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Upskilling Farmers and Agri-Entrepreneurs Through Artificial Intelligence (AI) Technologies

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Abstract

Agriculture is a key sector of the global economy. In developing nations like India, 42% of the workforce is engaged in it, and it contributes 18% to the country's gross domestic product (GDP). However, the agricultural sector faces many challenges, including low productivity, land fragmentation, vulnerability to climate change, and limited market access. The adoption of artificial Intelligence (AI) technologies in agriculture can enable farmers and agri-entrepreneurs to increase output and cut costs. These technologies can bring increased profitability, sustainability, and production. However, for farmers and agri-entrepreneurs, digital illiteracy, limited access to technology and the internet, resistance to change, traditional mindsets, high costs of AI implementation, and a lack of standardized training programs are barriers to the use of AI applications.

This review focuses on the challenges and opportunities faced by farmers and agri-entrepreneurs. This review used literature from the Scopus database, published between 2015 and 2025. Five empirical case studies from India, China, the Netherlands, and the United States were reviewed to highlight participatory approaches to AI training that improve yields, resource efficiency, and income.

The findings reveal that workshops, mobile platforms, and mentoring programs can be effective in increasing the use of AI. There are also hurdles, in the form of digital infrastructure limitations, cultural resistance, and a lack of training curricula that are responsive to changing contexts. The study advocates the formation of partnerships among multiple stakeholders, along with policy reforms, to create large-scale AI upskilling programs that support agricultural transformation, food security, and job opportunities for people living in rural areas.

Categories: Entrepreneurship in developing nations
Keywords: digital literacy, upskilling farmer, sustainability, artificial intelligence (ai) in agriculture, agri-entrepreneurship

Introduction And Background

Agriculture is the industry that employs 26.6% of the world population and contributes 4% of the world's gross domestic product (GDP) (Raza et al., 2024) and (World Bank, 2023). In a few of the developing nations, it contributes almost 25% of their GDP (Raza et al., 2024).

Agriculture is the backbone of the Indian economy. Its employs 42% of the population and accounts for 18% of its GDP (Sharma et al., 2025), (Trivedi and Patel, 2024), and (World Economic Forum, 2025). However, 74% of its population does not get the proper nutrition (Jain et al., 2024). These figures highlight the need for an immediate agricultural innovation that can not only secure food but also enhance nutrition. The fact that India is the third-largest digitalized country with 658 million internet users and 1.14 billion mobile connections offers a unique opportunity for leveraging the digital power of India (Jain et al., 2024). The rapid and cheap internet connection throughout the country can be one of the major factors in implementing artificial intelligence (AI)-based and agri-tech innovations (Dibbern et al., 2024) and (Mihret et al., 2025). Upskilling farmers and agri-entrepreneurs through AI technologies can be a real transformative agent to bring innovation in this sector (Skivko et al., 2024) and (World Economic Forum, 2025).

Agriculture in the United States is an advanced sector when it comes to the utilization of technology, and it gets that support from top-notch research institutions, strong digital infrastructure, and a well-established agri-tech ecosystem, which in return allows the very fast adoption of AI-based farming solutions (Bickley et al., 2025). AI implementations like precision farming, soil studies, and smart watering are put to work more and more to improve yield, save resources, and protect the environment (Lakshmi and Corbett, 2020) and (Masi et al., 2023). Nonetheless, access to AI training and upskilling is still quite uneven, especially for the small- and medium-sized farmer sector, which signifies the necessity of capacity-building initiatives that are more inclusive and scalable (Secinaro et al., 2022) and (Smith et al., 2024).

The Netherlands is a country that is often considered the best in the world when it comes to high-tech and sustainable agriculture, its innovation-oriented policies, close ties between researchers, organizations and farmers, and many skilled people working in the field (Wolfert et al., 2017). AI has been employed across different industries like precision farming, decision-support systems, and extension services, which helped in the resource allocation and productivity (Mihret et al., 2025). On the other hand, the introduction of very advanced AI tools has been the key reason why the farmers would need more and continuous structured upskilling programs so that they could always be at the level of data interpretation skill and be the ones deciding the long-term adoption (Rotz et al., 2019) and (Feitsma and Whitehead, 2025).

The agricultural sector of China is performing a vital function of supply food for the enormous population and at the same time it is experiencing rapid digital transformation through state-led investments in AI and smart farming technologies (Pan et al., 2024) and (Huang et al., 2025). The government has developed digital platforms and mobile-based AI applications to support the technology such as yield prediction, crop monitoring, and resource optimization (Wang et al., 2025). On the other hand, still, there exist big gaps in digital skills, regional infrastructures, and access to customized training, especially among smallholder farmers, that point out the necessity of systematic AI upskilling to support the inclusive and sustainable modernization of agriculture (Songol et al., 2021) and (Mishra et al., 2023).

Thus, agriculture is an important sector in both developed and developing nations with varied adoption of AI. AI adoption can be a solution to many of the challenges faced by farmers or agri-entrepreneurs. However, before the adoption of AI the farmer and agri-entrepreneurs require upskilling.

Upskilling means a people-building program wherein individuals are equipped for employment flexibly to meet the changing demand for skills posed by the rapidly evolving economy, especially through ongoing learning and training programs aimed at present or future skill demand (World Economic Forum, 2018). Upskilling in agriculture means ensuring farmers and agri-entrepreneurs gain knowledge-related changes and upskill technologically through digital methods and AI to create more efficient, sustainable, and data-oriented farming (Liu et al., 2022). This involves providing stakeholders in agriculture with fresh skill sets of machine learning, data analysis, and interpretation, precision farming technologies, remote sensing, and AI-based decision support systems.

A farmer is a person primarily engaged in agriculture, raising living organisms for food or raw materials (FAO, 2021). This includes crop cultivation, livestock breeding, and other related activities to produce food and non-food agricultural products. Smallholder farmers are usually defined as those who have less than one acre of land. They represent the world's largest food source. However, they are not very tech-savvy, which leads to their limited access to AI solutions (Dias et al., 2019).

Agri-entrepreneurship denotes the person's ability and determination to spot a feasible agri-business opportunity, collect resources, and successfully operate the farm business right from the beginning (Otache, 2017). Agri-entrepreneurs are those who earn their income through the careful management of agricultural businesses, the undertaking of financial risks, and the application of innovative ideas (Raman et al., 2014). In other words, agri-entrepreneurship is the formation of an enterprise that brings innovation into the agriculture sector (Yusoff et al., 2016).

AI denotes to a machine's capacity to execute tasks that usually require human intelligence, especially in the case of computer systems (Elufioye et al., 2024). The rapid progress in AI technology has transformed agriculture worldwide and enabled remarkable innovations to boost productivity, sustainability, and profitability (Bickley et al., 2025) and (Liu et al., 2022). The adoption of these technologies has transitioned farming from the old practices to modern methods like precision farming and the use of robots (Secinaro et al., 2022).

These assist in data-based decision-making, resource optimization, and better yield of crops, thus providing long-term solutions in food security, adaptation to the changing climate, and efficient supply-chain management (Wolfert et al., 2017). From the machine learning algorithm predicting the weather pattern or pest infestation to those AI-powered drones monitoring crop health, all have provided a potential way toward extreme efficiency or sustainability through integration within agricultural management (Masi et al., 2023).

AI can transform agriculture, but farmers and agri-entrepreneurs lack the knowledge needed to use it (Eastwood et al., 2019). This is true especially with developing countries where agri-entrepreneurs and farmers have not developed enough digital literacy skills and the necessary technical know-how to leverage such cutting-edge technologies (Klerkx and Rose, 2020) and (Secinaro et al., 2022). Although AI-based upskilling is often presented as a key solution for improving agriculture, existing research has not yet developed a clear and unified understanding of its real impact. Most studies are fragmented, focus on specific locations, and rely mainly on qualitative evidence or a small number of case studies. As a result, there is limited empirical evidence showing how AI upskilling affects farmers' and agri-entrepreneurs' productivity, income, sustainability, and long-term skill development. In addition, the literature lacks standardized and practical AI training models that can be applied across different regions and farming contexts through formal education and extension systems.

To examine how AI-based upskilling can support agricultural transformation, this study draws on a structured review of existing literature published between 2015 and 2025 in the Scopus database. Alongside the broader literature synthesis, the paper incorporates insights from five empirical case studies conducted in India, China, the Netherlands, and the United States, representing diverse agricultural and institutional contexts. These cases are used to illustrate how participatory and practice-oriented AI training approaches, including hands-on learning, digital platforms, and mentorship, can enhance crop yields, resource-use efficiency, and farm income, thereby highlighting the practical relevance of AI upskilling across both developing and developed agricultural systems. Based on the above, this research tries to answer the following research questions.

Research Questions Driving the Review

What are the opportunities and key barriers preventing farmers and agri-entrepreneurs from adopting AI technologies in agriculture?

What are the best practices and models from global case studies that can be adapted or scaled in diverse agricultural contexts, particularly for smallholder farmers?

What are the measurable impacts (e.g., yield improvement, cost reduction, sustainability) of AI-based upskilling on agricultural practices?

Review

The structure of this paper is shown in Table *1*.

Phase I	Definition of keyword search in the database
Phase II	Searching papers in the database
Phase III	Reading and selection of titles and abstracts
Phase IV	Reading and selection of full papers
Phase V	Analysis of papers

TABLE 1: Review structure

Source: (Thorpe et al., 2005)

Research methodology

Inclusion and Exclusion Criteria for the Review Article

The study took place in April 2025 and focused on articles in the Scopus database. The Scopus database was selected due to its being very popular in numerous reviews of the entrepreneurship sector and its being acknowledged as the largest database of abstracts and citations for peer-reviewed literature, which owns more than 60 million records, covering more than 21,500 peer-reviewed journals from over 5000 international publishers across different scientific disciplines (Raza et al., 2024) and (Palomo et al., 2017). In the first step, depicted in Figure *1*, the articles that contained the terms (agricultur* OR farm*) AND (entrepreneur* OR "agricultur* entrepreneur*" OR agripreneur* OR "agro-based entrepreneur*") in the title, abstract, and keywords in combination with ("Artificial intelligence" OR “AI”) were selected. These terms were also used in the review by Fitz-koch et al. (Fitz-koch et al., 2017) and yielded an initial pool of 85 documents. Only papers in the "English" language were taken into account, since scientific knowledge dissemination is basically done in this language, and it is a criterion that is applied across various reviews (López-Fernández et al., 2016). Thus, the total number of articles identified was 82. Since the purpose of this research is to explore the new literature, a decade-long period was chosen (McElwee and Atherton, 2005), from 2015 to 2025. Thus, out of 76 studies aimed for collection, one was excluded for lacking full text, which led to 75 studies remaining for eligibility evaluation.

In the eligibility stage, each record was carefully evaluated against the inclusion criteria. After reading the titles and abstracts, studies that did not focus on upskilling farmers or agri-entrepreneurs (24 studies) and those that did not address digital technology applications in agriculture (17 studies) were excluded. After this rigorous screening process, 34 studies were deemed eligible and included in the final review. These selected studies provided the foundation for analyzing how AI and other digital technologies contribute to enhancing agricultural entrepreneurship and capacity-building among farmers and agri-entrepreneurs. This methodical selection process underscores the rigor and transparency of the review, ensuring that only the most relevant, recent, and accessible studies were included.

FIGURE 1: Article search strategy

Criteria for the Case Study Selection

A structured analytical approach was adopted to select the five case studies, emphasizing diversity, scalability, and measurable impact. The cases from countries were selected based on the first-training methods, such as hands-on workshops, smartphone-based learning, online tutorials, and app-supported community programs. Second, the number of farmers engaged ranged from 2,000 to 50,000. This helped to have a mix of intensive training and wide area coverage. The selection was based on projects with measurable outcomes (yield gains, resource optimization, and reduced costs). Thus, the parameters of diversity in context, the mode of training, measurable outcomes, and scalability formed the framework for selecting the cases.

On the other hand, cases where the program was merely theoretical or not applied in practice were not considered. Initiatives that targeted only the corporate agribusinesses market, or those that conducted training in broad digital literacy, not specifically aimed at AI in agriculture, were also not considered. Further cases in which training and projects were completely non-participatory, non-interactive and which did not involve quantifiable data or separate stakeholder participation, were also ruled out. This filtering approach not only helped to eliminate the less suitable cases but also confirmed that the chosen ones would be able to contribute to the discussion on the role of AI in agriculture upskilling, being supported by robust empirical evidence.

Findings

Summary of literature reviewed can be seen in Table *2*.

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Topic	Key Points	References
AI in Agriculture	AI enhances efficiency, reduces costs, and supports sustainable farming via machine learning and IoT for predictive analytics in operations like soil monitoring and precision irrigation.	(Lakshmi and Corbett, 2020), (Wolfert et al., 2017), (Champia, 2025)
Barriers to Adoption	Lack of digital literacy, inadequate technical training, poor infrastructure, high cost, digital divide, and cultural resistance hinder AI adoption among smallholder farmers.	(Pan et al., 2024), (Skivko et al., 2024), (Klerkx and Rose, 2020), (Dias et al., 2019), (Ali et al., 2025), (Bickley et al., 2025)
Training and Capacity Building	Hands-on and participatory training workshops significantly boost farmers' willingness to adopt AI. Exposure to real AI tools helps improve understanding and productivity.	(Rotz et al., 2019), (Sharma et al., 2025)
Global Initiatives	India uses AI for real-time weather and soil insights. China employs AI for yield optimization. The Netherlands integrates AI into extension services and structured training.	(Huang et al., 2025), (Wei et al., 2025), (Feitsma and Whitehead, 2025), (Mihret et al., 2025)
Gaps in Training Programs	Lack of long-term, standardized AI training and absence of AI curriculum in agricultural education limit farmer learning. Cultural and language barriers further reduce accessibility.	(Smith et al., 2024), (Ismail, 2024), (Elufioye et al., 2024), (Mishra et al., 2023)
Need for Holistic Framework	A structured, ongoing training framework is needed emphasizing practical, localized, and mentorship-based learning, improved infrastructure, and affordable AI tools.	(Owino, 2023), (Kulkarni et al., 2022)
Future Research Directions	Focus on mobile-based AI learning platforms, AI-powered decision-support systems, and scalable, accessible upskilling models for smallholder farmers.	(Ansari et al., 2024), (Petcu et al., 2024), (Songol et al., 2021)

TABLE 2: Summary of literature review

IoT, Internet of Things; AI, artificial Intelligence

AI instruments such as machine learning, Internet of Things (IoT) sensors, and predictive analytics are acknowledged as significant drivers in agriculture. Their combined effects are manifested in increased productivity, cost reduction, and decreased environmental impact (Lakshmi and Corbett, 2020) and (Wolfert et al., 2017). Data-oriented decision-making is facilitated by these tools in areas like soil monitoring, precision irrigation, and climate risk management (Champia, 2025).

However, the deployment of AI largely depends on the digital and technical readiness of farmers and agri-entrepreneurs. These technologies remain out of reach for most in developing regions due to inadequate digital literacy, lack of adequate training (Pan et al., 2024) and (Skivko et al., 2024), internet facilities and the cost of training on AI tools (Klerkx and Rose, 2020) and (Dias et al., 2019). A strong cultural barrier and fear of robotization complexity are reasons for resistance to adopting AI (Ali et al., 2025) and (Bickley et al., 2025). Further, the lack of standardized, long-term courses on AI remains a big challenge (Smith et al., 2024) and (Ismail, 2024). Agricultural education systems still do not offer formal AI curricula, while language and contextual gaps add to comprehension problems (Mishra et al., 2023).

Major challenges in upskilling farmers and agri-entrepreneurs

Lack of Digital Literacy

Digital illiteracy of farmers and agribusiness people is a considerable obstacle to the adoption of AI in agriculture, especially in underdeveloped countries where the population has a low education level and poor access to technology (Smith et al., 2024). Many farmers might not have the simplest skills, and some might not even have the simplest reading skills, to operate a digital device or interact with an AI platform, making initial exposure to these technologies quite difficult (Smith et al., 2024) and (Dibbern et al., 2024). Farmers have difficulties performing basic digital functions, such as using a smartphone, a computer, or the internet, which makes it harder to engage with AI-enabled platforms, smart farming applications, and automated agricultural implements (Fragomeli et al., 2024). This lack of digital skills limits farmers' ability to understand and operationalize AI solutions that require interaction with data-driven dashboards, automated implements, and predictive analytics (Dibbern et al., 2024).

Limited Access to Technology and the Internet

Agri-entrepreneurs and farmers living in rural areas are not able to use AI tools due to weak internet connectivity and expensive digital hardware, exorbitant costs of internet services, and lack of access to smartphones or computers (Bickley et al., 2025) and (Songol et al., 2021). AI applications such as precision farming software, climate prediction models, and automated irrigation systems are predicated on real-time data exchange, which is rarely available in remote farming communities (Chandre et al., 2024).

Resistance to Change and a Traditional Mindset

Many farmers and agri-entrepreneurs, particularly older generations, are reluctant to leave established practices and implement AI solutions in their activities (En and Hui, 2024). There is an opinion that AI and machines could eventually take over human jobs and thus devalue the conventional agricultural skills. Traditional agriculture has a long history and its practitioners worry about the consequences of AI and automation for their labor; displacement or loss of traditional knowledge systems would be the repercussions that cause the reluctance to use technology (En and Hui, 2024) and (Fragomeli et al., 2024). They still opt for the old ways of farming as a result of their fear of depending on technology and the uncertainty about their labor force's benefits in the long run (Fragomeli et al., 2024).

High Costs of AI Implementation

The utilization of advanced AI technologies including autonomous tractors, smart irrigation systems, and AI-assisted pest control systems represents a huge economic challenge, coupled with the costs of hardware and software that are considerable (Bickley et al., 2025). Cost sensitivity remains a major factor, with smallholder farmers rarely able to afford the costly AI solutions comprising hardware, software, and training, thereby necessitating financial intervention or subsidies from the government or development organizations (Dias et al., 2019).

Lack of Standardized Training Programs

Most AI upskilling programs nowadays are too general and do not address farmers' real-life problems and challenges, specific to their particular locations (Ali et al., 2025). Language barriers, cultural differences, and disparities in farming methods make universal AI training models impractical to design and deploy across such diverse agricultural communities (Pan et al., 2024). The challenges are amplified by the absence of standardized or contextualized training programs that make AI solutions usable in practice, especially when training programs do not respect regional languages or consider crops or localized farm conditions (Ali et al., 2025) and (Mishra et al., 2023).

Major challenges in upskilling farmers and Agri-entrepreneurs and their proposed solutions can be seen in Table 3.

Challenges	Proposed Solutions	References
Lack of digital literacy	AI-driven education and e-learning platforms	(Smith et al., 2024), (Dibbern et al., 2024)
Limited access to technology and the internet	Expanding rural digital infrastructure and connectivity	(Bickley et al., 2025), (Songol et al., 2021)
Resistance to change and a traditional mindset	Demonstrations of AI success stories and peer learning	(En and Hui, 2024), (Fragomeli et al., 2024)
High costs of AI implementation	Government subsidies, low-interest loans, and financial aid	(Dias et al., 2019)
Lack of standardized training programs	Tailored AI upskilling initiatives based on regional needs	(Ali et al., 2025), (Mishra et al., 2023)

TABLE 3: Major challenges in upskilling farmers and agri-entrepreneurs and their proposed solutions

AI, artificial Intelligence

Opportunities in upskilling farmers and agri-entrepreneurs

Enhancing Productivity Through AI Training

The use of AI in agriculture makes it easier for farmers and agro-risk takers to be more productive, cut down on costs, and depend more on the data for crop production increase (Jain et al., 2024). AI training should be context-specific, practical, and simple, and the farmers should be selected based on the actual measures of AI-based insights in agriculture (Pivoto et al., 2018). The use of training materials, support in local languages, visual learning tools, AI simulation for interaction, and field demonstrations of user-friendliness should all be part of the program to increase understanding and usability (Dias et al., 2019). The opening of AI upskilling avenues through one of the most significant platforms is the creation of e-learning platforms powered by AI for education. Through online platforms, mobile apps, and interactive AI tutorials, farmers can slowly acquire these digital skills. The implementation of these upskilling opportunities will result in a rise in the agriculture sector's productivity, sustainability, and economic resilience (Ansari et al., 2024).

Integration of Smart Farming Technologies

Agri-entrepreneurs who undergo upskilling are able to utilize advanced technological tools such as precision agriculture, AI-driven pest control, predictive weather models, and smart irrigation systems (Mahesha, 2024). It can be seen that the farming process can be completely transformed by the different sophisticated technologies that include precision agriculture, embedded pest control, weather, and smart irrigation systems, among others (Smith et al., 2024). Masi et al. (Masi et al., 2023) suggest that governmental bodies, charities, and farming educational institutions could initiate and support localized AI training that would cater to regional languages so that the access to such programs could be further widened.

Upgrading Digital Infrastructures

Rural connectivity, which will facilitate access to inexpensive devices for agri-entrepreneurs, and the creation of AI learning hubs in rural areas are the main components of this project (Bickley et al., 2025). The funding of capital by the government and the private sector will guarantee farmers' unrestricted use of AI technologies. In areas with the least internet penetration, different methods such as offline modules, community radio programs, and SMS-based advisory services can be applied to train farmers in AI-assisted agricultural solutions (Chandre et al., 2024).

Promoting Real-World Demonstrations and Peer Learning

It will be the promotion of the real-world instances of the AI success stories that will help to get rid of the resistance associated with the change. Agricultural extension programs demonstrating that the farmers and agribusiness owners who adopted AI solutions had increased profitability and productivity can lead to such a change (Reardon et al., 2019). Peer learning models and mentors were found to be effective in building AI trust and acceptance in rural areas (Bickley et al., 2025). The connection of peer mentoring and community learning has proven to be successful in building trust and ensuring participation.

Financial Incentives for AI Adoption

Governments and financial institutions can support small farmers and agribusinesses in the form of financial incentives, low-interest loans, and grants, thus facilitating their access to AI tools (Champia, 2025). Moreover, financial assistance programs can reduce the initial cost outlay for the adoption of AI technology, thereby enabling farmers to easily access and operate AI solutions. Grant-funded or performance-based financial aid could also be used to support AI adoption that is solely based on outcomes.

Lessons from some existing case studies

The successful AI upskilling programs highlighted in the following case studies have enabled farmers and agri-entrepreneurs to successfully implement AI technologies. The case studies illustrate real-world situations, instructional strategies, and observable successes, supporting the claim that upskilling reduces the knowledge gap and enhances agricultural outcomes.

Case Study 1: AI for Agriculture Innovation Initiative (Telangana, India)

In support of the smallholder chilli farmers of India, the AI for agriculture innovation initiative was launched in Telangana in 2023 by the World Economic Forum and the government as a novel solution. The main objective was to introduce farmers to AI technologies in order to raise agricultural productivity and decrease production costs (World Economic Forum, 2024). Farmers from over 7,000 Indian farms took part in hands-on workshops to get familiar with AI tools, such as predictive pest detection systems and the analysis of drone images. The training was situational and useful to the local context so that the farmers could go through the initial resistance to change and the subsequent overcoming of the difficulties more easily. Consequently, farmers could cut down on their pesticide use by 9%, their net income increased by 18%, and the yield of their chillies rose by 21% (World Economic Forum, 2024).

The above case shows that if AI is employed in a non-discriminatory and educational manner, it can truly be a boon for smallholder farmers. This scenario not only reinforces the argument for the local AI-skilling initiatives but also strengthens the business case for them. It means that government backing and collaborative governance are the key factors that can assure the successful adoption of AI in a scalable and sustainable manner (Cavazza et al., 2023) and (Rotz et al., 2019).

Case Study 2: Kisan e-Mitra Chatbot (India)

The PM Kisan Samman Nidhi program offers farmers assistance through the multilingual, AI-powered Kisan e-Mitra chatbot. Introduced in 2023 with an extended version rolled out in 2024, the initiative aimed to skill farmers by providing real-time crop management tips, weather forecasts, and government programs using simple voice and text interaction via regional languages (IndiaAI, 2024). Agricultural extension officers trained over 5,000 farmers to use the chatbot over smartphones and delivered real-time insights about data to farmers, improving access to information for intervention decisions, and reportedly achieved a 15% increase in timely pest interventions (Bharti et al., 2024). The importance of AI tools and training that are accessible and language-based is thus demonstrated, addressing barriers such as digital illiteracy and poor infrastructure (Kamilaris and Prenafeta-Boldú, 2018).

Case Study 3: CropX Soil Health Monitoring (United States)

Cropx, an AgriTech company, in 2024, carried out an AI upskilling program that aided American farmers with soil health monitoring using IoT sensors and machine learning. The initiative then proceeded to train more than 2000 rural farmers via online tutorials and field demonstrations in the application of a user-friendly app for the analysis of soil moisture, nutrient levels, and vegetation indices (CropX, 2022). Farmers who relied on AI-based soil monitoring systems reported an increase in their crop yields of up to 27% because of timely and accurate interventions and resource optimization. Moreover, smart irrigation practices led to a reduction in water use by about 25%, while the reduction in wastage of fertilizer was 15% as a result of targeted applications (CropX, 2022). Furthermore, the operational efficiency was also boosted as nearly 70% of the farmers who were using AI tools reported up to 20% improvement in overall farm management. This case illustrates the impact of e-learning and practical demonstrations on improving digital literacy and resource efficiency and, therefore, supports the importance of practical AI training (Masi et al., 2023).

Case Study 4: Netherlands Agricultural Innovation Hubs

In the Netherlands, agricultural innovation hubs began integrating AI training modules into their extension services in 2022, with the number massively increasing by 2025. The hubs had an impact on more than 10,000 farmers who were trained in AI-based decision-making skills, with the major focus being on the precision farming tools, like the automated irrigation and crop health monitoring systems. The training consisted of both classroom teachings and on-the-farm mentoring where the experienced AI users were helping their less experienced colleagues. The feedback showed that there was a 25% increase in the yield of crops and a 30% reduction in the utilization of resources among the participating farmers (Feitsma and Whitehead, 2025). This highlights that mentorship combined with structured AI education can help overcome resistance to change (Rotz et al., 2019).

Case Study 5: Smart Farming Project (China)

The smart farming project of China, launched in 2023, trained more than 50,000 farmers on using AI-enabled platforms for yield improvement. This program, subsidized by the government, trained farmers on machine learning algorithms that derived trends from historical data and predicted crop growth trends. Training methods were app and community escort, whereby the farmers learned how to tackle AI-based insights to fit within planting and harvest schedules. The above project was able to have a production increase by 20% and reduce operational costs by 10% (Wang et al., 2025). This is evidence that AI literacy-promising government and mobile-based training can solve infrastructural challenges toward sustainable farming (Huang et al., 2025).

Table *4* summarizes existing case studies.

Case Study	Location	Training Methods	Number of Farmers Trained	Key Outcomes
AI for Agriculture Innovation Initiative	Telangana, India	Hands-on workshops (drone analytics, AI insights)	7,000	21% yield increase, 9% less pesticide, 5% decrease in fertilizer usage, 18% net income increase
Kisan e-Mitra Chatbot	India	Smartphone training by extension officers	5,000	15% increase in timely pest interventions
CropX Soil Health Monitoring	United States	Online tutorials, field demonstrations	2,000	50% less water, 15% less fertilizer, up to 20% yield increase
Netherlands Agricultural Innovation Hubs	Netherlands	Classroom sessions, on-farm mentorship	10,000	25% yield improvement, 30% less resource use
Smart Farming Project	China	App-based, community escort training	50,000	20% production increase, 10% reduced operational costs

TABLE 4: Summary of existing case studies

The findings show that the AI upskilling programs were most successful when the adoption was affected by the contextual relevance rather than the technological sophistication. The programs that paired AI tools with local crops, agro-climatic conditions, and immediate farm decisions (e.g., pest control, and irrigation) made the process less abstract and more useful from the farmers' view, thus leading to a greater uptake of the technology. Practical, learning by doing approaches, convinced the farmers even more since they could see the upper hand of adoption during the course of a growing season; hence, the perceived complexity and risk were lessened. Social learning mechanisms, such as peer mentoring and extension services, were very important in removing cultural resistance and gaining trust, especially in more conservative farming communities. Moreover, adoption was made easier by the availability of cheap, mobile-based platforms, which through the use of simplified local-language interfaces, overcame the shortcomings of digital literacy and infrastructure. Further, support from policymakers and institutions, in the form of subsidies and integration into the extension systems, not only decreased the cost barrier but also went a long way in making AI technology acceptable on the farm. When taken together, all these factors point to the conclusion that the success of AI upskilling is a matter of relating it to social, economic and learning contexts of farmers; thus, human capability and institutional support play the role of the central driver of agricultural AI adoption over technology alone.

The research adds value to the existing body of work regarding AI in the agricultural field by shifting from technology-focused discussions to a thorough investigation of AI upskilling as a human and organizational capability. This study differs from previous ones that are disjointed, limited in scope, or mainly narrative in nature; it combines a narrative review with cross-case global comparisons in order to reveal the reasons behind the success of some AI upskilling programs and the failure of others. The study is able to attribute the results of adoption to such aspects as context-dependent training, hands-on learning, coaching, universal access, and strong policies, which lead to a more detailed understanding of the AI adoption process instead of merely reporting outcomes. Theoretically, it enlarges the scope of Resource-Based Theory (RBT) by portraying AI literacy and lifelong learning as crucial non-material resources that give rise to competitive edge for both farmers and agri-entrepreneurs, with smallholders being the most pronounced beneficiaries. The research also provides a practical evidence-based framework for the design of AI training that is inclusive and of large scale, which directly advises the policymakers, extension systems, and agri-tech developers aiming at accelerating sustainable agricultural transformation in diverse institutional and developmental contexts through the use of AI technology.

Discussion

The merging of AI with agri-entrepreneurship bears significant theoretical implications for digital transformation literature in rural development. This study supports RBT by positioning AI literacy as a core capability for competitive advantage in smallholder farming (Petcu et al., 2024). RBT explains that sustainable performance and competitive advantage arise from an organization's unique internal resources and capabilities, rather than external market conditions. It marks the necessity of local AI training, which is context-linked and does not create barriers regionally. Such training can include mobile-based tutorials, peer learning, and offline-installable modules, particularly in areas with low internet connectivity (IndiaAI, 2024) and (Rotz et al., 2019). From a policy perspective, a favorable environment would require public-private partnerships and financial incentives through subsidies or low-interest loans to facilitate adoption (Champia, 2025).

The success of AI upskilling depends on many factors. Digital literacy gaps exist among farmers unfamiliar with the most basic digital tools (Smith et al., 2024). Lack of infrastructure, including poor internet and electricity, limits AI access (Songol et al., 2021). Resistance due to culture and fear of job loss also prevents adoption (Fragomeli et al., 2024). High costs and lack of contextualized training are also barriers to progress (Dias et al., 2019) and (Mishra et al., 2023). Community learning models based on mentorship can help in dealing with the barriers (Feitsma and Whitehead, 2025).

The comparative analysis of the five case studies discusses the differences in the effectiveness of AI-driven agricultural initiatives in developed and developing contexts. In the case of developed countries, including the United States and the Netherlands, very good digital infrastructure, higher baseline digital skills, and efficient training systems contribute to AI adoption in agriculture. The farmers earn profits through precision farming, resource optimization, and sustainable production practices. On the other hand, the case studies from India and China show the basic problems of limited digital literacy and restricted access to technology. They rely on app-based or community-supported training models. However, such projects, keeping in mind the context sensitivity and scalable AI, can make a difference even where there are structural limitations. Therefore, the level of digital maturity in a country, the institutional support provided, and the kind of training designed are important factors in determining the transformation of agriculture through AI.

Theoretical Implications

This research adds to the RBT by proposing that AI literacy and continuous training can be regarded as strategic intangible resources that grant farmers and agri-entrepreneurs access to sustainable competitive advantages. The results show that value is not created by technology alone; on the contrary, it is through the integration of AI skills with human skills, experiential learning, and support systems that value becomes visible. The study broadens the theory of digital transformation in agriculture and considers the farmers as active entrepreneurial agents who control AI-driven outcomes through their learning and adaptive capacity, shifting the focus of the analysis from technology adoption to capability development.

Practical Implications

The study has real-life applications for policymakers, training organizations, NGOs, and agri-tech firms. First, training should be localized and modular, imparted in regional languages, and hands-on to improve adoption (Rotz et al., 2019) and (Dias et al., 2019). Second, financial incentives such as subsidies and microloans from the governments can help counterbalance the high costs for AI tools (Champia, 2025). Third, developing institutionalized Private Partnership Proprietaries for farmer-centric AI platforms, including advisory services on mobiles and offline applications, can be of great help (Chandre et al., 2024) and (IndiaAI, 2024). Finally, peer-learning and mentorship arrangements can help build trust among rural people and reduce resistance to change (Reardon et al., 2019).

Future Scope of the Study

This study gives qualitative insight into AI-driven upskilling. Future researchers need to explore quantitative measures to assess the effect of AI in agriculture on productivity, income, and sustainability (Ansari et al., 2024). New technologies, such as generative AI, AI-robotics, blockchain-integrated decision tools, and their applications in training and agri-value chains, can also be studied further (Wang et al., 2025). Policy research is needed to design sustainability-oriented financing mechanism interventions, such as AI training subsidies, adoption-linked performance incentives, and cooperative AI infrastructure models (Trivedi and Patel, 2024) and (Raza et al., 2024). Lastly, there is a need to integrate AI literacy across all formal agricultural education systems to upskill at scale (Ismail, 2024) and (Elufioye et al., 2024).

Conclusions

The narrative review shows that AI technologies are important for promoting decision-making, productivity, and sustainability in agriculture. AI technologies, when integrated into agricultural activities, have the capability to bring about a significant improvement in agricultural land productivity, sustainability, and overall farm profits. This technology can be implemented when farmers and agri-entrepreneurs are trained in different areas of digital literacy, such as operating smartphones, navigating agricultural apps, entering and interpreting digital data, and understanding AI-based instruments. The literature review points out five main challenges: the continued existence of digital illiteracy, limited access to technology and the internet, resistance to adopting technology, the high cost of AI implementation, and the lack of standardized training programs. The assessment of case studies highlights the practices that AI-enabled advisory platforms, precision-farming tools, and collaborative public-private training models, tailored to local contexts and smallholder farmers' needs, can facilitate the adoption of AI in agriculture. People upskilling programs have started in India, China, and the Netherlands, concentrating on regional tools and localized delivery models.

Thus, there is a dire need for a holistic and adaptive upskilling framework that empowers diverse farming communities through mentorship, online-offline access, localization, and continuing education. The support of infrastructure and policies will be the way through which these gaps can be bridged.

The partnership of government, industry, research, and educational institutions is the condition sine qua non for a comprehensive, long-term AI training project to be carried out at all levels. The area's particularities should also be taken into account. Furthermore, public-private partnerships, financial incentives, and policy interventions will facilitate the setting up of AI upskilling programs. Educating farmers and empowering them digitally will not only create a world of AI-powered agriculture for everyone, but it will also be a world where small-scale farmers and large agribusinesses are all included. The adoption of AI, through the creation of a tech-enabled agriculture ecosystem, would herald the arrival of innovation, render the agri-entrepreneurs' environment economically resilient, and help in the attainment of the world's sustainability targets. This will thus result in a safe and prosperous future for agriculture.

Additional Information

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All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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