

Artificial Technology (AI) Development in Argiculture Sector in Malaysia

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ABSTRACT

This paper examines the development and adoption of Artificial Intelligence (AI) in the Malaysian agriculture sector through a structured narrative conceptual review. The paper is not an empirical survey; instead, it synthesises peer-reviewed research, Malaysian government and institutional documents, Food and Agriculture Organization (FAO) publications, and relevant technology-adoption literature to develop and explain a conceptual framework for AI adoption and agricultural outcomes. The study retains the authors' original conceptual model, in which AI Technology Adoption is the independent variable and Agricultural Productivity and Efficiency is the dependent variable. AI Literacy and Education, Training and Support, and Culture and Labour are retained as mediating variables; Government Policies and Support is retained as a moderating variable; and Farm Size and Resources and Market Demand are retained as control variables. The framework is theoretically supported by the Technology–Organization–Environment perspective, Diffusion of Innovations, and the Unified Theory of Acceptance and Use of Technology. The review shows that AI and related digital technologies can support precision agriculture, crop monitoring, input management, aquaculture, automation and supply-chain activities, but the benefits of adoption depend on human capability, training, labour conditions, infrastructure, financial resources, market incentives and government support. Malaysian evidence includes farmer acceptance of agricultural drones, MARDI precision and digital technologies, and national policy initiatives that identify agriculture as a priority area for AI application. The paper distinguishes existing Malaysian applications from emerging and potential applications and discusses socioeconomic implications including changing labour requirements, digital inequality and possible smallholder exclusion. The review concludes that AI should be approached as a socio-technical transformation in which technology adoption is translated into productivity and efficiency through human, institutional and market conditions. The conceptual framework provides a basis for future empirical testing using Malaysian farm-level data.

Keywords: Artificial Intelligence (AI), Food Security, Agricultural Productivity, Sustainable Agriculture, Smart Farming

INTRODUCTION

The Malaysian agricultural sector continues to play an important role in economic activity and national food security. Recent official statistics indicate that the agricultural sector recorded growth of 3.1% in 2024, compared with 0.2% in 2023. Palm oil remained the largest contributor to agricultural value added, while production also increased for several commodities, including natural rubber and selected fruits (Department of Statistics Malaysia [DOSM], 2025). The diversity of Malaysian agriculture, which includes plantations, food crops, livestock, fisheries, aquaculture and smallholder production, means that technological transformation cannot be understood through one uniform production model.

At the same time, Malaysian agriculture faces persistent pressures involving labour availability, production costs, resource efficiency, food demand and the need to improve the quality and reliability of production. The original

manuscript identifies rising labour costs, declining interest among younger people in agricultural work, dependence on foreign labour and increasing food demand as important pressures. These pressures provide a context in which AI, automation, precision agriculture and other digital technologies may become increasingly relevant. However, technology should not be presented as an automatic solution. The effectiveness of AI depends on whether farmers have the resources, knowledge, infrastructure and institutional support required to use it productively.

AI in agriculture refers in this paper to the use of computational systems capable of analysing data, recognising patterns, generating predictions, supporting decisions or performing tasks with a degree of automation. Examples include machine learning, computer vision, predictive analytics, AI-assisted sensing, autonomous or semi-autonomous robotics and decision-support systems. Related technologies such as drones, Internet of Things (IoT) sensors and precision agriculture are included where they provide the data or operational infrastructure through which AI can function. The distinction between AI and broader digital agriculture is maintained throughout the paper because not every sensor, drone or digital platform is itself an AI system.

The Malaysian literature already provides evidence of agricultural technology adoption. Azizul et al. (2023), for example, studied 204 rice farmers in Kota Bharu Utara, Kelantan, who hired drone operators for rice cultivation. Their findings identified 15 factors related to acceptance, with drone roles and drone-handling skills among the highly significant factors. Aris et al. (2023) similarly examined Agricultural Revolution 4.0 adoption among approximately 378 Malaysian agro-based small and medium industries and found positive relationships between adoption and antecedents including strategy, technology readiness, food security and food safety. These studies demonstrate that agricultural technology adoption involves technical, organisational and human factors rather than technology availability alone.

The objectives are to examine the Malaysian agricultural context and the drivers of AI adoption; review documented and emerging AI and smart-farming applications in Malaysia; explain the relationships among the variables in the authors' conceptual model using established theory and prior research; discuss adoption barriers and socioeconomic implications; examine policy and institutional requirements; and identify future research directions. The paper does not claim to validate the framework empirically. Instead, it develops a theory-informed framework that can subsequently be tested through Malaysian empirical research.

METHODOLOGY

The present study uses a structured narrative review methodology. The use of a structured narrative review is due to the emerging nature of AI research in Malaysian agriculture and the heterogeneity of the evidence. Information is distributed among peer-reviewed agricultural technology studies, technology adoption research, Malaysian government statistics, research institute technology descriptions, national policy documents and international evidence from FAO. A narrative synthesis is thus used to synthesize evidence of these sources and to explain the relationships between them in the conceptual model. The paper is not a systematic review or meta-analysis on AI and agriculture in Malaysia and is not claimed to have identified all the papers. In this review, we used five evidence categories. The first category was peer-reviewed Malaysian studies on AI, Agricultural Revolution 4.0, drones, digital agriculture and acceptance of technology. The second consisted of international studies and theoretical literature on technology adoption, innovation diffusion and technology use. The third category was Malaysian official documents such as DOSM, MARDI, MOSTI and national development planning documents and were used to build current agricultural statistics, documented technologies and policy direction. The fourth category included FAO reports and technical studies on agricultural automation, digitalisation, labour, smallholders and inclusive adoption. The fifth was the institutional and research documents of Malaysian agricultural technology programmes or applications which were not supported by peer-reviewed evidence.

The synthesis was organised around seven topics: Malaysian agricultural context and the reason for AI adoption; AI and smart farming applications and their development; adoption mechanisms and conceptual framework; barriers to AI adoption; labour and smallholder welfare; government and institutional needs; future research. The sources were examined on the basis of relevance, empirical evidence, institutional weight as well as on the basis of current information in the context where relevant. We also distinguish AI from IoT, drones and precision

farming and hence AI and AI-related technologies. This distinction is needed and is essential, since using a drone or sensor in a farm is not evidence of AI. The review process was interpretive rather than statistical. The evidence was compared across sources and then used to justify the conceptual relationships shown in Figure 1. If the Malaysian evidence supports a relationship directly then we call it as such. When the evidence is international or related to agricultural technologies rather than AI specifically, we are stating this limitation. This approach allows us to retain the conceptual framework but not make any claims that the proposed relationships have already been empirically established in Malaysia.

Conceptual Framework of AI Technology in Malaysia

The conceptual framework is retained from the original manuscript and is grounded in established technology-adoption perspectives. The Technology–Organization–Environment (TOE) framework explains technology adoption through technological characteristics, organisational conditions and the external environment (Tornatzky & Fleischer, 1990). This perspective is appropriate because AI adoption in agriculture depends on the technology itself, the resources and capabilities of the farm or agricultural organisation, and external conditions such as policy, infrastructure and market conditions. The framework therefore supports the inclusion of Farm Size and Resources, Government Policies and Support and Market Demand alongside the core AI adoption variable.

Diffusion of Innovations provides a second theoretical foundation. Rogers (2003) explains adoption in relation to perceived relative advantage, compatibility, complexity, trialability and observability. These concepts are relevant to agricultural AI because farmers are more likely to integrate technologies when the technology is perceived as useful, compatible with existing practices, manageable in complexity and capable of demonstrating observable benefits. Culture and Labour in the authors' model is particularly relevant to compatibility because farming practices are embedded in established routines, skills and social expectations.

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides an additional explanation of technology use through constructs including performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). In the present framework, AI Literacy and Education and Training and Support are closely related to facilitating conditions because users need the knowledge, skills and support required to turn access to technology into actual use. These theories are complementary: TOE explains the wider adoption environment, Diffusion of Innovations explains characteristics and perceptions of an innovation, and UTAUT helps explain users' movement from intention and capability toward actual use.

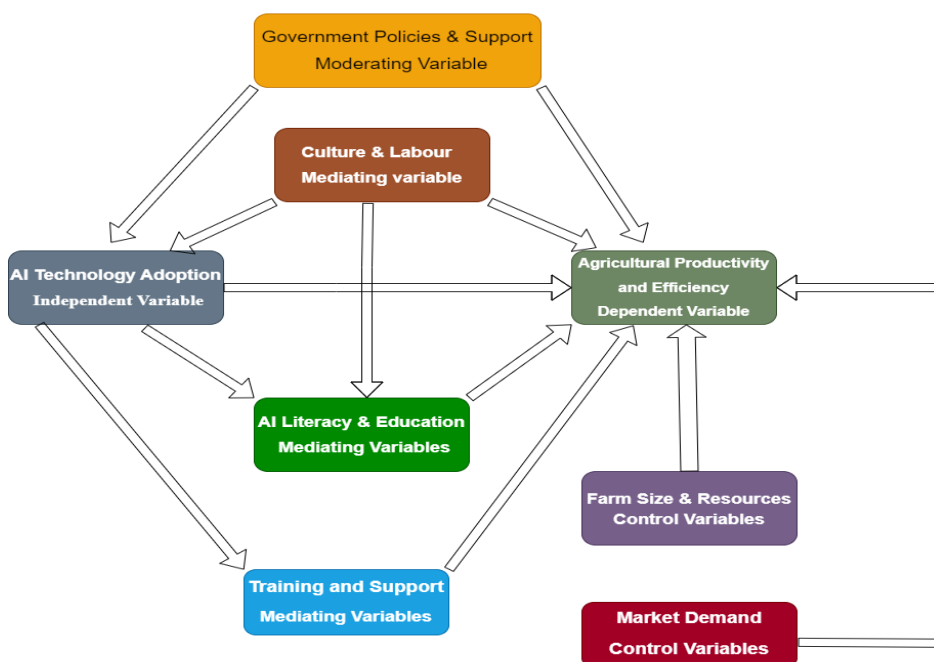


Figure 1: Conceptual Framework Model of AI Technology in Malaysia

The model proposes that AI Technology Adoption influences Agricultural Productivity and Efficiency because AI can improve the speed and accuracy of information processing, support precision in production decisions, automate repetitive activities and improve resource allocation. FAO evidence indicates that agricultural automation, including digital and AI-enabled technologies, can increase productivity, resilience, efficiency and resource-use efficiency, although the benefits depend on adoption conditions (FAO, 2022). Malaysian evidence from AR4.0 adoption also shows that technology readiness and related strategic conditions are associated with adoption among agro-based industries (Aris et al., 2023). Thus, the direct relationship in Figure 1 is theoretically grounded in the expected relative advantage and performance benefits of AI-enabled technologies.

AI Literacy and Education are treated as a mediating variable because adoption alone does not guarantee effective use. Farmers must understand how to operate AI-enabled tools, interpret outputs and incorporate recommendations into production decisions. This is consistent with UTAUT's emphasis on facilitating conditions and with Diffusion of Innovations, where complexity and compatibility influence adoption and use (Rogers, 2003; Venkatesh et al., 2003). Malaysian evidence supports this mechanism indirectly and directly through agricultural technology acceptance: Azizul et al. (2023) found that drone-handling skills were among the highly significant factors associated with acceptance among the sampled rice farmers. The proposed mediation therefore means that AI adoption can be more effectively translated into productivity when users possess the education and literacy needed to use the technology appropriately.

Training and Support are also treated as a mediating variable. Training helps farmers acquire operational and technical skills, while continuing support can assist with installation, maintenance, troubleshooting, interpretation of results and integration into existing practices. FAO evidence identifies lack of digital skills and knowledge as a major barrier to agricultural digitalisation and automation, particularly for small-scale producers (McCampbell, 2022). Consequently, the framework proposes that training and support strengthen the pathway between adoption and productive use. The Malaysian evidence on drone-handling skills provides additional support for the importance of practical capability (Azizul et al., 2023).

Culture and Labour are retained as a mediating variable because agricultural technology is introduced into existing work practices and labour arrangements. Diffusion of Innovations emphasises compatibility between an innovation and existing values, experiences and needs (Rogers, 2003). In agriculture, farmers may evaluate AI according to whether it fits established routines, whether it is understandable and whether it complements rather than disrupts their knowledge and work. Labour availability can also create an incentive for automation when farms face labour shortages. The role of Culture and Labour in the model should therefore be understood as a mechanism through which social readiness, established practices and labour conditions influence the integration of AI into agricultural activity.

Government Policies and Support are retained as a moderating variable because policy conditions can strengthen or weaken the relationship between AI adoption and agricultural outcomes. Financial assistance, extension support, infrastructure, standards, regulation, research programmes and training can change the environment in which technology is adopted. Malaysia's National AI Roadmap identifies agriculture and forestry as one of five priority areas for national AI use cases and emphasises responsible AI principles, while the Thirteenth Malaysia Plan identifies applications such as high-precision crop monitoring, real-time weather forecasting, sustainable resource utilisation and robotics in agriculture (MOSTI, 2023; Ministry of Economy, 2025). These policy documents do not prove that all proposed applications are already implemented, but they establish a policy environment relevant to the moderator in Figure 1.

Farm Size and Resources are retained as control variables because farms differ in financial capacity, land area, equipment, labour and access to technical services. These differences can influence both AI adoption and productivity, making farm size and resources important variables to control when examining the relationship between AI adoption and agricultural outcomes. FAO research shows that high investment costs and unequal access to infrastructure and skills can constrain adoption among small-scale producers (FAO, 2022; McCampbell, 2022). The variable therefore helps prevent differences in resources from being attributed entirely to AI adoption.

Market Demand is retained as a control variable because farmers and agricultural organisations make technology decisions within markets. Demand for quality, consistency, traceability, timely supply and cost-efficient production can affect the perceived value of AI and the resources available for investment. Market conditions may therefore influence both adoption and productivity. Treating Market Demand as a control variable allows future empirical research to separate the effect of AI adoption from productivity differences associated with market incentives.

Based on the relationships in Figure 1, the conceptual review proposes that AI Technology Adoption is positively associated with Agricultural Productivity and Efficiency; that AI Literacy and Education, Training and Support, and Culture and Labour help explain the translation of adoption into agricultural outcomes; that Government Policies and Support can strengthen or weaken the effectiveness of adoption; and that Farm Size and Resources and Market Demand should be controlled when examining these relationships. These are conceptual propositions for future empirical testing rather than statistically verified hypotheses in the present paper.

Malaysian Agricultural Context and Drivers of AI Adoption

The Malaysian agricultural sector has a diverse production structure, and recent statistics demonstrate its continuing economic importance. DOSM reported agricultural-sector growth of 3.1% in 2024, with palm oil contributing 36.8% of agricultural value added and livestock contributing 16.9% (DOSM, 2025). This diversity is important for AI adoption because different commodities have different production cycles, labour requirements, environmental conditions and data needs. A technology suitable for a large plantation may not be suitable for a small fruit farm, rice holding or aquaculture operation.

Labour pressure is one of the drivers identified in the original manuscript. The sector has traditionally depended substantially on manual work, while the availability and cost of labour can affect farm profitability. The adoption of automation can reduce the labour required for specific tasks and can address labour bottlenecks. However, FAO evidence cautions that the labour effects of automation are context dependent. Where labour is scarce or wages are rising, automation may allow producers to expand production; where labour is abundant and low-skilled workers have few alternatives, automation can create greater displacement risks (FAO, 2022; Charlton et al., 2022). The Malaysian discussion should therefore focus on changing task requirements rather than assuming universal job elimination.

Food demand is another driver. The original manuscript links urbanisation, population and changing consumption patterns to the need for more productive and reliable agricultural systems. AI may contribute through precision resource use, disease detection, yield prediction and supply-chain management. Nevertheless, productivity gains depend on technology fit, data quality, human skills and investment capacity. AI should therefore be considered one component of a wider strategy for agricultural productivity and food security rather than a stand-alone solution.

The current technology environment provides a foundation for further AI adoption. MARDI documents a smart fertigation system based on IoT, a variable-rate seed-sowing system and the RiceFert location-specific fertilisation technology. MARDI reports that RiceFert-OC had been accepted across major rice granaries in Peninsular Malaysia and areas outside the granaries by 2022, with digital mapping and fertilisation recommendations provided through a national geospatial platform. These technologies are not necessarily AI themselves, but they illustrate the digital and data infrastructure on which more advanced AI applications can build (MARDI, 2025).

Documented and Existing AI-Related Applications in Malaysia

The first application area is agricultural drone technology. Azizul et al. (2023) investigated the acceptance of drones among 204 rice farmers in Kota Bharu Utara, Kelantan. The study found 15 factors related to acceptance and identified drone roles and drone-handling skills as highly significant. MARDI also reports research and collaboration on the effectiveness of drone use in rice-crop management. A 2024 MARDI study further documented the use of drones for pesticide application in paddy fields and noted that drone technology has been used in major paddy granary areas in Peninsular Malaysia for spraying, crop monitoring and related precision-

agriculture activities. These are documented Malaysian technology applications and should therefore be distinguished from claims that fully autonomous AI farming is already widespread (Azizul et al., 2023; MARDI, 2024).

The second area is precision input management. MARDI's smart fertigation system uses IoT to manage water and nutrients according to crop requirements, while RiceFert provides location-specific fertilisation recommendations for rice. MARDI also describes a variable-rate seed-sowing system using GPS sensors and geospatial processing to generate treatment maps for rice sowing. These applications demonstrate the growing use of data-driven agricultural management in Malaysia. They should be described accurately as digital, IoT or precision-agriculture systems unless the source explicitly establishes an AI component (MARDI, 2025).

The third area is urban and controlled-environment agriculture. MARDI has developed the TUBE Plot vertical vegetable-growing system for urban agriculture and smart fertigation technologies for managing crop water and nutrient requirements. These systems create controlled environments in which data can be collected systematically. AI could subsequently be integrated for optimisation, prediction and automated decision-making, but the existence of a digital or IoT system should not automatically be described as AI adoption. This distinction strengthens the reliability of the manuscript's evidence. Aquaculture is another area identified in the original manuscript. Water-quality variables such as temperature, pH and dissolved oxygen can be monitored using sensors and used to support feeding and water-management decisions. Malaysia has a significant aquaculture sector, and DOSM reported increases in freshwater aquaculture production in 2024 (DOSM, 2025). However, the present review distinguishes the documented use of sensors and automated monitoring from claims of widespread AI-based aquaculture management. Where a particular AI system is not supported by a Malaysian primary source, it is treated below as an emerging or potential application rather than an established national practice.

Emerging and Potential Applications of AI in Malaysian Agriculture

A number of AI applications are technically relevant to Malaysia but should be described as emerging or potential unless direct evidence of operational deployment is available. These include machine-learning models for yield prediction, computer vision for crop-disease identification, AI-assisted irrigation scheduling, autonomous or semi-autonomous agricultural robots, automated grading and sorting, predictive maintenance and AI-supported demand forecasting. International evidence indicates that digital automation can improve productivity, resilience and resource-use efficiency, but adoption is constrained by cost, digital skills, infrastructure and enabling institutions (FAO, 2022; McCampbell, 2022).

High-value fruit production provides a potential area for AI-based image analysis because disease, pest and stress detection can be supported by imagery collected from drones or other sensors. Similarly, plantation agriculture may benefit from predictive models that combine weather, soil and production information. These possibilities are consistent with the national direction in the Thirteenth Malaysia Plan, which identifies high-precision crop monitoring, real-time weather forecasting, sustainable resource utilisation and robotics as agricultural AI applications (Ministry of Economy, 2025). They remain future-oriented in this review unless specific farm-level Malaysian evidence demonstrates operational use.

AI-supported supply-chain management is another potential application. Automated grading, demand forecasting, inventory management, route optimisation and traceability could improve efficiency beyond the farm gate. However, the Malaysian evidence base should identify whether a technology is a research prototype, pilot project, commercial service or routine farm practice. Future research should document the crop, location, user group, technology type, scale of implementation and measured outcome so that claims about AI adoption can be evaluated accurately.

Factors Influencing AI Adoption

The adoption of AI in Malaysian agriculture is influenced by technological, human, organisational and environmental conditions. Aris et al. (2023) found that strategy, technology readiness, food security and food safety had positive relationships with AR4.0 adoption among Malaysian agro-based industries. Research on AI

adoption among Malaysian SMEs in Sabah also found significant relationships between organisational readiness, top-management commitment and AI adoption, although several other examined factors were not significant (Lada et al., 2023). Although these studies are not identical to farm-level AI adoption, they provide Malaysian evidence that adoption depends on readiness and organisational conditions rather than technology availability alone.

Technology characteristics are important because farmers evaluate whether a technology provides sufficient benefit relative to its cost and complexity. Diffusion of Innovations identifies relative advantage, compatibility and complexity among the characteristics that shape adoption (Rogers, 2003). AI technologies that are difficult to operate, require unreliable connectivity or produce recommendations that do not fit local farming practices may be less likely to be integrated. Conversely, technologies that solve a visible problem and demonstrate practical benefits may be easier to adopt.

Human capability is central to the authors' AI Literacy and Education and Training and Support variables. The Malaysian drone study provides direct evidence that practical handling skills are associated with technology acceptance (Azizul et al., 2023). FAO likewise identifies digital skills and knowledge as important barriers to agricultural automation, particularly for small-scale producers (McCampbell, 2022). Training should therefore be designed around actual agricultural tasks, including device operation, data interpretation, troubleshooting and decision-making, rather than providing only general awareness of AI.

Infrastructure is also a critical adoption condition. AI systems may depend on internet connectivity, electricity, mobile devices, cloud services, sensors and data transmission. The original manuscript identifies rural infrastructure and connectivity disparities as barriers. FAO evidence similarly identifies enabling infrastructure as a major factor in inclusive agricultural automation. Without reliable infrastructure, even technically appropriate AI solutions may be difficult to operate consistently (FAO, 2022).

Financial resources affect adoption because AI-related equipment, software, sensors, drones, data services and technical support can require substantial investment. This is particularly important for smallholders, who may not be able to absorb high fixed costs. FAO identifies investment costs as a significant barrier to inclusive adoption, while Malaysian research on AR4.0 also highlights constraints affecting smaller agricultural actors (FAO, 2022; Aris et al., 2023). This provides support for retaining Farm Size and Resources as a control variable. Farmer attitudes and agricultural culture also matter. Resistance should not be described simply as ignorance or unwillingness to modernise. Concerns about cost, reliability, loss of control, complexity and compatibility with established practices can be rational responses to risk. Diffusion of Innovations suggests that compatibility with existing values, experiences and needs affects adoption (Rogers, 2003). The Culture and Labour variable in the authors' model therefore captures a legitimate social and organisational dimension of agricultural technology adoption.

Socioeconomic Implications: Labour, Inequality and Smallholder Inclusion

The socioeconomic consequences of AI adoption are an important part of the manuscript and should be retained. The most frequently discussed concern is possible labour displacement. The original paper identifies the risk that automation may reduce demand for unskilled workers. This possibility should be stated cautiously. FAO finds that automation can alleviate labour shortages and improve productivity, while the employment effects depend on the availability of labour, wage conditions, technology costs and the wider economic environment. In some settings, automation can create opportunities for expansion and new employment; in others, low-skilled workers can face displacement risks (FAO, 2022; Charlton et al., 2022).

In the Malaysian context, the more defensible argument is that AI may change the composition of agricultural work. Some repetitive or physically demanding activities may require fewer workers, while new roles may emerge in drone operation, equipment maintenance, digital monitoring, data management and technology-supported farm management. This does not mean that all displaced workers can automatically move into new jobs. Retraining, extension support and accessible technical education are therefore important institutional responses to technological change.

Digital inequality is another concern. Farmers with larger farms, stronger financial resources, better connectivity and greater technical capability may adopt advanced technologies earlier than smaller producers. FAO warns that uneven adoption can deepen inequalities when automation is inaccessible to small-scale producers and other disadvantaged groups (FAO, 2022). This provides a strong empirical basis for the authors' concern about smallholder exclusion and supports the inclusion of Farm Size and Resources in the conceptual framework. Farmer resistance should likewise be considered in relation to trust, perceived risk and compatibility. Demonstration projects, farmer field schools, extension programmes and service-based technology models may help reduce uncertainty by allowing producers to observe results before making large investments. Such approaches are consistent with the trialability and observability principles of Diffusion of Innovations (Rogers, 2003).

Government Policy and Institutional Requirements

Government Policies and Support remain central to the authors' conceptual model because public institutions can influence the conditions under which AI adoption occurs. Malaysia's National AI Roadmap identifies agriculture and forestry as one of five national priority areas for AI use cases and emphasises responsible AI principles including fairness, reliability, privacy, inclusiveness, transparency and accountability (MOSTI, 2023). This policy direction supports the conceptual role of government as an external condition that can influence technology adoption and its outcomes.

The Thirteenth Malaysia Plan, 2026–2030, further identifies AI applications in agriculture, including high-precision crop monitoring, real-time weather forecasting, sustainable resource utilisation and robotic technology in oil-palm plantations, with the stated objective of improving productivity and reducing dependence on foreign workers (Ministry of Economy, 2025). These are national policy intentions and should not be presented as evidence that all applications are already operating at scale. Their significance for the present paper is that they establish a policy environment that can support the development and adoption of agricultural AI.

Government support can operate through finance, infrastructure, research, training, extension and regulation. Smallholders may require grants, concessional finance, shared-service schemes or cooperative models to access technologies that would otherwise involve high fixed costs. Rural connectivity and electricity infrastructure can expand the practical reach of AI systems. Research agencies can improve the availability of local datasets and validation environments. Extension services can translate technical information into practical farm decisions. These mechanisms explain why Government Policies and Support is positioned as a moderator rather than simply another independent variable. Data governance and responsible AI are also important. Agricultural AI depends on data concerning farms, production, weather, soil, pests, prices and other variables. Policies should encourage reliable data collection and interoperability while protecting privacy and ensuring appropriate data use. Standards are also needed for technology reliability, safety and accountability. The National AI Roadmap's emphasis on responsible AI principles provides a national policy basis for these requirements (MOSTI, 2023).

Limitations of the Review

This review has several limitations. First, it is a structured narrative review rather than a systematic review or meta-analysis. Source selection and interpretation therefore involve judgement, and the review cannot claim exhaustive coverage of all publications. Second, Malaysia-specific empirical research that directly measures AI adoption and agricultural productivity remains limited. Some available Malaysian evidence concerns drones, IoT, precision agriculture or Agricultural Revolution 4.0 more broadly rather than AI specifically. Third, the rapid development of AI means that technologies, costs, policies and applications can change quickly, potentially making some descriptions time-sensitive. Fourth, evidence concerning labour displacement, inequality and retraining is partly drawn from international agricultural automation research, so these findings should not be treated as direct empirical predictions for Malaysia. Fifth, the conceptual model has not been statistically validated in this study. The proposed direct, mediating, moderating and control relationships therefore require future empirical testing. Finally, the quality and availability of Malaysian agricultural datasets may limit the ability of future researchers to measure AI adoption and productivity consistently across commodities and farm sizes.

CONCLUSION

This paper has been revised as a structured narrative conceptual review in response to the examiner's comments. The paper clearly identifies its manuscript type, provides a review methodology, reorganises the discussion into coherent themes, distinguishes existing Malaysian applications from emerging and potential applications, strengthens the evidence base with Malaysian studies, government and institutional sources and FAO evidence, discusses socioeconomic implications cautiously, and includes a dedicated limitations section.

The authors' conceptual model remains the central framework. AI Technology Adoption is positioned as the independent variable and Agricultural Productivity and Efficiency as the dependent variable. AI Literacy and Education, Training and Support, and Culture and Labour remain mediating variables; Government Policies and Support remains the moderating variable; and Farm Size and Resources and Market Demand remain control variables. The theoretical foundations explain why AI adoption may influence productivity, why human capability and labour culture affect the translation of technology into practice, why government support may strengthen or weaken outcomes, and why farm resources and market demand need to be controlled.

The Malaysian evidence shows that the country already has an emerging foundation of digital and precision agriculture, including agricultural drone use, smart fertigation, variable-rate systems and location-specific rice fertilisation. At the same time, advanced AI applications should be distinguished between those documented at farm or institutional level and those that remain potential applications. This distinction is important for maintaining academic credibility. The evidence also indicates that adoption is shaped by skills, organisational readiness, resources, infrastructure, perceived benefits and institutional support. Overall, AI should be understood as part of a broader transformation of Malaysian agriculture rather than as an isolated technological intervention. Its contribution to productivity and efficiency is likely to depend on how successfully technology is integrated with farmer knowledge, training, labour arrangements, farm resources, market conditions and public policy. The retained conceptual framework provides a structured basis for future empirical research and can subsequently be tested using Malaysian farm-level data.

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