Indonesian Journal of Sustainable Agriculture and Environmental Sciences (IJSAES) E-ISSN 3109-1377
Vol. 2 No. 2, 126-145, 2026 https://doi.org/10.65896/ijsaes.v2i2.38

Artificial Intelligence Adoption in Smart Agriculture: A PRISMA-Based Systematic Comparative Review across Australia, South Korea, Indonesia and Pakistan

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Article history: submitted: July 19, 2026; accepted: August 30, 2026; available online: August 31, 2026

Abstract
Background: Artificial intelligence (AI) is steadily changing the agricultural systems around the world. However, its adoption remains uneven between developed and developing economies, creating significant inequality in productivity, technological access and food security. **Aim:** This systematic review determines the adaptation of AI in agriculture across Australia, South Korea, Indonesia and Pakistan. Prior systematic reviews of AI in agriculture have largely examined technical performance within single countries or technology categories, without directly comparing adoption pathways across countries at different stages of economic development. This review addresses that gap. **Methods:** This study addresses a critical research gap by following PRISMA 2020 guidelines. A systematic search of the Scopus database showed 940 records. Out of these, only 47 peer-reviewed studies (2015-2024) were included after screening for qualitative synthesis and thematic analysis. Extracted data were coded and grouped into four themes aligned with the review objectives, and the percentages reported below reflect the proportion of the 47 included studies in which each theme, technology, barrier or benefit was identified during coding. **Results:** The most prominently reported AI approaches in the studies were Machine learning (51.1%), precision farming (48.9%) and computer vision (46.8%). Developed economies demonstrated advanced integration of precision agriculture and automation. Developing economies mainly use AI for disease detection, crop monitoring and yield forecasting. The most common challenges reported were the high cost of implementation (38.3%), limited infrastructure (36.2%) and poor data quality (31.9%). The most frequently reported benefits were improved crop yields (61.7%), better resource use efficiency (51.1%) and more effective disease management (46.8%). These percentages show how many studies reported each benefit, but they do not indicate the actual level of improvement achieved. C**onclusion:** Overall, the findings suggest that the adoption of AI depends not only on the availability of technology but also on infrastructure readiness, supportive policies and strong institutional capacity. This review highlights the need for context-specific strategies, greater investment in rural digital infrastructure and inclusive innovation frameworks to support fair and sustainable agricultural development.

Keywords: agricultural automation; artificial intelligence (AI); digital agriculture; precision farming; PRISMA Guidelines

1. Introduction

The agricultural sector plays an important role in global food security, rural livelihoods and economic stability. However, agriculture is still facing many problems because of population growth, climate change, labor shortages & the depletion of natural resources. These pressures play out very differently across countries: Australia and South Korea confront them from a position of advanced infrastructure and institutional capacity, whereas Indonesia and Pakistan face them alongside more limited digital and rural infrastructure, a contrast that motivates the four-country comparison developed in this review. There is also a growing need for sustainable intensification to meet future food demands (FAO, 2023; IPCC, 2022; UN, 2022; Lobell & Asseng, 2017). Traditional farming systems rely on general management practices, slow decision-making and inefficient use of resources. These approaches have become increasingly inadequate for addressing these interconnected challenges. (Klerkx et al. 2019; Wolfert et al. 2017). In response to these challenges, agriculture is transitioning toward smart agriculture, a data-driven paradigm that integrates sensing technologies, automation, digital analytics and decision-making tools. This improves productivity, efficiency and resilience (Liakos et al. 2018; Wolfert et al. 2017). For consistency, this review uses "smart agriculture" as the primary umbrella term throughout. "Smart farming" is used interchangeably with the same meaning. It is consistent with usage in the source literature and is retained, where it appears in country-specific program names or in quoted technology categories.

Artificial Intelligence (AI) is emerging as one of the key technologies driving this transformation. AI incorporates technologies such as machine learning, deep learning, computer vision, robotics, expert systems and IoT-integrated platforms. These are capable of processing complex agricultural datasets to support adaptive decision making (Javaid et al. 2023; Liakos et al. 2018). These technologies are used for crop disease diagnosis, yield forecasting, irrigation optimization, nutrient management, weed detection, autonomous monitoring and precision spraying (Kamilaris & Prenafeta-Boldu, 2018; Talaviya et al., 2020). Their significance is not only based on their advanced technology but also helps in solving long standing agricultural inefficiencies by improving prediction accuracy, increasing automation and optimizing resource use.

However, the transition from AI capability to practical implementation is constrained by substantial barriers. These barriers include high investment costs, digital infrastructure limitations, data quality issues, technical complexity and insufficient institutional. These barriers differentially affect developed and developing agricultural systems (Eastwood et al. 2019; Klerkx & Rose, 2020; Rose et al. 2021). AI adoption pathways differ substantially across national contexts. The differences lie in the variations in technological readiness, agricultural structures, governance capacity and socioeconomic conditions (OECD, 2019; World Bank, 2023).

This review interprets adoption patterns through the Technology Organization Environment (TOE) framework (Tornatzky & Fleischer, 1990), which explains adoption as jointly shaped by technological attributes, organizational readiness (farm and institutional capacity) and environmental conditions (infrastructure and policy). This lens, complemented by insights from Diffusion of Innovation theory (Rogers, 2003) on how relative advantage and complexity shape uptake, is used in Section 4 to interpret why AI adoption pathways diverge between developed and developing economies.

Australia, South Korea, Indonesia and Pakistan provide a strategically relevant comparative framework. Australia represents an advanced agricultural economy, having strong integration of digital agriculture and precision farming (Eastwood et al. 2019). South Korea reflects a highly digitalized innovation environment with government-led smart-farming initiatives. Indonesia and Pakistan represent developing agricultural economies, where agriculture remains socio-economically vital. Digital transformation in the later countries faces problems related to infrastructural, institutional and financial limitations. Comparing these countries enables a nuanced understanding of how AI adoption evolves under contrasting developmental conditions.

Despite rapid growth in AI-agriculture research the literature is still poorly integrated. Most reviews are focusing primarily on technical performance measures. Which gives comparatively less attention to adoption barriers, implementation feasibility, comparative readiness and policy relevance (Kamilaris & Prenafeta-Boldu, 2018; Liakos et al., 2018). Existing systematic reviews of AI in agriculture (Kamilaris & Prenafeta Boldu, 2018; Liakos et al., 2018) have synthesized technical performance within single countries or technology families, but have not directly compared adoption pathways, barriers and outcomes across countries positioned at different points on the development spectrum. There is still a lack of systematic comparative research on AI adoption across developed and developing economies. Australia, South Korea, Indonesia and Pakistan were selected because, taken together, they span a wide range of infrastructural readiness, governance capacity and agricultural structure while sharing a common Asia-Pacific regional context, making them a meaningful basis for comparison. This review fills this gap.

2. Methods

2.1 Search Strategy and Eligibility Criteria

This review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines (Page et al. 2021; Moher et al. 2009; Shamseer et al. 2015). The Scopus database was searched for peer-reviewed studies published between 2015 and 2024, a period of rapid advances in AI and precision agriculture (Kamilaris & Prenafeta-Boldu, 2018; Liakos et al., 2018). The final search was executed on 07 May 2026.

The primary search string used AI terms ("artificial intelligence," "machine learning," "deep learning," "computer vision," "neural network") with smart agriculture terms ("smart agriculture," "precision agriculture," "smart farming," "digital agriculture"). This was combined with country-specific filters for Australia, South Korea, Indonesia and Pakistan, and an additional adoption-focused string ("adoption," "implementation," "barriers," "challenges") to strengthen policy relevance. Searches were conducted within titles, abstracts and keywords.

The full Boolean search string applied in Scopus was: TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "neural network*") AND ("smart agricultur*" OR "precision agricultur*" OR "smart farming" OR "digital agricultur*") AND ("Australia" OR "South Korea" OR "Republic of Korea" OR "Indonesia" OR "Pakistan") AND ("adopt*" OR "implement*" OR "barrier*" OR "challenge*")), limited to English-language documents published 2015-2024. The 2015-2024 window was chosen because it captures the period of rapid growth in AI and precision-agriculture research identified by Kamilaris and Prenafeta Boldu (2018) and Liakos et al. (2018), while a single database (Scopus) search kept coverage of peer-reviewed, indexed literature consistent across the four countries; the resulting trade-offs for non-English and non-Scopus indexed literature are discussed as a limitation in Section 2.5.

Studies were included if they met the following criteria: (1) they were peer-reviewed journal articles or conference papers, (2) focused on AI application, adoption or implementation in smart or precision agriculture, (3) conducted within or directly comparing the four focal countries, and (4) published in English or with an English abstract sufficient for screening. Excluded sources were grey literature, editorials, conference abstracts without full text, thesis studies without a direct AI focus, studies outside the four focal countries without comparative elements and duplicates or irretrievable full texts. To provide a balanced analysis of AI integration across different economic contexts, this review selectively focuses on two developed nations (Australia and South Korea) and two developing nations (Indonesia and Pakistan) within the Asia-Pacific region.

2.2 Study Selection Procedure (PRISMA 2020)

Identification, screening, eligibility and inclusion were the four stages of the selection process. The initial Scopus search yielded 940 records. After removing 16 duplicates, 924 records underwent title and keyword screening, during which 482 studies were excluded due to technological, agricultural, geographical or conceptual irrelevance. The remaining 442 studies proceeded to abstract screening. After a detailed assessment, 395 studies were excluded due to insufficient AI adoption focus, limited smart agriculture relevance and absence of comparative or policy insights or weak methodological alignment. The final qualitative synthesis used only 47 studies that met all inclusion criteria. Screening was conducted based on title/abstract and full text by two independent reviewers. They checked against the eligibility criteria specified in Section 2.2, and any disagreements were resolved through discussion until a consensus was reached. Where necessary, a third reviewer was consulted to resolve disagreements. Formal inter-rater reliability was not quantified. A formal chance-corrected agreement statistic (Cohen's kappa) was not calculated because screening decisions were reconciled to full consensus through discussion rather than retained as independent ratings; the two-reviewer plus arbitrator procedure was adopted instead as the primary safeguard against selection bias. Figure 1 presents the complete PRISMA 2020 flow diagram, and a completed PRISMA 2020 checklist is provided as supplementary material (Page et al. 2021).

2.3 Quality Assessment

Methodological quality was analyzed through a structured six-criterion framework adapted from established systematic review quality evaluation tools (Kitchenham & Charters, 2007; Page et al., 2021). Criteria included: (1) clearly defined research objectives, (2) an appropriate description of the agricultural context, (3) an explicit description of AI technology, (4) adequate methodological rigor, (5) a clear presentation of findings, and (6) relevance to the review objectives. Each criterion was scored as 1 (satisfied) or 0 (not satisfied), yielding a total score of 0-6. Studies were grouped as high quality (5-6), moderate quality (3-4) or low quality (0-2). Quality scores informed synthesis confidence but were not used for exclusion. As all retained studies were peer-reviewed and met predefined inclusion criteria. This six-criterion framework, adapted from Kitchenham and Charters (2007) software engineering review guidelines, was selected because the included literature spans engineering, computer science and agricultural science studies for which no single domain-specific appraisal tool (a purely agronomic or purely biomedical checklist) adequately covers both the AI-methodological and agricultural context dimensions being synthesized. The six criteria were chosen to capture both dimensions explicitly. This is treated as a limitation of the review in Section 4.

2.4 Data Extraction and Thematic Analysis

A structured data extraction framework was used to collect key information from each study. This included the author(s), publication year, country, economic classification, agricultural sector, crop, AI technology used, application purpose, adoption barriers, opportunities and benefits, productivity impacts and the main findings. All 47 studies were compiled into a master extraction database. Following the extraction, thematic synthesis was conducted to analyze and interpret evidence across four major themes corresponding to the four research objectives (Thomas & Harden, 2008).

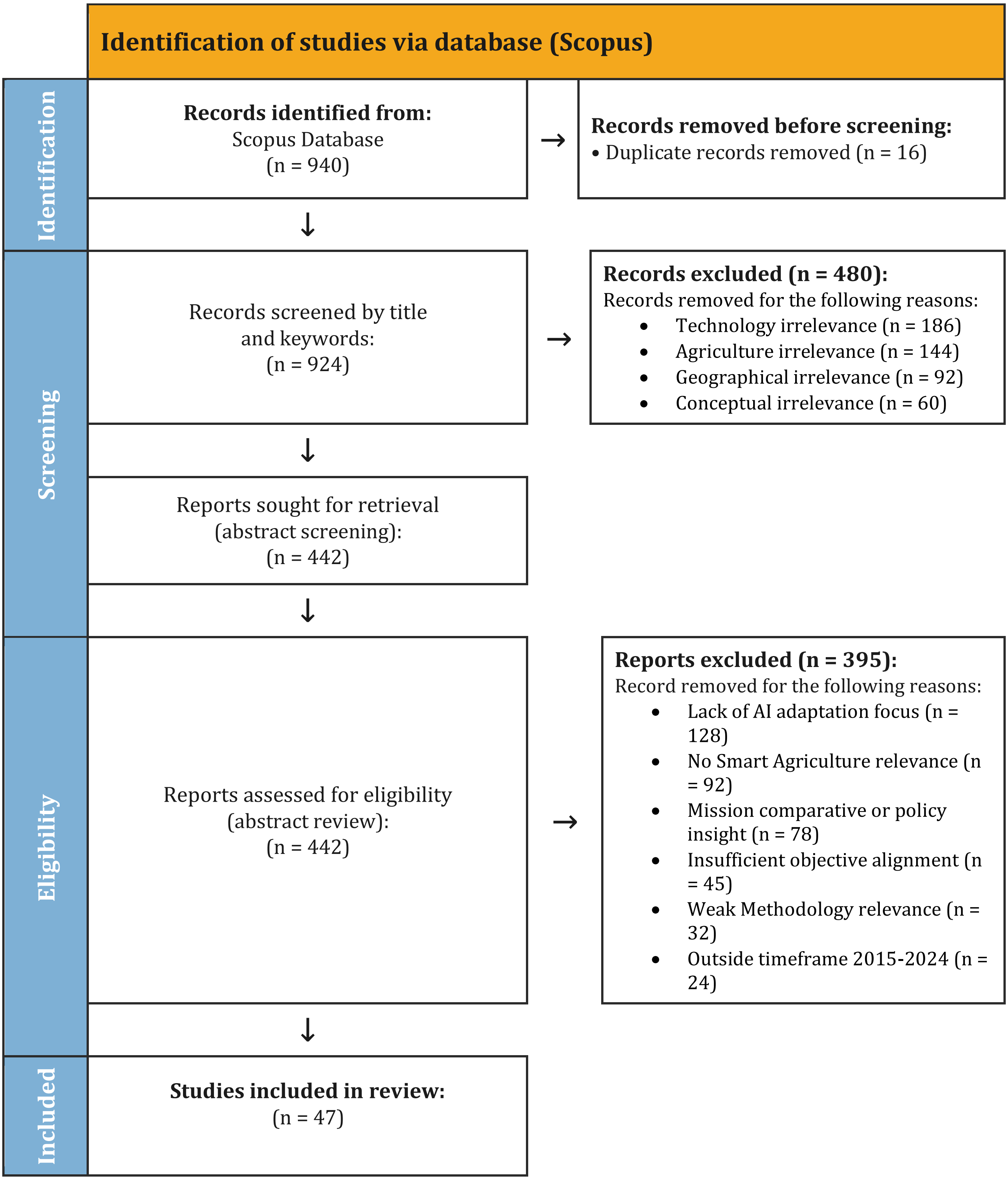

Figure 1. PRISMA 2020 flow diagram shows the identification, screening, assessment for the studies.

Thematic synthesis was used instead of statistical meta-analysis. This was due to the diversity of methodologies, AI technologies, agricultural systems and outcome indicators across the included studies. Thematic synthesis followed the three-stage procedure of Thomas and Harden (2008). First, each extracted study was open-coded line by line against the extraction fields (AI technology, barriers, benefits, country context). Then codes were grouped inductively into descriptive themes, which were iteratively merged and refined by cross-checking against the four review objectives until four stable analytic themes were reached (Sections 3.2-3.5). Themes were validated by re-reading a sample of the source studies against the assigned codes and resolving discrepancies through discussion between reviewers, after which the frequency counts reported in Tables 2, 4 and 6 were finalized.

2.5 Risk of Bias Assessment

In addition to the methodological quality assessment described in Section 2.4. the risk of bias was evaluated at the review level for the included studies. Three sources of potential bias were assessed qualitatively (1) publication bias given that the reliance on a single database (Scopus) and English-language sources may under represent studies published in non-English journals or grey literature, particularly for South Korea, where relevant work may appear in Korean-language outlets indexed in databases such as the Korean Citation Index (KCI) (2) selective outcome reporting, since included studies varied in which adoption barriers, technologies or impact categories they reported, meaning frequency counts in this review reflect what was reported rather than an exhaustive assessment of all possible outcomes and (3) geographic and country evidence imbalance as the number of studies conducted directly within each focal country differed substantially with South Korea in particular represented mainly through international collaborative studies rather than domestic research. These risks were not used to exclude studies but are considered when interpreting the strength and generalizability of the review's findings.

3. Results and Discussion

3.1 Characteristics of Included Studies

The review included only 47 studies published between 2015 and 2024. The publication trend indicates growing research interest. As AI applications in smart agriculture are particularly accelerating after 2018, consistent with rapid expansion in machine learning, deep learning & precision agriculture technologies (Kamilaris & Prenafeta-Boldu, 2018; Liakos et al., 2018; Javaid et al., 2023). Publication output peaked in 2022-2023, reflecting intensifying global attention to agricultural digitalization (figure 2).

The included studies were published across a diverse set of outlets, with a concentration in agriculture-focused engineering journals, Computers and Electronics in Agriculture, Sensors and Information Processing in Agriculture; each contributed multiple studies, alongside remote sensing (Remote Sensing) and regional or discipline-specific outlets (Smart Agricultural Technology, Precision Agriculture). Designs were predominantly empirical case studies and model development or model evaluation studies rather than randomized or longitudinal designs, and sectors spanned field crops (sugarcane, wheat, rice, coffee), horticulture (durian, pakcoy) and mixed cropping systems. Consistent with the geographic imbalance already noted in Section 2.5, South

Korea contributed comparatively few directly attributable studies within the 47 retained records where South Korean evidence appears; it is largely through internationally coauthored studies rather than nationally focused publications, which limits the granularity of country-specific conclusions for South Korea relative to the other three countries.

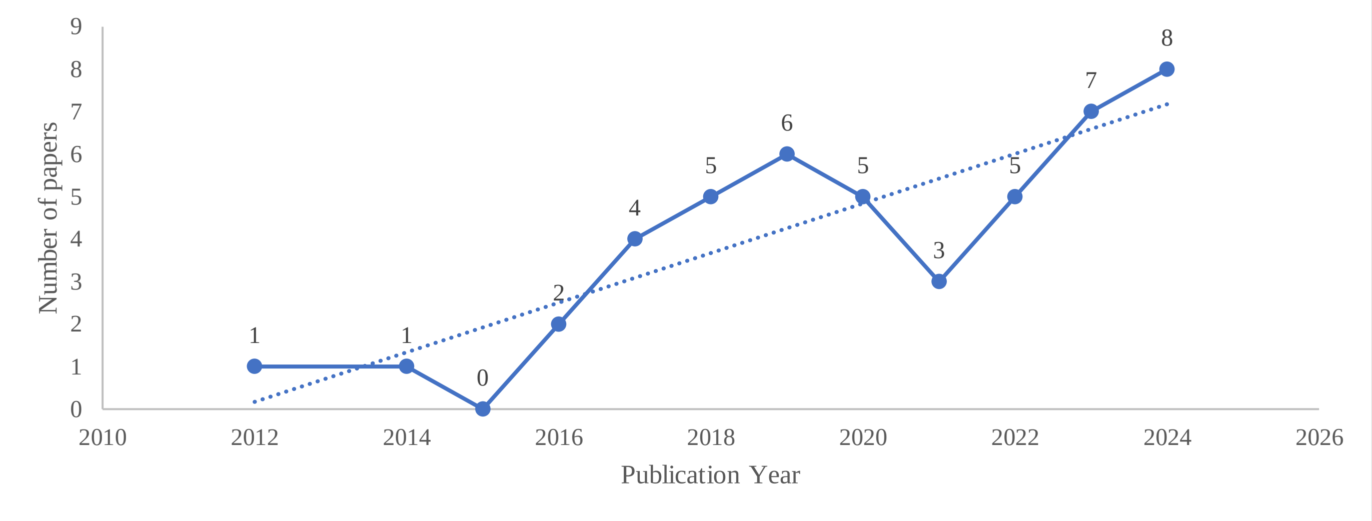

Figure 2. Publication trend of included studies.

Geographically, studies were concentrated in Asia and Oceania (Figure 3). Global/Others contributed the highest overall number of publications in the broader AI-agriculture literature. It is retrieved during screening, consistent with its position as a leading global contributor to this research area. However, other countries were only included in this review to support, which is designed specifically to compare Australia, South Korea, Indonesia and Pakistan. Among these four focal countries, Australia contributed the highest number of publications, followed by Indonesia, Pakistan and South Korea. Asia accounted for 59.6% of included studies, highlighting increasing AI-driven agricultural innovation across the region (FAO, 2023; Javaid et al., 2023).

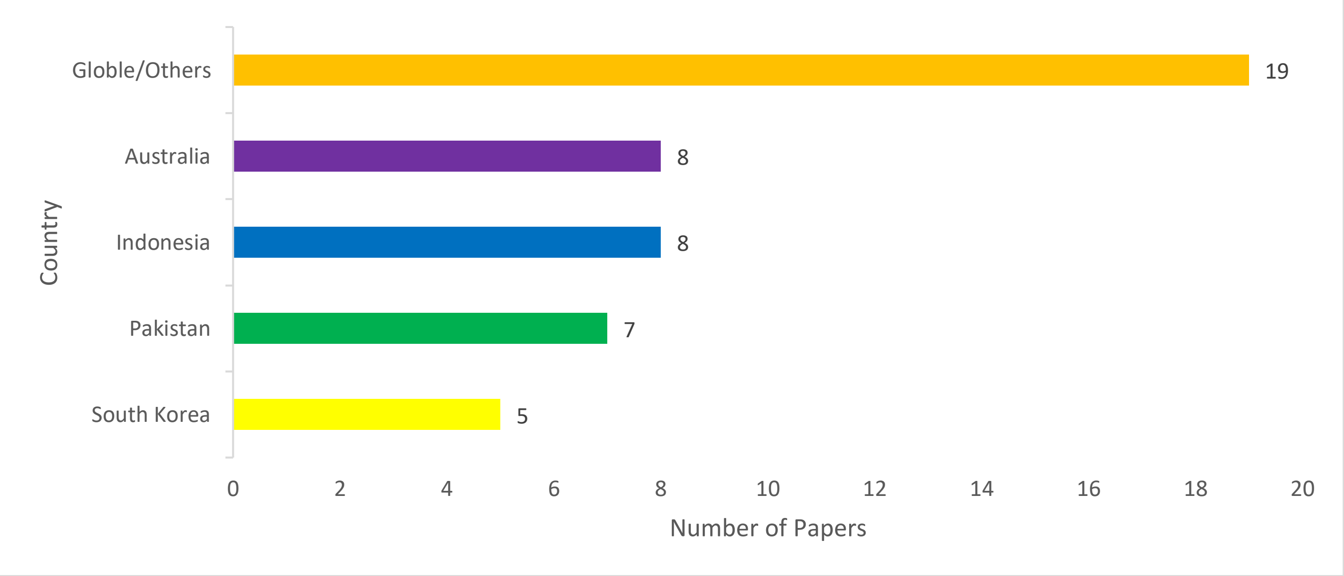

Figure 3. Geographical distribution of included studies by country

With respect to development status the developing economies accounted for the largest proportion (48.9%), followed by developed economies (36.2%) and mixed-country studies (14.9%), as shown in figure 4.

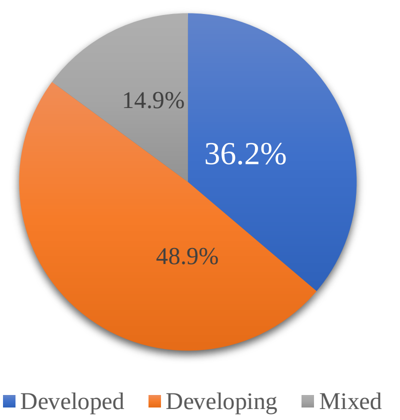

Figure 4. Distribution of included studies by development status (n = 47).

Table 1. Summary Characteristics of Included Studies (n = 47)

Variable	Category	Frequency (n)	Percentage (%)
Development Status	Developed	17	36.2
	Developing	23	48.9
	Mixed	7	14.9
Continent	Asia	28	59.6
	Oceania	8	17.0
	North America	4	8.5
	Mixed/Global	7	14.9
Objective Alignment	Obj 1 AI Technologies	41	87.2
	Obj 2 Barriers & Challenges	22	46.8
	Obj 3 Economic/Productivity Impacts	29	61.7
	Obj 4 Comparative Insights	34	72.3

Note. Studies are categorized by development status, continent and objective alignment.

3.2 AI Technologies Adopted in Smart Agriculture

Analysis of the 47 included studies identified six major categories of AI technologies. Machine learning, precision farming tools, computer vision, remote sensing, UAV-based systems, deep learning and IoT-integrated sensor systems (Table 2; Figure 5). Machine learning emerged as the most frequently reported technology (51.1%), followed by precision farming tools (48.9%) and computer vision (46.8%).

The most commonly used machine learning algorithms were Random Forest, Support Vector Machine (SVM), Artificial Neural Networks (ANN), Extreme Learning Machine (ELM) and ensemble methods. These were widely used for yield prediction, disease classification, crop monitoring and decision support (Akbarian et al. 2024; Colaco et al. 2024; Kouadio et al. 2018; Chlingaryan et al. 2018; Khaki & Wang, 2019; Belgiu & Drăguț, 2016). Computer vision and deep learning using CNN, YOLO, ResNet and MobileNet architectures were primarily employed for image-based disease detection, pest identification, fruit recognition, as well as field monitoring (Arsalan et al. 2024; Feroza et al. 2023; Khan et al. 2022; Wijayanto et al. 2024; Boulent et al. 2019; Li et al. 2014; Sa et al. 2016; Xu et al. 2023; Yamamoto et al. 2017; Zheng et al. 2019; Xu et al. 2020).

E-ISSN 3109-1377
https://doi.org/10.65896/ijsaes.v2i2.38

Remote sensing and UAV-assisted systems were frequently integrated with AI algorithms. It improves crop surveillance, yield estimation, nutrient management and precision interventions (Akbarian et al. 2024; Tilse et al. 2022; Daud et al. 2023; Virnodkar et al. 2020; Weiss et al. 2020; Zhang & Kovacs, 2012; Zhang et al. 2019; Xu et al. 2020; Shendryk et al. 2021). IoT-integrated AI systems, though less frequently reported (14.9%), combined sensors, environmental monitoring and real-time analytics to support irrigation and smart farming operations (Ahmed et al. 2024).

Table 2. AI Technologies Adopted in Smart Agriculture

AI Technology Category	Frequency (n)	Percentage (%)	Main Applications
Machine Learning	24	51.1	Yield prediction, disease classification, decision support
Precision Farming Tools	23	48.9	Site-specific management, nitrogen management and precision spraying
Computer Vision	22	46.8	Disease detection, crop and fruit recognition, image analysis
Remote Sensing/UAV	17	36.2	Crop monitoring, yield estimation, nutrient management
Deep Learning	14	29.8	CNN/YOLO-based disease and pest detection, image segmentation
IoT-Integrated Systems	7	14.9	Smart irrigation, environmental monitoring, sensor analytics

Note. Categories are not mutually exclusive, one study may report more than one AI technology.

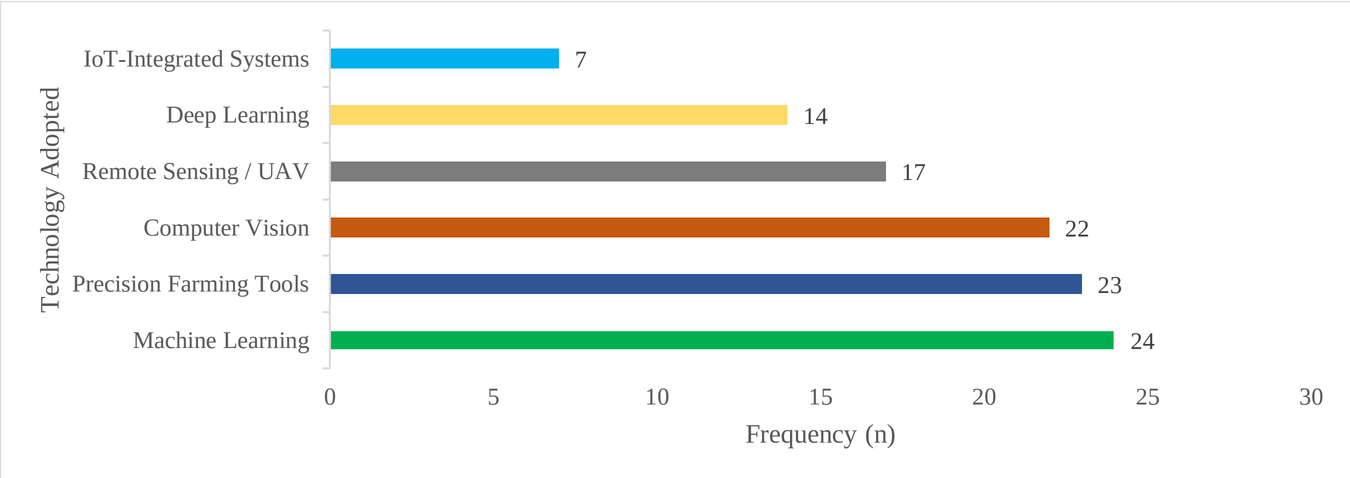

Figure 5. Frequency of AI technology categories identified in included studies.

Cross-country analysis revealed notable differences in technological adoption (Table 3). Australian studies were dominant with machine learning, remote sensing, UAV-assisted monitoring & precision agriculture (Colaco et al. 2024; Tilse et al. 2022). Indonesian studies showed stronger emphasis on computer vision and disease detection within rice systems (Wijayanto et al. 2024). Studies from Pakistan frequently used machine learning as well as deep learning for disease classification, yield prediction and precision spraying. (Arsalan et al. 2024; Khan et al. 2022; Ahmad et al. 2024). South Korean evidence appeared primarily through collaborative research. It focused on smart farming technologies (Moon et al. 2018) and automated agricultural systems rather than through studies conducted directly within South Korea.

Table 3. Cross-Country Comparison of Dominant AI Technologies

Country	Dominant AI Technologies	Main Applications	Context Notes
Australia	Machine Learning, UAVs, Precision Farming, Remote Sensing	Yield prediction, crop-water management, resource optimization	Strong digital infrastructure and an advanced precision agriculture ecosystem (Shendryk et al. 2021). Australian studies demonstrate extensive integration of satellite imagery and environmental data for field-level yield prediction.
South Korea	IoT, Smart Farming Platforms, AI Decision Support	Automated monitoring, greenhouse management, decision support	Government-led digital agriculture initiatives with strong smart farming subsidies. Evidence appears primarily through collaborative research (Moon et al. 2018). reflecting a well-established innovation ecosystem but limited domestic publication in international databases.
Indonesia	Computer Vision, Machine Learning, CNN, UAV	Rice disease detection, crop monitoring, pest diagnosis	Application specific AI adoption, limited digital infrastructure in many rural areas (Iwahashi et al. 2023). Research demonstrates effective use of UAV multispectral imagery for drought damage assessment and crop insurance applications.
Pakistan	Machine Learning, Deep Learning, YOLO-based CNN	Disease diagnosis, yield prediction, precision spraying	Rapid growth in AI research but adoption is constrained by infrastructure and cost. Studies primarily employ deep learning architectures for disease classification and precision spraying applications (Arsalan et al. 2024; Khan et al. 2022; Ahmad et al. 2024)

3.3 Barriers and Challenges to AI Adoption

The reviewed studies revealed that despite growing AI adoption several barriers continue to constrain effective implementation. The most frequently reported challenges were high implementation costs (38.3%), inadequate infrastructure (36.2%), limited data availability and quality (31.9%), technical complexity (29.8%), insufficient digital literacy (25.5%) and policy or institutional constraints (21.3%). These barriers were evident across both developed and developing economies. Although their relative importance varied considerably among the compared countries (Table 4; Figure 6).

Economic constraints emerged as the most commonly reported barrier. High investment costs associated with sensors, drones, IoT devices, software platforms and AI-enabled machinery, limited adoption, particularly among smallholder farmers and resource-constrained systems (Klerkx & Rose, 2020; Rose et al., 2021). Infrastructure-related challenges include poor internet connectivity, limited digital technology access and unreliable power supply. These were especially prominent in Indonesia and Pakistan (Javaid et al. 2023; Klerkx & Rose; Venkatesan et al. 2022). Data-related issues like difficulties in collecting, standardizing, and managing high-quality agricultural datasets reduce model accuracy and constrain AI scalability (Kamilaris & Prenafeta-Boldu, 2018; Liakos et al., 2018).

Technical complexity and digital literacy constraints were frequently reported. Many farmers lacked the skills necessary to operate AI-enabled systems or interpret analytical outputs (Rose et al. 2021). Policy and institutional barriers that include weak regulatory frameworks, insufficient government support and limited public-private collaboration. These were more pronounced in developing economies like Indonesia and Pakistan (Eastwood et al. 2019; Klerkx & Rose, 2020).

Table 4. Major Barriers to AI Adoption in Smart Agriculture

Barrier Category	Frequency (n)	Percentage (%)	Key Examples
High implementation cost	18	38.3	Sensors, UAVs, software, AI infrastructure
Infrastructure limitations	17	36.2	Connectivity, power supply, digital platforms
Data availability & quality	15	31.9	Fragmented and inconsistent training datasets
Technical complexity	14	29.8	Technical expertise, system calibration, AI management
Digital literacy	12	25.5	Farmer training, extension service gaps
Policy & institutional	10	21.3	Regulatory frameworks, government support

Note: Frequency reflects the number of studies explicitly reporting each barrier category.

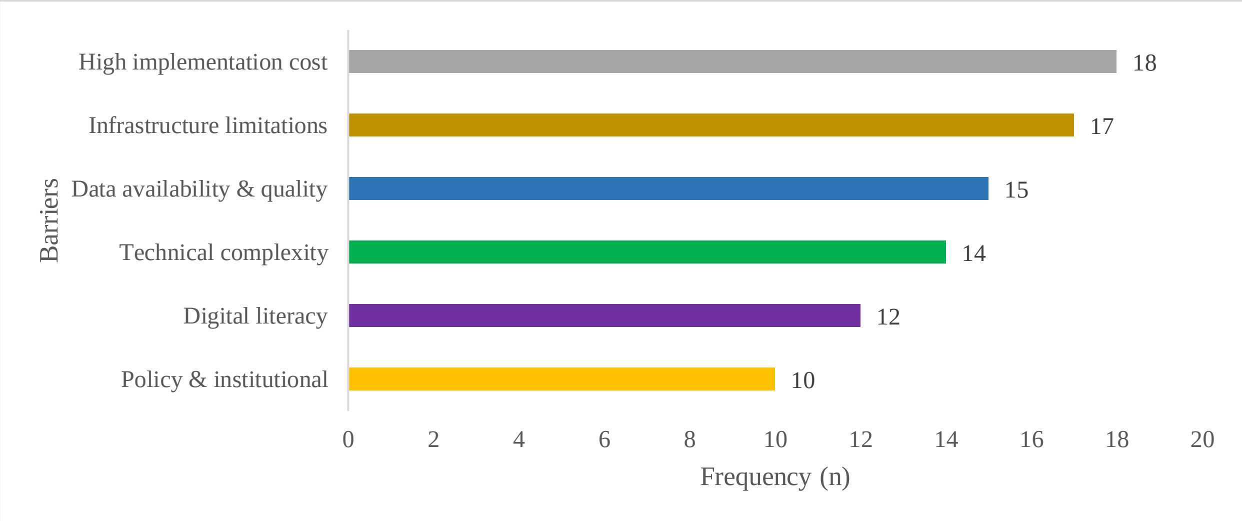

Figure 6. Frequency of major barriers to AI adoption reported across included studies.

Table 5. Comparison of AI Adoption Barriers between Developed and Developing Economies

Barrier	Developed Economies	Developing Economies	Recommended Response
Cost constraints	Moderate (infrastructure ROI)	High (affordability, smallholders)	Financial support and subsidy mechanisms
Infrastructure	Low–Moderate (largely resolved)	High (rural connectivity gaps)	Rural broadband expansion and energy investment
Data availability	Moderate (interoperability issues)	High (fragmented, limited datasets)	National data platforms and open-data initiatives
Technical complexity	High (system integration and scalability)	Moderate (basic access barriers)	Extension services and digital skills training
Digital literacy	Moderate (farmer adoption challenges)	High (limited training programs)	Capacity building and e-learning programs
Policy support	Moderate–Strong (established innovation ecosystem)	Limited (fragmented policy frameworks)	Comprehensive digital agriculture policy agendas

Note: Severity assessments are based on relative frequency of barrier reporting within developed versus developing economy studies.

3.4 Economic and Agricultural Productivity Impacts of AI Adoption

The reviewed studies demonstrated that AI adoption contributes to a range of economic, productivity and sustainability outcomes (Table 6; Figure 7). Yield improvement was the most commonly reported benefit (61.7%) with machine learning effectively identifying complex drivers of productivity variation (Jones et al. 2022), followed by resource use efficiency (51.1%), disease and pest management (46.8%), labor optimization (38.3%), sustainability enhancement (36.2%) and food security contribution (27.7%).

Machine learning, remote sensing and precision farming technologies were widely applied to optimize crop management decisions, improve forecasting accuracy and increase production efficiency (Akbarian et al. 2024; Colaco et al. 2024; Kouadio et al. 2018). AI supported irrigation scheduling, fertilizer management and precision input application contributed to improved utilization of water, nutrients and energy (Liakos et al. 2018; Tilse et al. 2022; Fuentes et al. 2021; Zhang & Wang, 2023). Computer vision and deep learning systems helped identify crop diseases and pests quickly, reducing crop losses and improving farm management effectiveness (Arsalan et al. 2024; Feroza et al. 2023; Wijayanto et al. 2024).

Cross-country evidence showed that Australia and South Korea primarily reported productivity gains with the help of precision farming, automation & advanced decision support systems (Pivoto et al. 2018). In contrast, Indonesia and Pakistan frequently emphasized disease detection, crop monitoring and yield forecasting, which improve production efficiency within resource constrained environments.

Table 6. Economic and agricultural productivity impacts of AI adoption

Impact Category	Frequency (n)	Percentage (%)	Mechanism
Yield improvement	29	61.7	Machine learning and precision agriculture tools were used to improve crop management and predict crop yields.
Resource use efficiency	24	51.1	AI-guided irrigation, fertilizer application and input optimization
Disease & pest management	22	46.8	Computer vision enables rapid image-based disease and pest diagnosis
Labor optimization	18	38.3	Automated monitoring and UAV-assisted field inspection reduce labor requirements
Sustainability enhancement	17	36.2	Reduced input waste and climate responsive decision making improve sustainability
Food security contribution	13	27.7	Improved forecasting, resilience and production stability enhance food security

Note. Impact categories reflect the most frequently reported outcomes across included studies.

3.5 Comparative insights between developed and developing economies

Comparative analysis revealed substantial differences in AI adoption patterns, implementation readiness, barriers and outcomes across the four countries (Table 7, Figure 8). While all four countries demonstrated increasing interest in AI enabled smart agriculture. The nature and maturity of adoption varied considerably according to technological infrastructure, policy support, institutional capacity and agricultural system characteristics.

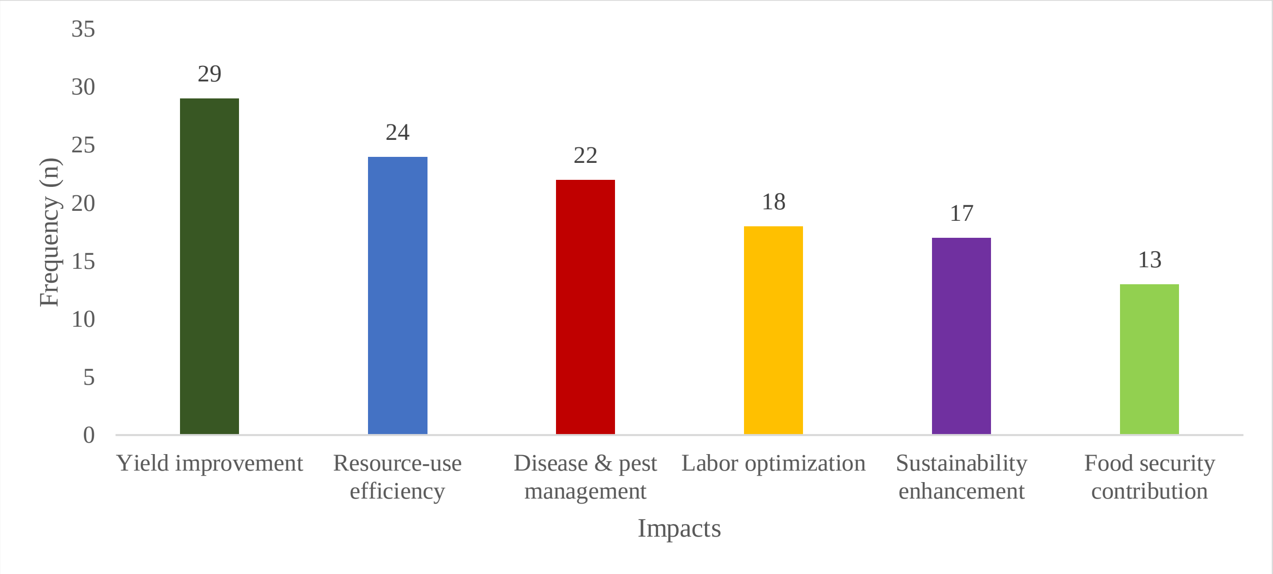

Figure 7. Frequency of economic and agricultural productivity impacts reported in included studies.

Australia exhibited the most advanced implementation of AI-supported precision agriculture. The literature showed extensive application of machine learning, remote sensing, UAV-assisted monitoring and precision farming tools. AI tools were used for yield prediction, irrigation management, crop surveillance and resource optimization (Colaco et al. 2024; Tilse et al. 2022; Dale et al. 2023). South Korea demonstrated substantial progress in smart farming. They use IoT-enabled monitoring systems, automated greenhouse technologies and AI-assisted decision support platforms, supported by government led digital agriculture initiatives (Eastwood et al. 2019).

Table 7. Comparative AI adoption profile across studied countries

Dimension	**Australia**	**South Korea**	**Indonesia**	**Pakistan**
Adoption Maturity	High	High	Moderate	Moderate–Low
Dominant AI Technologies	Machine Learning, UAV, Precision Farming	IoT, Smart Farming, AI Platforms	Computer Vision, Machine Learning, CNN	Machine Learning, Deep Learning, YOLO
Infrastructure	High	High	Moderate	Low–Moderate
Policy Support	Strong	Strong	Moderate	Limited
Primary Barriers	Integration, technical complexity	Scalability, system integration	Infrastructure, implementation cost	Infrastructure, affordability
Top Opportunity	Precision agriculture	Smart farming automation	Crop disease monitoring	Yield prediction
Main AI Impact	Resource-use efficiency	Automation and productivity	Disease management	Yield improvement
Farmer Readiness	High	High	Moderate	Low–Moderate
Research Evidence	Strong (farm-scale studies)	Strong (national-level studies)	Moderate (laboratory and field studies)	Moderate (primarily laboratory studies)

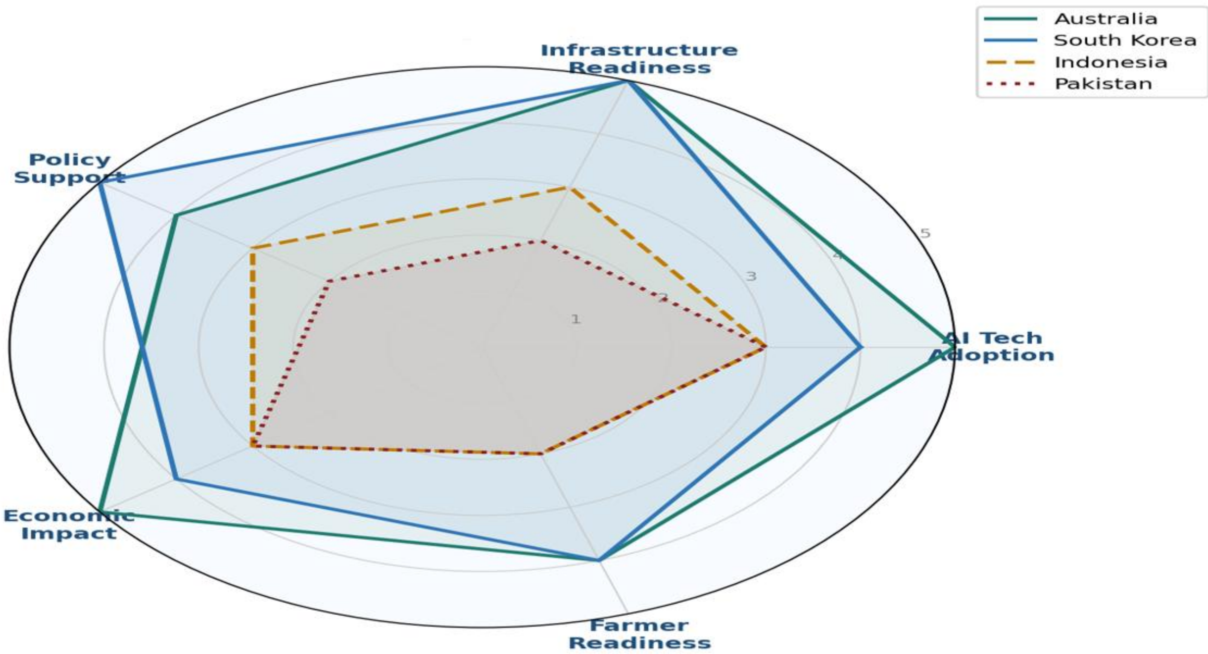

Figure 8. Comparative AI adoption profile radar chart. Scale: 1 = Low, 5 = High.

In contrast, AI adoption in Indonesia and Pakistan was characterized by stronger emphasis on application specific solutions. Computer vision-based disease detection and crop monitoring were primarily focused studies on rice systems (Wijayanto et al. 2024), though farmer technology acceptance still remains a key implementation challenge (Larasati et al. 2024). Disease diagnosis, yield forecasting and precision spraying were the main applications of machine learning and deep learning in Pakistani studies (Arsalan et al. 2024; Khan et al. 2022). Implementation in both countries was often constrained by infrastructure limitations, affordability concerns and limited digital agricultural services.

3.6 Synthesis and Discussion

The results show that the adoption of AI in agriculture is expanding in both developed and developing economies. Yet their implementation is still uneven. Success depends more on infrastructure, institutional capacity and policy support than on technology availability alone (Eastwood et al. 2019; Klerkx & Rose, 2020). Read through the TOE framework introduced in Section 1, this pattern indicates that the environmental (infrastructure, policy) and organizational (institutional capacity) dimensions of adoption are currently the binding constraints across all four countries, rather than the technological dimension; this is consistent with Diffusion of Innovation theory's emphasis on how contextual complexity, not the intrinsic advantage of a technology, governs the pace of adoption. Machine learning was the most frequently reported AI technology (51.1% of studies), followed by precision farming (48.9%) and computer vision (46.8%). This suggests AI adoption remains prediction oriented rather than automation oriented. Machine learning is accessible because it generates insights from existing data without heavy infrastructure investment. In contrast, IoT and robotics require greater resources, explaining their lower adoption despite strong potential (Kamilaris & Prenafeta-Boldu, 2018; Liakos et al. 2018; Klerkx & Rose, 2020; Rose et al. 2021).

The four countries' comparison reveals distinct pathways. Australia had the most advanced use of AI, applying machine learning, remote sensing, UAVs and precision farming across agricultural practices. These technologies are used for yield prediction and resource management (Colaco et al. 2024; Eastwood et al. 2019; Tilse et al. 2022). South Korea showed progress through government-led smart farming initiatives, but the evidence is limited and mainly from collaborative research (Eastwood et al. 2019).

South Korea has stronger infrastructure and policy support than Indonesia. However, Indonesia's AI adoption focuses on specific applications like rice disease detection and crop monitoring using computer vision (Wijayanto et al. 2024; Feroza et al. 2023), constrained by infrastructure and affordability. Pakistan lags behind Indonesia with even greater infrastructure gaps and weaker institutional support. Pakistani studies use machine learning for disease diagnosis and yield prediction only. Their implementation remains small-scale and research-oriented (Arsalan et al. 2024; Khan et al. 2022). Both Indonesia and Pakistan prioritize short-term solutions over integrated systems, consistent with developing economies adopting technology in response to immediate pressures (Klerkx & Rose, 2020).

Among the four countries, Australia has the most mature AI ecosystem. Nevertheless, even in advanced settings, adoption faces socio-digital challenges related to data governance and farmer readiness (Marshall et al. 2022). To close the gap, South Korea should strengthen its domestic evidence base. Indonesia and Pakistan need investments in rural connectivity, farmer training, affordable AI tools and public-private partnerships in order to move from isolated applications to integrated systems.

Structural barriers remain critical. High costs (38.3%), poor infrastructure (36.2%) and data quality issues (31.9%) limit adoption, especially for smallholders (Javaid et al. 2023; Kamilaris & Prenafeta-Boldu, 2018; Klerkx & Rose, 2020; Liakos et al. 2018; Rose et al. 2021). These findings reinforce that agricultural digitalization is a socio-technical process, requiring coordinated investment (Klerkx & Rose, 2020).

Positive outcomes were frequently reported in yield improvement (61.7%), resource efficiency (51.1%) and disease management (46.8%). Benefits were greatest when AI was integrated with precision agriculture systems (Akbarian et al. 2024; Kouadio et al. 2018; Khaki & Wang, 2019). AI also supports sustainability through reduced water and chemical use (Javaid et al. 2023; Liakos et al. 2018). However, it may increase reliance on digital infrastructure.

Developed economies are advancing toward integrated systems. Whilst developing economies risk widening inequality. Policymakers should invest in rural connectivity, farmer training and subsidies for smallholders tailored to local conditions (FAO, 2023; World Bank, 2023). Australia should focus on integration and interoperability, South Korea on building evidence, Indonesia on rural connectivity and affordable tools, and Pakistan on foundational infrastructure and training.

Future research needs interdisciplinary approaches, long-term adoption studies and better evidence on farmer acceptance and governance. Specifically, longitudinal cohort studies would clarify whether early AI adopters sustain gains over time, mixed methods designs combining farmer surveys with technical performance data would connect adoption theory to lived farmer decision making and as the evidence base grows, meta-analytic pooling of comparable outcome measures (yield or resource-efficiency gains) would allow effect sizes to be compared quantitatively across countries in a way the present thematic synthesis cannot. Novel AI architectures also include large language model-based diagnostic systems that represent emerging opportunities (Hue et al. 2024). Addressing evidence gaps, especially for South Korea and improving system transferability across contexts are priorities. The principal theoretical contribution of this review is to show, empirically across four contrasting national contexts, that the organizational and environmental dimensions of the TOE framework currently explain more of the observed variation in AI adoption than the technological dimension, extending prior single-country applications of TOE and Diffusion of Innovation theory in agriculture to a comparative developed-developing setting.

4. Limitations and Future Directions

Several limitations exist. South Korea's evidence is thin and collaborative, which limits conclusions. Reliance on Scopus and English sources may miss regional literature. The quality framework was adapted from software engineering. Domain-specific tools are better. Thematic synthesis prevents pooling effect sizes. Most studies are cross-sectional, limiting insights into long-term adoption.

5. Conclusion

This systematic review examined AI adoption in smart agriculture across Australia, South Korea, Indonesia and Pakistan using evidence from 47 peer-reviewed studies. The findings show that AI is transforming agriculture through machine learning, deep learning, computer vision, remote sensing, IoT as well as precision farming. The most widely adopted approach emerged as machine learning due to its versatility in yield prediction, disease detection, crop monitoring and decision-making. The review revealed clear differences in adoption pathways between developed and developing economies. Australia and South Korea demonstrated more advanced integration of precision agriculture, automation and digital decision support. On the other hand, Indonesia and Pakistan primarily used AI for specific challenges such as disease diagnosis, crop monitoring and productivity improvement. These differences highlight the critical importance of infrastructure readiness, institutional capacity, digital literacy and policy support, which help in shaping agricultural digital transformation.

Despite promising benefits including enhanced productivity, resource efficiency, disease management and resilience, several barriers continue to limit implementation. The significant challenges are high costs, inadequate infrastructure, poor data quality, technical complexity and weak institutional support, especially in developing agricultural systems. AI adoption success depends not only on technology but also on the broader socioeconomic and policy environments. This helps enable implementation. Future policies should prioritize investment in rural digital infrastructure, farmer training & agricultural data systems. They should also support inclusive innovation frameworks to promote wider and more equitable AI adoption in agriculture. Stronger collaboration is needed among governments, researchers, technology developers & agricultural stakeholders. Such collaborations are important for promoting equitable AI adoption. Future research must move beyond technical evaluation. We must examine long-term adoption dynamics, economic feasibility, farmers' acceptance and governance mechanisms to support sustainable agricultural transformation globally.

For developed economies such as Australia and South Korea, the priority for future research and policy is deepening system integration, interoperability and evidence generation for developing economies such as Indonesia and Pakistan, the priority is foundational rural connectivity, affordable entry level tools and farmer training. Future studies should pursue longitudinal designs that track adopters over multiple seasons, mixed methods research pairing farmer acceptance data with technical performance metrics, and, as more comparable outcome measures accumulate, meta analyses that quantify effect sizes across countries rather than relying on the thematic synthesis used here. Closing the AI adoption gap between developed and developing agricultural economies is not only a matter of technological access but a precondition for a more equitable and resilient global transition to sustainable, data-driven agriculture.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors declare that ChatGPT (OpenAI) was used only as an auxiliary tool during manuscript preparation, mainly for language polishing, wording refinement, and translation support. All outputs generated with AI assistance were critically evaluated, verified, and substantially modified by the authors. The authors remain fully accountable for the accuracy, originality, integrity, and academic content of the manuscript.

Authorship Contribution Statements

Conceptualization MF; methodology, MM; software, NA; validation, MTN; formal analysis, MF; investigation, MF; resources, MM; data curation, MM writing–original draft preparation, BHT; writing–review and editing, visualization, MF and MTN; supervision, BHT; project administration, MTN. All authors have read and agreed to the published version of the manuscript.

Declaration of Competing Interest

The Authors declare that there is no conflict of interest.

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