et al., 2024). Besides, AI algorithm trust and data-driven information trust is also of significant importance in making adoption decisions because farmers might be doubtful with the interpretability and validity of analysis based on AI (Mohammed et al., 2021). Social legitimacy of AI technologies also results from social dynamics because peer influence and group decision processes determine technology adoption among farming groups (Maged et al., 2023). For improved adoption of AI, scholars suggest participatory processes where farmers take part in co-design and testing of AI solutions so that the farmers feel a sense of trust towards digital innovations. In addition, localized AI solutions that are designed on the particular requirements and issues of palm farming communities should be developed to make AI-based agricultural interventions culturally appropriate.

Policy and regulatory frameworks are the basis of AI integration in palm farming. Proper governance frameworks must be put in place to deal with issues of data privacy, cybersecurity, and moral use of AI in agriculture (Diaz-Rodriguez et al., 2023). Some regulatory frameworks for AI use in agriculture are weak in many countries, giving rise to ambiguity regarding liability, in addition to algorithmic transparency (Al-Khayri et al., 2021). Policymakers need to devise clear guidelines for AI adoption in a manner that protects farmers' rights and interests while encouraging innovation in agricultural technology. International collaboration and scientific exchange can also enable more efficient knowledge sharing and best practices in AI-driven palm farming for support developments in smart agriculture (Ahmed et al., 2023). Government intervention in the form of AI-driven extension services and digital innovation hubs has been suggested as a way of easing the adoption of AI and enabling farmers to have access to technical expertise and technical knowledge (Mohammed et al., 2021). Regulatory incentives like tax relief and AI-specific agricultural grants can also incentivize private investment in AI-driven innovations for palm farming. Use of AI in palm cultivation is a technology-scarce, economy-scarce, society-scarce, and regulation-scarce process. While AI technology can provide best leverage in precision farming, automated irrigation, and disease control, their large-scale implementation depends on the removal of digital infrastructure barriers, financial constraints, and information asymmetry.

These challenges should be addressed by collaboration among policymakers, researchers, technology developers, and farming communities to establish an enabling environment for AI innovation. Future studies need to address the development of affordable AI solutions adapted to farmers' needs, estimating the long-term economic effect of AI adoption.

1.1 The Role of AI in Sustainable Palm Farming

The application of AI in palm farming is rapidly being identified as an integral means of improving farming sustainability, increasing productivity, and maximizing the utilization of resources. AI-driven solutions, such as machine learning models,

computer vision, and IoT-enabled monitoring systems, are disrupting conventional farming practices through real-time information on the soil's health, wealth destruction through infestation, and yield predictions (Hessane et al., 2025). AI based automation of disease diagnosis and pest control has reduced the use of toxic pesticides and yield loss, making palm farming sustainable (Hamriri et al., 2023). Predictive analytics allow farmers to make informed decisions regarding irrigation scheduling, fertilizer application, and harvest timing, to conserving water and developing crop resistance to drought conditions (Mohd Nain et al., 2022). AI becomes increasingly employed in palm plantation supply chains with stronger traceability, alignment to sustainability, and market maximization (Abubakar & Ishak, 2024).

1.2 Challenges in AI Adoption for Palm Farming

Although the use of AI has many benefits, its use in palm farming is faced with many challenges in regions with minimal technological infrastructure and digital literacy among farmers. High initial expenses in AI research-gear, such as sensors, drones, and self-driving cars, normally deter small-farmers from the adoption of such technologies (Abu Hanieh et al., 2020). Moreover, the use of big data by AI models is a key concern, as most of the palm farms are not well-organized and of good quality past data required for well-informed AI-prediction-based predictions (Hamriri et al., 2023). Research also points out that farmers' hesitation to adopt AI-based precision farming from conventional practices is attributed to low awareness, technical know-how deficiency, and data privacy concerns (El-Mously, 2019). Further, the integration of AI into conventional farming systems needs multidisciplinary collaboration of agronomists, data scientists, and policymakers to develop user-friendly AI tools addressing farmers' requirements. Enacting these challenges necessitates responsive government policies, economic incentives, and comprehensive training programs that can drive the rate of AI adoption and make the economic viability farmers need.

1.3 AI and Sustainability in Palm Farming: Future Directions

AI has a critical role to play in promoting sustainable agriculture by promoting reduction of environmental degradation and higher resource efficiency.

AI waste management technology is also being developed to turn palm biomass waste into biochar, bioethanol, and organic fertilizer and thus foster circular economy trends (Giwa et al., 2019; Castillo et al., 2023). Climate modeling technology also based on AI assists palm planners in predicting climatic patterns to foster adaptive farming systems that adapt to climate change effects (Abubakar & Ishak, 2024). Studies indicate that integrating AI with solar-powered irrigation systems and AI-activated water conservation methods can decrease the carbon intensity of palm cultivation (Hamriri et al., 2023). Upcoming AI-driven smart agricultural systems need to pay attention to designing low-carrier, farmer-centric AI systems that can be adopted in a wide range of farming ecosystems. Follow-up research must examine the potential for the combination of real-time soil health monitoring, blockchain to supply chain transparency, and AI-driven regenerative agriculture methods to provide long-term food production sustainability.

UTAUT offers a comprehensive framework to measure AI adoption among palm farming. The model that measures performance expectancy, effort expectancy, social influence, and facilitating conditions has found successful application in research on precision farming and smart agriculture (Wang et al., 2023). UTAUT enables researchers to look at how farmers view the benefits and limitations of AI and consequently make decisions to adopt it. Research has emerged to present perceived usefulness, tech trust, and government subsidies as major drivers in the adoption of AI-based farming applications by farmers (Li et al., 2024). Incorporating UTAUT into AI adoption research in palm farming enables a rigorous analysis of both facilitators and inhibitors to adoption.

As Table 1 illustrated, there is focus in current literature on technicalities of adopting AI or technical considerations and, with limited exploration of farmer attitudes, behavior drivers, and context-specific barriers. The empirical qualitative research conducted here fills this gap through the incorporation of UTAUT with empirical qualitative research and thus presents comprehensive understanding of AI adoption dynamics in the case studied here, that of palm cultivation.

Table 1. Related Studies on AI Adoption in Agriculture and Palm Farming

Study	Application Area	Technology Used	Findings
Jintasuttisak et al. (2022)	Tree detection in drone imagery	YOLO-V5, CNN	YOLO-V5m achieved 92.34% mAP in dense plantation environments
Mohammed et al. (2021)	IoT-based subsurface irrigation system	IoT sensors, ThingSpeak, cloud automation	Sensor-based irrigation scheduling reduced water usage by 64.1%
Khan et al. (2021)	Machine learning in oil palm agriculture	Machine learning with classification/regression techniques	Machine learning enables yield prediction and plant health classification
Ahmed & Ahmed (2023)	Palm tree disease classification	ResNet, Inception-ResNet, transfer learning	High accuracy in leaf disease classification (up to 100%)
Meixner et al. (2023)	Sustainability assessment of palm oil production	Analytic Hierarchy Process (AHP), expert interviews	Environmental sustainability was rated as the most important factor by experts; RSPO-certified palm oil was assessed to have a sustainability level close

			to that of European rapeseed oil.
Rodthong et al. (2023)	Adoption of sustainable palm oil practices (RSPO) in Thailand	Survey of 723 smallholders (333 adopters, 390 non-adopters); Weighted Average Index analysis	Adopters had more favorable perceptions of RSPO; financial support and expectation of premium prices were key motivators. Documentation was a major challenge but did not deter future interest.

With the integration of economic, behavioral, and technological views, developing models offer great insights to policymakers and agricultural technology developers. Future work needs to be geared towards transforming AI tools into something accessible to farmers, designing training programs, and building digital access to help facilitate widespread adoption of AI (Miah et al., 2024). Studying and improving the variables will enhance palm farming technologically driven and sustainable. Studying and improving the variables will enhance palm farming technologically driven and sustainable.

1.4 Potential Risks and Ethical Considerations

The adoption of AI in farm work—palm plantation, to be precise—also holds colossal opportunities to reshape food systems through efficiency, precision, and sustainability. Its technology advancement, however, is plagued with high risk and ethics that cry out for an urgent balancing in ensuring effective and equitable utilization. AI agricultural technologies significantly depend on the harvesting and processing of huge amounts of data from farms, such as environmental data, operational data, and even personal data. Without governance systems, the data could be manipulated and can be led to data privacy and digital sovereignty issues, specially in low-regulatory environments (Diaz-Rodriguez et al., 2023). Besides, the AI models are only as good as the training data set. The further limited or unrepresentative your data set is, the more likely biased and therefore incorrect will be, resulting in suboptimal recommendations for fertilization, irrigation, or pest control. Such errors can lead to loss of business, environmental pollution, or may low crop yield (Floridi et al., 2018). High setup charges of AI technologies such as sensors, drones, and software can also exclude smallholder farmers who lack the financial capabilities to invest in these technologies. This expands the digital divide and generates disproportionate opportunities within the agricultural sector (Elbasi et al., 2022). To offset the probable risk from the use of AI in agriculture, there is a requirement to follow ethical standards. Explainability and transparency must be embedded within AI systems to make results comprehensible and actionable to farmers so that they are able to make evidence-based decisions and, when required, contest automated suggestions (Floridi et al., 2018).

This paper was cleared by the Committee of Research Ethics at Qassim University for formal ratification; reference number 25-28-07, March 6, 2025. The ethics clearance ensures that the research procedure is one of integrity and assures all stakeholders in data collection and analysis that their rights are respected in providing assurance that the study is open and respectful.

Essential partnership between the developers of the technology and the farmers is critical to affective and inclusive adoption of AI in agriculture. The partnerships should focus on two aspects: hands-on practice and knowledge transmission. Provide locally targeted hands-on practice to farmers that improve their digital capacity and demystify AI technologies when practiced on a daily basis in their routine agricultural activities. This is complemented by the imperative for developers to engage directly with agricultural societies in a way that enables them to gain insights into real issues on the ground and hence be in a position to design AI products that are more relevant, accessible, and culturally customized. This interaction guarantees double learning, reduced resistance to change, and renders solutions by AI technically sound as well as accessible.

3. Methodology

This study uses a qualitative design involving in-depth, semi-structured interviews to examine the use of AI in palm farming for sustainable agriculture. Qualitative interviewing provides a more defined understanding of expert opinion, decision-making, and the contextual challenges and opportunities of AI adoption in agricultural environments (Warren, 2001). Due to the intricacy of AI adoption, semi-structured interview design was employed to provide variation of inquiry within a stringent framework, providing adequate data collection coverage (Edwards & Holland, 2013). Follow-up questions can be constructed to enable in-depth probing of participants' perceptions, expectations, and experiences of AI application in palm farming (DiCicco-Bloom & Crabtree, 2006). The study consisted of interviewing four experts and farm managers who had direct experience in palm cultivation and the utilization of agricultural technology.

The interviewees were chosen because they were familiar with AI-driven farming practices, different management activities, and participation in technology adoption decision-making (Morgan et al., 2013). The interviews were semi-structured to enable key issues—such as technological feasibility, economic effects, adoption obstacles, and contributions to sustainability—while giving respondents the autonomy to explain things (Wildemuth, 2016). In-depth interviews were useful in revealing qualitative information that may not be quantitatively expressed from surveys, especially to learn about social, economic, and infrastructural problems (DiCicco-Bloom & Crabtree, 2006). Data were processed using thematic analysis, with systematic coding of interview transcripts to establish recurring themes and patterns. Analytical activities were informed by qualitative content analysis guidelines to ensure meaningful extraction of meaning without diluting context and richness of expert witness testimonies (Edwards & Holland, 2013). Ethical aspects were appropriately accorded highest priority throughout the study, e.g., informed consent, confidentiality, and voluntary participant involvement (Wildemuth, 2016).

Semi-structured interviews are best for this study since they provide flexibility in the questions while ensuring thorough data collection (Kallio et al., 2016).

This approach facilitates intimate questioning into the views, beliefs, and insights of farm managers and AI professionals in palm cultivation, generating high-quality qualitative data that are unavailable through quantitative alone (Adhabi & Anozie, 2017). The interview design adopts a systematic methodological process, wherein primary themes of AI adoption, technical issues, financial viability, and sustainability effects are adequately explored (Turner & Hagstrom-Schmidt, 2025). The semi-structured interview method enabled flexible questioning and improvisation to allow participants to clarify significant issues of embracing AI, challenges, and opportunities within palm farming (Alsaawi, 2014).

The interview guide was constructed in accordance with best practice qualitative research, including open-ended questions that encouraged full responses and the provision for asking probes to collect additional data (Qu & Dumay, 2011). Face-to-face interviews were used to facilitate unencumbered conversation while permitting researchers to recognize non-verbal communication and contextual factors that contributed to having more responses (Talja, 1997). Also, ethical concerns regarding informed consent, privacy, and voluntary participation were adhered to based on mandated study procedures (Gill et al., 2008).

After the interviews, thematic analysis was used to scrutinize the data. Systematic coding of the interview transcripts was used to pinpoint the prevailing themes, emergent patterns, and foundational findings regarding AI uptake in palm farming (Kallio et al., 2016). Discourse analytic understanding was also employed to comprehend how the participants construct accounts on AI in farming and thereby enable sociocultural interpretation of data at a greater level (Talja, 1997). The results of these interviews have implications for deconstructing the drivers and impediments of the adoption of AI in palm agriculture and as a basis for policy action and guidelines to boost sustainable agricultural output.

3.1 The Unified Theory of Acceptance and Use of Technology (UTAUT) Model

UTAUT model, proposed by Venkatesh et al. (2003), is a theoretical framework for studying technology use based on the synthesis of components from eight earlier proposed models. The UTAUT model specifies four determinants, which are the key drivers of technology use and behavioral intention: performance expectancy, effort expectancy, social influence, and facilitating conditions (figure 1). These constructs are mediated by age, experience, voluntariness of use, and gender to derive a more awareness-based understanding of determinants of technology adoption across various groups (Im et al., 2023). On account of its high explanatory power, the UTAUT model has gained substantial usage in various fields including precision agriculture, intelligent farming, and digital transformation of agriculture (Xie et al., 2022). In palm cultivation, where conventional agriculture is normally predominant, the use of AI technologies presents opportunities and challenges.

AI technologies, including precision monitoring, automated irrigation, and disease detection systems, necessitate a systematic comprehension of adoption behavior

(Ronaghi & Forouharfar, 2020). The UTAUT model offers a systematic means of measuring farmers' and agricultural managers' perceptions and adoption of AI tools in their farm businesses, providing insight into the determinants that facilitate or impact extensive adoption (Salleh et al., 2024).

3.2 Applying UTAUT to AI Adoption in Palm Farming

Theoretical framework that has been used to analyze the major determinants and inhibitors of AI adoption in palm farming, as in this study, is the UTAUT model. The four main determinants of the model have been adopted as follows:

- **Performance Expectancy** measures whether palm farmers see AI instruments as useful to enhance productivity, resource efficiency, and sustainability. Studies have shown that if farmers feel that AI-based applications will increase yield, cost savings, and crop quality, they are likely to implement such technology (Ronaghi & Forouharfar, 2020).
- **Effort Expectancy** is the degree to which individuals find it easy to use AI technology. The simplicity of technology needed training, and technical ease to integrate it with current practices are strong drivers for adoption (Xie et al., 2022). They might adopt against if they perceive using AI as being highly complex or technically sophisticated.
- **Social Influence** highlights the role of peers, government support, and advisory groups in farmers' decision-making. Evidence implies that advice from agricultural institutions, and other producers has a critical role in shaping helpful attitudes of AI technologies (Salleh et al., 2024).
- **Facilitating Conditions** are the readiness of infrastructure, financial encouragements, training, and policy support to support the adoption of AI. Without the right technical backup, government assistance, or AI-compatible farming tools, shift towards AI-based farming is challenging (Im et al., 2023).

By the intersection of these determinants, this research examines how palm farmers assess, adopt, and utilize AI-based farming solutions in a bid to eventually lead towards a better and sustainable palm farming sector.

3.3 Implementation Strategy for UTAUT

For an effective application of the UTAUT model, this study employs the qualitative approach through semi-structured interview of four experts and farm managers who are directly engaged in palm farming and AI adoption. This allows one to extensively research behavioral intention, technology issues, and adoption facilitators (Siregar et al., 2022). The interview guide attempts to analyze the effect of performance expectancy, effort expectancy, social influence, and facilitating conditions on the participants' intention to adopt AI-based farming solutions (Salleh et al., 2024). Additionally, the current study adds to the original UTAUT model by presenting context-specific elements that have been used to examine the adoption of AI in smart agriculture (Xie et al., 2022). Thematic analysis from interviews will be carried out with the aim of creating meaningful patterns and emerging themes so that an effective understanding of socio-technical dynamics in adopting AI in palm farming is realized.

Based on the UTAUT model as a conceptual framework, this study seeks to offer practical recommendations to policymakers, agri-tech developers, and farmers to increase the adoption and sustainable utilization of AI-based technologies in palm farming.

3.4 Extending the UTAUT Model in the Context of AI Adoption in Palm Farming

UTAUT has been widely applied to account for technology adoption but requires an extension to account for the complexity of a given industry when used in the agricultural industry, such as AI-based palm farming. To effectively adopt UTAUT, qualitative data from four semi-structured interviews of farm managers are included in this study. Whereas the original UTAUT model considers performance expectancy, effort expectancy, social influence, and facilitating conditions as predictors of technology adoption (Dwivedi et al., 2019), these interviews also highlight other factors like trust in AI-based decision-making, and economic constraints. To expand the UTAUT model in this study, there needs to be added context-dependent variables like perceived risk, cost effectiveness, and policy aspect that manifested as fundamental drivers of AI adoption in palm farming. Evidence of adoption of AI by palm farmers being more than just technology issues comes out clearly from the results of the interviews.

Although performance expectancy and effort expectancy remained pivotal to adoption decision, financial risk and ambiguity related to AI-based agriculture appeared as the key hurdle (Dwivedi et al., 2017). In addition, the role of industry peers, government support, and train scheme availability were also identified as important determinants of adoption (Rana et al., 2021). As a move to expand UTAUT model, the current study inserts the factors established in this study into the existing model to facilitate wider consideration of AI adoption. With this expanded model, there is improved predictive capacity in examining palm farm managers' perception and reaction to AI innovations and providing a more nuanced view of incorporating technology into sustainable farm practice.

4. Data Analysis Using Thematic Analysis

Thematic analysis is a popular qualitative technique for finding, analyzing, and reporting themes or patterns of meaning in data. It provides a systematic but versatile approach to interpreting rich qualitative data in a way that allows researchers to find insights which are richly contextualized within participants' lives (Braun & Clarke, 2006). Thematic analysis was utilized in this study to examine data from semi-structured interviews carried out with four farm managers who possess first-hand experience of AI deployment in palm farming. The process utilized Braun and Clarke's six-step procedure involving familiarization with data, initial code generation, searching for themes, review of themes, definition and naming themes, and production of the final report (Vaismoradi et al., 2016). Through thematic analysis, the research was able to determine explicit and implicit thought processes, challenges, and motivations of incorporating AI in palm farming (Roberts et al., 2019). Rigor and credibility were ensured in the research by developing a codebook throughout the data analysis process.

The coding system was crafted iteratively to represent pre-specified categories from the study design and emergent themes from participants' reports (Jnanathapaswi, 2021). The themes were cross-validated by inter-coder reliability tests to ensure analysis was reproducible and objective (Roberts et al., 2019). Since qualitative research is most often prone to issues of replicability, meticulous documentation of the process of coding and theme discovery upholds the validity of findings (Sgier, 2014). Context-specific influencing factors of AI adoption in palm farming were some of the greatest implications of this thematic analysis.

Besides the foundational UTAUT model constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions), some other concerns that arose are economic risks, and technical support and training requirements (Vaismoradi & Snelgrove, 2016). The content analysis identified the point that even though AI has the potential to increase sustainability in palm production, it is still heavily dependent on socio-economic and legislative considerations. By systematic coding and interpretation of such results, thematic analysis enabled in-depth understanding of farmers' attitudes, technology acceptance issues, and the overall agriculture innovation environment. The results offer actionable recommendations for policymakers, agritech innovators, and stakeholders in advocating AI-driven sustainable agriculture practices.

Data obtained from the four semi-structured interviews were coded and analyzed on thematic analysis guidelines, using Braun and Clarke's six-step guide (Braun & Clarke, 2006). This method allowed systematic identification, labeling, and interpretation of salient patterns (themes) of the dataset. Thematic analysis was adopted with regard to its flexibility and ability to identify both overt and latent meanings of participants' answers. The procedure involved data familiarization, initial code generation, theme searching, theme exploration, labeling and describing themes, and making final reports. From the process, we were able to generate a number of major themes that capture the advantages, challenges, as well as drivers for adopting AI in palm farming. This study uses Braun and Clarke's (2013) six-step thematic analysis approach to conduct four expert interviews of applying AI in palm cultivation to achieve sustainable agriculture. This procedure provides a systematic and rigorous examination of qualitative data to ascertain important themes, findings, and issues

Step 1: Familiarization with Data

The first step involved the constant reading and reading-through of interview transcripts to gain a thorough familiarity with participants' perceptions.

There was note-taking to highlight prevailing concepts, response patterns, and inconsistencies. Major themes repeatedly emerged like AI potentiality in irrigation management, pest management, cost reduction, and barriers to adoption like the economic factor. A2" One of the interviewees emphasized that AI can be employed to determine the real farm requirements, including the required water and fertilizer quantity, so as to minimize operational costs. Step 2: Generation of Initial Codes

Secondly, the information was coded in a systematic way to extract main ideas. Coded were comments on AI benefits (efficiency, cost-effectiveness, decision-making), barriers (outrageous cost), and support systems required (government incentives,

training schemes, investment in infrastructure). For instance, A3 stated that "The outrageous cost of smart devices, e.g., sensors and drones, makes it difficult for small-scale farmers to invest in them without government intervention." was coded as financial barriers.

Step 3: Theming Codes into Themes

The codes were then merged into larger themes to determine whether there were overall patterns across the interviews. major themes identified were financial investment, technical knowledge, training programs, and technology infrastructure was highlighted.

Step 4: Reviewing Themes

All of the themes were thoroughly explored to ascertain that they were new, evidence-based, and pertinent to the research question. Some of the codes were rephrased so that they could be clearly understood, and sub-themes from each main theme were identified. For instance, under challenges, financial constraints and lack of technical expertise were rephrased as separate sub-themes because while both were general barriers, they meant different things.

Step 5: Defining the Significance of Themes

The second step involved defining the most important themes that were used to explain AI adoption in palm farming.

The high-cost challenge and the need for government support were specifically applicable in all four interviews. One of the interviewees said, A3 "If incentives are not given by the state to farmers, then there will be no incentive in adopting technology." Another emphasized awareness and training, saying, A1 "Farmers have to see practical demonstrations of AI to believe in its effectiveness."

Step 6: Reporting of Findings

The last step was to write a detailed report that highlights the key themes and their implications. The study indicates that although AI presents immense advantages in palm farming, its adoption is based on economic limitations, limited knowledge, data privacy, availability of data and trust. Institutional assistance is essential to overcome these variables, with the importance of government incentives, training programs, and infrastructure investment. These findings can then be employed to create strategies for encouraging AI adoption in sustainable palm farming such that they are more beneficial than any perceived risk and limitation.



Fig. 2: Six-step thematic analysis process for AI adoption palm farming.

Figure 2 is a concise graphical overview of the six steps of analysis that were used in thematic analysis of interview data. The steps are: data familiarization, systematic coding, categorizing codes into themes, refining and reviewing emerging themes, determining their significance, and finally, reporting findings. This systematic process allowed the researchers to derive effective patterns in respect to perceived advantages and disadvantages of AI application in palm cultivation and ascertain institutional support necessary for viable implementation (Braun & Clarke, 2006).

Thematic Analysis for Identifying the Factors

Thematic analysis of interview data adheres to Braun and Clarke's (2013) six-step process, with UTAUT as the general analytical framework. Major UTAUT themes of performance expectancy, effort expectancy, social influence, and facilitating conditions were derived from responses, along with longer factors such as costs, and availability of data.

UTAUT-Based Themes

1. Performance Expectancy – Interview participants indicated that AI had the capability to optimize irrigation, pest control, and estimate yields, so they would become far more effective. According to one interviewee, A2" AI will determine the actual needs of the farm, such as the water and fertilizers it requires, thus reducing the costs." Another mentioned the use of AI as reducing the reliance on human hands and improving precision in decision-making.

2. Effort Expectancy – Overall, the AI technology was perceived as being easy to use but that there are farmers who were mentioned by participants as likely having difficulty in learning the technology without training. A3 said, "There are some challenges, such as a lack of knowledge among some workers on how to use it, so they require extensive training."

3. Social Influence – Government endorsement, expert advice, and peer adoption were identified as key drivers for AI adoption. A4 "If farmers saw their peers using AI and getting more benefites, then they are likely to do the same activity."

4. Facilitating Conditions – Availability of infrastructure, funding, and training programs proved to be a determinative factor. A1 "Farmers require government support, primarily infrastructure and capital to implement these technologies." Compared to. Infrastructure constraints may be, non-availability of good internet connection and absence of tools compatible with AI were as barriers towards utilization of AI in palm farming. Non-availability of good internet connection, absence of AI-compatible tools, and absence of good electricity supply were experienced as hindrances. According to one scholar, A2 "There is not much use of smart devices and sensors since there is no adequate supporting infrastructure."

4.1 Extending the UTAUT Model: Incorporating Additional Factors for AI Adoption

1. Financial Barriers

Another greatest difficulty in applying AI to palm plantation is the monetary constraint. It is too pricey for small- and medium-sized farmers to acquire the equipment and technology of AI, such as sensors, drones, automatic watering systems, and AI-based diagnosis kits for disease. "The expensive nature of smart devices, including sensors and drones, puts off small-scale farmers from using them without subsidization by government." (A3)

2. Data Privacy Concerns

Farmers were concerned about data security with the use of AI-powered tools. With AI relying on gathering and analyzing huge volumes of data, questions about what happens to the data storage, sharing, and usage are raised. "There is a fear of data being shared with tech companies. Farmers are afraid of who uses data and who analyzes it." A4

3. Data Availability

AI-based agriculture solutions need quality data in a proper format to provide forecasts and effective decisions. Lack of proper data and data documentation is a hindrance.

"AI can calculate the real requirements of the farm, i.e., how much water and fertilizers are required, but we don't have structured data to provide correct predictions." (A2)

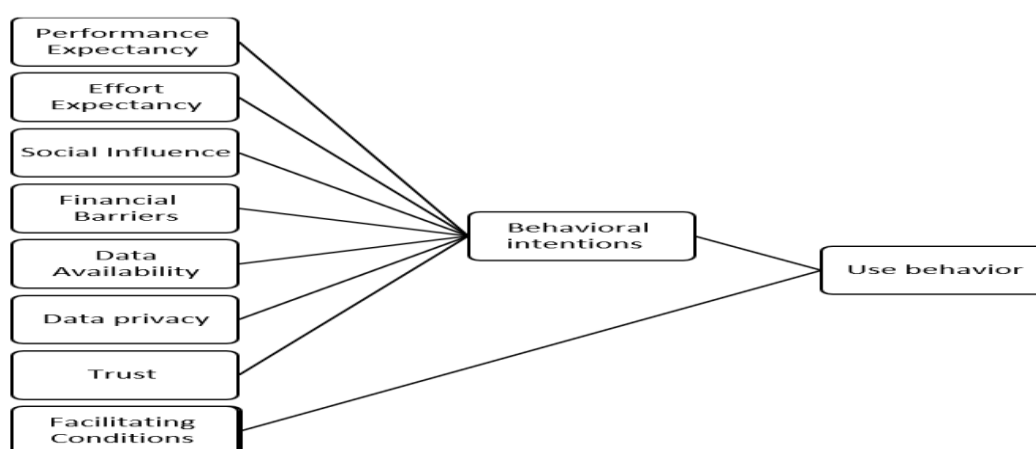
4. Trust and Acceptance of AI

While AI is promising, most farmers are not convinced of the reliability of AI and would rather stick to conventional methods of farming than make decisions based on

data. "A farmer will only believe in AI when he sees practical examples of AI in operation, so there should be actual trials and results." (A1)

Results and Discussion

The results of this study show the revolutionizing potential of AI in palm farming as well as robust barriers and determining factors, which influence its adoption. The deployment of AI technologies has proved promising in complementing farm practice, streamlining efficiency, and facilitating sustainability. A number of challenges, such as inadequate funds, and distrust, nonetheless still limit widespread adoption. Through the analysis of information via the UTAUT model, this research provides a thorough insight into the enablers and inhibitors of AI uptake in palm farming. Also, some context-specific variables apart from the traditional UTAUT model were revealed, further cementing the technology adoption framework for agriculture.



3: Fig Study Framework

Figure 3 of this study shows the main drivers of adoption of AI in palm farming, balancing them as drivers of technology adoption and context-dependent barriers. To provide a comprehensive overview, Table 2 summarizes the major factors of AI adoption in palm farming, bringing together both the UTAUT-based and context factors. Every factor is operationalized of adoption, as emerged through thematic analysis of interviews with stakeholders and informed by the literature.

Table 2. Key factors of AI Adoption in Palm Farming: Definitions and Impacts

Factors	Definition
Performance Expectancy	The degree to which farmers believe AI will improve efficiency and output.
Effort Expectancy	Perceived ease of using AI technologies.
Social Influence	Influence from peers, experts, or government agencies.
Facilitating Conditions	Availability of infrastructure, funding, and support.

Factors	Definition
Financial Barriers	High cost of AI equipment and maintenance.
Data Privacy Concerns	Fear over misuse or unauthorized access to farm data.
Data Availability	Access to reliable and structured data for AI tools.
Trust	Confidence in AI outputs and its integration into farming practice.

The four factors which are Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions are derived from the UTAUT model. Performance Expectancy is that farmers would like AI to introduce efficiency, maximize the use of resources, and improved productivity. Effort Expectancy points toward perceived ease of use, i.e., farmers' AI adoption intention is based on ease of use and access to such technologies. Social Influence deals with word of mouth from colleagues, governmental support, and industry endorsement to influence farmers' trust in AI. Finally, Facilitating Conditions are the availability of infrastructure, finance, training initiatives, and policy support that help AI adoption. Aside from UTAUT determinants, Figure 3 is covering the context-specific concerns arising from thematic analysis which include Financial Barriers, Data Privacy Concerns, Data Availability, and Trust in AI.

Financial Barriers represent the high expenses of adopting AI, for example equipment, training, and maintenance, making AI solutions unaffordable for small-scale farmers. Data Privacy Concerns reflect farmers' unwillingness to share agricultural data. Data Availability is also a critical issue since AI applications need to be based on well-structured, high-quality datasets to provide the right decisions, which most farmers do not have. Lastly, Acceptance and Trust of AI are crucial, considering that the majority of farmers are not hopeful about AI-driven suggestions, demanding traditional methods of farming over algorithm-based decision-making.

4.2 Challenges affecting AI Adoption in Palm Farming

Though promising, AI adoption in palm plantation is excluded by several challenges that make it non-scale. The main challenge is the high cost of implementation since sophisticated AI machinery, sensors, and automation systems are expensive to acquire. Small- and medium-scale farmers lack the necessary capital to implement AI on their farms without grants or other support. In addition, scarce digital literacy on the part of farmers poses constraints to adoption as the use of AI solutions demands specialized training and expertise. Moreover, limited accessibility to infrastructure, most notably inferior internet connectivity and inability to properly support AI-friendly devices, makes large-scale application even more complicated. Expanding the UTAUT Model with Context-Specific Factors

Even though the UTAUT model gives a robust structure for technology acceptability and technology behavior, this study finds some other determinants that affect palm farming AI usage.

Financial sustainability is another key driver, where cost implications are a significant consideration in adoption, or non-adoption. Trust in AI decision-making was also a key driver, where farmers did not want to entirely rely on AI recommendations to manage farms. Concerns over environmental sustainability also drive the degree of adoption, where AI can facilitate more sustainable and efficient agriculture to be attained. These findings suggest that an extension of the UTAUT model with these context-specific variables is a more realistic and nuanced model for predicting AI adoption in agriculture.

5. Implications for Future AI Implementation in Agriculture

Solving the issues of AI adoption in palm farming involves a multi-pronged strategy with mechanisms for financial support, infrastructure improvement, and capacity-building activities. Providing subsidies, support, government-backed loans, and cost-sharing schemes will reduce the economic burden and make the technology of AI affordable. Improving digital literacy through training sessions and education programs will make it easier for farmers to use AI-based equipment. Supporting internet connection and access to farm technology compatible with AI will also trigger adoption. Moreover, the formation of partnerships among technology firms, agricultural operators, and research centers will also help to drive the shift towards AI-facilitated farming. Addressing these will make AI a driver of sustainable, technology-enabled palm farming toward a more robust and efficient agricultural sector.

6. Future Research Directions

Follow-up studies on AI use in palm agriculture need to address a number of key areas to advance the knowledge and implementation of AI-led solutions in sustainable agriculture. To start with, studies on economic viability of AI use by farm size and financial arrangements will inform cost-friendly solutions and financial arrangements for small and medium-sized palm farmers. Besides, research must also study the long-term implications of AI on productivity, environmental sustainability, and resource optimization in a bid to ensure that innovations introduced by AI are aligned with sustainability goals at a global level. Digital literacy and farmer training is another important area of focus, as understanding how training impacts AI adoption can assist in how more efficient models of learning appropriate for farmers can be constructed. Future research must also look at how AI interacts with proximate technologies like the Internet of Things, blockchain to enable supply chain visibility, and climate modeling software to make farm systems stronger and more efficient. There needs to be studies that look and search about policy environments and regulatory considerations, and addresses questions regarding matters relating to concerns regarding data security, privacy, and ethics in the adoption of AI. Through advances in such areas, palm farmers can be more effectively matched with AI-innovations and a transition to sustainable, technology-based farming techniques becomes a more feasible proposition.

Conclusion

AI use in palm plantation offers an enabling platform for improving efficiency, sustainability, and decision-making in farming. In this research, it has been established that AI solutions such as predictive analytics, automated irrigation, and machine learning for controlling pests have a big potential in optimizing resource utilization, minimizing costs, and maximizing overall production. However, AI usage is still marred with funding constraints and technical issues. Despite that the UTAUT model had provided a paradigm for AI adoption analysis, for this research other contextual factors such as trust towards AI and readiness of infrastructure had been emphasized to impact farmers' willingness to adopt technological innovations. These issues were capable of being addressed by the efforts of multi-stakeholder in the forms of government stimulus, industrial alliance, and capability-building programs aimed at providing the farmers with capacity and equipment for effectively adopting AI. With the deployment of policy-influenced support infrastructure and access to technology, AI can be the central point to sustainable palm farming, leading to long-term farming resilience and innovation. The way forward must include furthering approaches to AI adoption, further boosting data-driven decisions, and improving cooperation among policymakers, researchers, and agricultural constituents to guarantee ultimate gains of AI in palm agriculture.

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