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Artificial Intelligence Reshaping Agricultural Knowledge Systems: Paradigm Shifts and Implementation Challenges

Zhehao Hu

Beijing New Oriental Foreign Language School, Yangzhou; Jiangsu, China
Corresponding author: counselling_yz@xdf.cn

Abstract:

As global agricultural digital transformation accelerates, data-driven technologies are reshaping traditional agricultural practices—yet their role in facilitating farmers' knowledge evolution remains underexplored in existing research. This study focuses on three core digital tools to investigate how they transform the carriers and application of farmers' knowledge. Empirical cases from agricultural fields demonstrate tangible impacts: smart drip irrigation systems optimized via reinforcement learning reduce water consumption, while large-scale smart agriculture deployments in sugarcane fields achieve 47% water savings and 20% fertilizer reduction. Convolutional neural networks also enable 3-day-ahead prediction of bovine mastitis, aiding early disease intervention. However, significant challenges persist, 78% of smallholder farmers cannot afford AI-driven equipment, provincial agricultural datasets remain isolated and unintegrated, and elderly traditional laborers face barriers to adapting to digital tools. Proposed solutions include low-cost smart equipment leasing, AI voice advisors tailored for low-literacy farmers, and microcluster edge computers to address internet deprivation in remote areas. Additionally, the study identifies a critical dilemma: the risk of AI knowledge monopoly versus the potential for symbiosis between digital tools and traditional knowledge—resolving this requires prioritizing equity through building inclusive, accurate agricultural datasets and preventing algorithmic biases. It offers key insights to promote the inclusive adoption of digital tools, ensuring they empower rather than marginalize farmers in the digital agricultural transition.

Keywords: Data-driven agricultural technology; farmer knowledge carrier; smart agriculture; AI adoption challenge; agricultural digital transformation.

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1. Introduction

Currently, agriculture is facing a binary problem that concerns survival. By 2050, the world will need to feed 9.7 billion people without causing further ecological damage. In the face of this contradiction, the experiential farming model of „looking at the sky to cultivate the land" in traditional agriculture is no longer able to meet the needs of efficiency and ecological balance. The emergence of artificial intelligence is not a simple improvement of agriculture, but a complete transformation, becoming a new paradigm and ontology in the field of agriculture. It can integrate multiple sources of agricultural knowledge and efficiently transmit it to practitioners, becoming the core technology to solve this contradiction.

Artificial intelligence has replaced the empirical cognitive approach of „touching the soil with hands" with algorithm-driven predictive capabilities. These technologies enable convolutional analysis of soil features using neural networks, diagnosis of pathogens at the plant level using convolutional neural networks, and development of irrigation plans using reinforcement learning. For instance, convolutional neural networks have demonstrated remarkable capabilities in livestock management, enabling the prediction of bovine mastitis up to 3 days in advance [1]. Related research will explore the possible development directions of this technology in the field of agriculture, as well as whether algorithmic intelligence can truly bring new insights into the underlying laws of agricultural science research. In traditional agriculture, ‚who owns the land is not important, only being able to cultivate it is important, , but now the situation is completely different. Soil is no longer the only carrier of agricultural knowledge, replaced by silicon-based data systems, rather than a single bloodline inheritance and farming experience. Research shows that in arid areas, precision agriculture models achieved through artificial intelligence precision irrigation technology (which transmits sensor signals to transit satellites) have reduced water resource consumption by 47%. Moreover, innovations in edge computing infrastructure are crucial for deploying these AI solutions in resource-limited settings, such as the localized rice blast prediction systems that function as a „computerized immune system" for paddy fields [2]. Behind this achievement is the efficient integration and application of artificial intelligence in agricultural knowledge, such as soil moisture and crop water requirements.

2. Application Background

2.1 New Ways of Precise Planting

Nowadays, sugarcane fields in Guangxi continuously generate data and have become a typical scenario for artificial intelligence to transmit agricultural knowledge. Digital sensors are scattered throughout the soil, with sensors buried in sugarcane fields continuously monitoring soil osmotic pressure and nitrogen content. Artificial intelligence transforms the knowledge of „judging water and fertilizer needs based on experience" in traditional sugarcane cultivation into a quantitative model, and optimizes irrigation and fertilization through predictive analysis technology, achieving a water and fertilizer utilization rate of 95% while reducing fertilizer demand by 20%, helping farmers quickly master precise water and fertilizer management knowledge.

The collaborative operation of various intelligent devices has formed an efficient knowledge application system. The Beidou Navigation Tractor converts agricultural knowledge of „precise sowing row spacing" into practical instructions, and the sowing error is controlled within 2 centimeters. Based on the knowledge of „precise prevention and control of pests and diseases", the drone swarm achieves micro-spraying of pesticides, reducing the loss of chemical substances by 33.2% [3]. In the wheat planting area of Shandong, drones collect crop spectral characteristics and generate plant quarantine heat maps ranging from deep red to ochre color, transmitting knowledge of „crop disease visualization recognition" to farmers. Combined with variable fertilizing devices, they provide „micronutrient therapy" for crops. Agricultural planting has been redefined as „precise diagnosis and treatment for plants", making complex plant protection knowledge easier to understand and apply.

2.2 Digital Transformation of Livestock Management

In the „FPF Future Pig Farm" complex of Wen Group, the algorithm controls the ventilation system, and blockchain biosensors monitor the cortisol levels, feed-to-meat ratio, and body temperature changes of the pig herd in real time. Artificial intelligence transforms traditional farming knowledge, such as „pig growth environment regulation" and „health monitoring," into real-time data models. This bioinformatics technology has reduced the mortality rate of live pigs by 19%, accelerated their growth rate, and achieved „data-driven knowledge landing" in the breeding process.

The „AI4DLLM" dairy farming model developed by China Agricultural University analyzes real-time data from 210000 Holstein cows and transforms professional knowledge, such as „early diagnosis of cow mastitis" and „nutritional requirement matching" into executable instructions. It can predict the risk of cow mastitis three days in advance and then send precise intervention suggestions to ranch management personnel, such as „increasing the humidity in the cowshed 7 to 65%" and „adding additional vitamin D to the trough 3". Under the guidance of this model, the fat content of milk increases, the use of antibiotics decreases, and dairy farming has become a „paradigm driven by silicon-based technology to implement professional knowledge" [1].

2.3 De Intermediation of the Agricultural Industry Chain

The „Mr. Lan" orchid intelligent question and answer robot from Guangdong has broken down the information and knowledge asymmetry barriers in the agricultural industry chain. Flower farmers ask artificial intelligence, „Why is the root system of Phalaenopsis withered?" The robot can instantly call the phenotype database, local meteorological data, and Shanghai flower auction price information, integrating „Phalaenopsis cultivation technology" with „market dynamic analysis" knowledge to provide highly scene-specific solutions, allowing flower farmers to master complex planting and market knowledge without a professional background.

In addition, agricultural intelligent systems, such as the „Pineapple King" system that serves tropical fruit cultivation, have become a bridge connecting field production and the market, condensing knowledge such as „pineapple planting cycle management" and „market demand forecasting" to shorten the planting decision-making cycle from „season-based" to „second-based". The Henan Pork Traceability Consortium and other „blockchain+artificial intelligence" teams have built an immutable traceability ledger, transforming knowledge such as „pig farming standards" and „food safety testing" into visual information. Consumers can scan the QR code to view the vaccination records, feed formulas, and even the carbon footprint of pigs. „Transparency" has become a high-value credit attribute of agricultural products, making it easier for consumers to access food safety knowledge.

3. Technological Frontiers

3.1 Intelligent Agricultural Machinery Ecosystem

The Zoomlion DV4004 hybrid tractor adopts a hybrid transmission system (MiDD) of „diesel power+electric precision control", which can absorb agricultural knowledge of „different soil traction requirements" through machine learning, adapt to various soil environments from heavy clay to sandy loam, and reduce fuel consumption by 8%. This „mechatronics integration" technology is the foundation for the future development of low-carbon agriculture, achieving intelligent matching of „soil characteristics and agricultural machinery operation" knowledge.

In addition to hybrid tractors, Carbon Robotics' LaserWeeder G2 laser weeding machine transforms professional plant protection knowledge into automated operations through „image recognition+weeding knowledge model". This device has the capability of „computerized weed control". By training a deep convolutional neural network with 40 million images to absorb knowledge of „weed and crop recognition", it can accurately remove weeds to the millimeter level, while protecting corn crops and reducing the loss of chemical herbicides from the source, which is of great significance for ecological protection. Before the naked eye could detect the weed cotyledons next to cabbage seedlings, this weed killer was able to remove the white rust fungus (Ch. albume) and achieve „digital weeding" through photochemical action, with an annual weeding cost of about $380 per acre [4].

3.2 Agricultural Language Model

The „Tian Gong Kai Wu" agricultural model from Harbin Institute of Technology can process massive amounts of meteorological, soil, and genomic data, absorb agricultural knowledge from multiple fields such as „crop growth patterns" and „water and fertilizer management technologies", predict the growth trends of 24 major crops, and send specific instructions to farmers, such as „corn sowing postponed to May 7th" and „application of potassium sulfate in plot D". This plant informatics technology has increased crop yields by 5 percentage points, while transforming complex agricultural knowledge into simple instructions, reducing the threshold for farmers to absorb knowledge.

The „Shennong Baixiao" agricultural teaching system of China Agricultural University has been applied in classrooms in many parts of the country. The system transforms traditional agricultural knowledge, such as „crop hybridization breeding" and „pest control," into virtual experimental scenes. Students can quickly carry out crop hybridization breeding experiments in virtual greenhouses, and the knowledge absorption efficiency is 30% higher than in traditional classrooms. Agricultural education is undergoing digital transformation, and the knowledge system of the new generation of agricultural practitioners has been deeply integrated with digital technology.

4. Implementation Challenges

4.1 Economic Barriers

The cost of a smart greenhouse can reach over 1.2 million US dollars, which is difficult for small-scale farmers with scattered crop varieties to afford. These smart devices are not only production tools, but also carriers of agricultural knowledge. For example, the environmental control sys-

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tem in smart greenhouses contains knowledge of „crop growth environment optimization“, but small farmers are unable to access the devices and naturally cannot absorb the knowledge. Although tomato growers in Anqiu, Shandong, can obtain a 20% product premium through smart greenhouse cultivation, 78% of farmers lack the collateral required for technology leasing. This „smart agriculture access threshold“ forms a screening effect similar to „robot access control“, where some farmers can enter the technology dividend market to absorb advanced knowledge, while most small farmers are excluded.

4.2 Shortcomings in Cognition and Infrastructure

4.2.1 Cognitive shortcomings

Elderly farmers in rural Guangdong are generally unable to operate touch screens. Although the nematode prevention and control recommendations pushed by artificial intelligence are scientifically effective (containing professional knowledge such as „nematode habits“ and „timing of drug use“), they cannot be read due to „interface operation barriers“. Elderly farmers have long relied on the traditional way of acquiring knowledge through oral transmission, and their unfamiliarity with digital devices directly leads to the difficulty of accessing advanced agricultural knowledge.

4.2.2 Shortcomings in infrastructure

There is a problem of „data silos“ in agricultural data in various provinces. The soil database in Guangxi (containing knowledge of „southern soil fertility management“) and the pest and disease prediction platform in Shandong (containing knowledge of „northern crop pest and disease control“) have incompatible data formats, forming the „Agricultural Data Tower of Babel“. Cross-regional agricultural knowledge cannot be transmitted through data sharing, for example, the experience of wheat disease and pest control in Shandong is difficult to assist sugarcane planting in Guangxi, hindering the coordination of agricultural knowledge nationwide.

4.3 Labor Market Shocks

The popularization of drone technology has significantly reduced the number of manual spraying positions, which not only affects employment but also involves the iteration of knowledge and skills. Traditional manual spraying relies on the knowledge of „judging the spraying amount and scope based on experience“, while drone operation requires new knowledge, such as „drone flight control“ and „precise positioning of pests and diseases“. Pesticide-spraying workers in Shandong are facing a salary decline, while drone operators are paid 30% more due to their mastery of new knowledge. If this „skill gap“ is not filled through training, it will result in some farmers losing their jobs and being unable to absorb the agricultural knowledge behind the new technology.

5. Strategic Path

5.1 Policy-Driven Inclusive Development

The technology coverage can be expanded by forming an artificial intelligence agricultural equipment leasing alliance (such as the drone cooperative in Zhejiang), allowing small farmers to access knowledge carriers at low cost. Small farmers can rent agricultural robots (AGVs) at a price of $5 per acre. These robots are equipped with knowledge models such as „precision seeding“ and „variable fertilization“, and farmers can gradually absorb relevant knowledge during use. At the same time, the technical costs are shared through harvest sharing.

In addition, the mandatory policy of data interoperability should be implemented to integrate agricultural data from various provinces into the machine learning system, unify data formats and standards, and build a nationwide „agricultural neural network“. This network can transfer agricultural knowledge across regions, such as transforming soil management experience in Guangxi into data models, providing a reference for soil improvement in Shandong, and achieving nationwide agricultural knowledge sharing and collaboration.

5.2 Human-Centered Design Innovation

Developing voice-interactive artificial intelligence agricultural consultants based on the cognitive characteristics of elderly farmers is key. The „Gao Zhili“ voice interaction artificial intelligence agricultural consultant prototype developed by Guangdong can bridge the digital divide. When illiterate farmers ask „Why do lychee leaves turn yellow?“ (implying the need for „lychee nutrition deficiency judgment“), artificial intelligence can provide answers in dialect form, transforming professional knowledge such as „lychee branch deficiency symptom recognition“ and „fertilizer remediation measures“ into oral expression, reducing the knowledge absorption threshold for elderly farmers [5].

At the same time, the promotion of edge computing micro clusters can solve the problem of knowledge transfer in areas with weak infrastructure. Edge computing equipment can achieve „localized data processing“ in the field without relying on the cloud. Solar-powered plant sensors can run lightweight algorithms (containing „early identification of rice blast“ knowledge), achieve accurate identification before the rice blast fungus (Magnaporthe oryzae) infects the rice field, and pass prevention and control knowledge to farmers in the form of local early warning, becoming the „computerized immune system“ of paddy fields [2].

5.3 Research and Development of Next Generation Agricultural Technologies

Developing a „generative digital twin“ for orchards, absorbing knowledge such as „meteorological disaster warning“ and „fruit tree growth cycle management“ through microclimate impact simulation, predicting disasters such as frost and drought, and pushing intervention plans in advance, enabling farmers to master coping knowledge before disasters occur; Autonomous cluster robot technology is also expected to accelerate its implementation, with unmanned aerial vehicle swarms responsible for pollination (based on knowledge of „crop pollination timing“), and ground robots completing weeding according to distributed artificial intelligence instructions (based on knowledge of „weed recognition and removal“), achieving an intelligent planting mode of „heaven earth collaboration“ and further expanding the application scenarios of agricultural knowledge.

6. Integration of Agricultural Knowledge Transformation Driven by Algorithms

6.1 Technological Transformation and Reconstruction of Agricultural Knowledge System

There is ample research evidence to suggest that artificial intelligence has transformative potential in improving the efficiency of agricultural resource utilization. Water consumption in arid areas has been reduced by 47%, and fertilizer utilization in controllable planting environments has been increased by 20%. The essence of these achievements is the reconstruction of the agricultural knowledge system by artificial intelligence, from „experience-based scattered knowledge“ to „data-driven systematic knowledge“.

Traditional agricultural knowledge is mostly „tacit knowledge“ accumulated by farmers through long-term practice (such as „judging fertility by leaf color“), while artificial intelligence transforms these tacit knowledge into quantitative models (such as determining nutritional needs through spectral analysis), while integrating multiple sources of „explicit knowledge“ such as meteorology, soil, and genome to form a more comprehensive knowledge system. For example, artificial intelligence can predict mastitis in cows up to 3 days in advance and achieve precise clearance before weed cotyledons germinate, all of which stem from the deep integration of knowledge such as „physiological characteristics of cows“ and „weed growth patterns“[1,4]. Nowadays, data has replaced land as the core carrier of agricultural knowledge and the core element of agricultural production.

6.2 Unequal Absorption of Knowledge

Although artificial intelligence can improve the efficiency of agricultural knowledge transmission, its benefits are significantly uneven at the group and regional levels. Technologies such as blockchain+artificial intelligence traceability platforms and autonomous agricultural machinery require huge capital investment, which marginalizes small farmers who lack funds and cannot absorb the advanced knowledge contained therein[4,6]. While voice interactive AI consultants, edge computing and other technologies provide the possibility of „low-cost knowledge popularization“, forming two development paths: „capital-intensive intelligent farm knowledge monopoly“ and „popular low technology AI-assisted knowledge popularization“[5].

From the application data of Guangdong intelligent Q&A robots and Henan blockchain pork traceability platform, it can be seen that there are significant differences in knowledge absorption among different groups. Small farmers obtain basic planting and breeding knowledge through artificial intelligence to solve practical problems in production; large-scale enterprises, on the other hand, rely on advanced tools such as traceability technology and digital twins to absorb more complex knowledge, such as „supply chain management“ and „brand operation“, and occupy the high-end market. If this difference is not narrowed through policy intervention, it may exacerbate the knowledge gap in the agricultural sector.

6.3 Sustainability Trade-offs and Knowledge Ethics Risks

Behind the agricultural knowledge revolution driven by artificial intelligence lies a complex balance between ecology and society. Firstly, there is a contradiction between resource conservation and the cost of knowledge carriers. Although laser weeding machines reduce herbicide loss, the „weed identification knowledge“ behind them can also help farmers improve their prevention and control efficiency [4]. However, high computing infrastructure may increase carbon footprint, and the cost of such high-end knowledge carriers is relatively high, making it difficult for small farmers to afford. Secondly, labor substitution and knowledge and skill transformation have reduced the chemical exposure risk of pesticide-spraying workers through autonomous tractors and drone swarms [3]. The „precision operation knowledge“ contained in them is also more efficient, but it threatens rural employment. If skill training is not carried out synchronously, farmers will face

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the dual dilemma of „losing their jobs+unable to absorb new knowledge“. The „Shennong Baixiao“ system of China Agricultural University has, to some extent, filled this gap by cultivating digital agricultural talents, helping farmers absorb the knowledge behind new technologies. Thirdly, there is a risk of knowledge sovereignty. IoT sensors and livestock biometric monitoring can collect a large amount of agricultural production data (containing core planting and breeding knowledge of farmers) [7]. If these data are monopolized by agricultural technology giants, it may lead to farmers losing control over their own knowledge achievements and becoming „data providers“ rather than „knowledge owners“.

6.4 Future Direction

The generative digital twin and cluster robots outline the future vision of „digital physical integration agriculture“, with the core of „artificial intelligence and human co-creation and absorption of agricultural knowledge“[8]. However, the realization of this vision depends on whether the following core contradictions can be resolved. One is algorithmic bias and knowledge inclusiveness. If the artificial intelligence training dataset is mainly based on single-crop planting data, it may overlook biodiversity agricultural scenarios, leading to a „single crop knowledge monopoly“ and exacerbating the knowledge gap under different planting modes. The second is the feasibility of knowledge integration[9]. Successful cases such as „Mr. Lan“ orchid artificial intelligence (combining phenotype databases with local meteorological data) have shown that the symbiotic model of „algorithm knowledge+farmer experience knowledge“ is feasible. Artificial intelligence absorbs scientific knowledge from the system, and farmers provide localized practical knowledge. The combination of the two can form a more complete agricultural knowledge system. The third is fairness guarantee and knowledge inclusion. If there is no policy support (such as edge computing subsidies for small farmers, construction of an agricultural knowledge sharing platform), traditional agricultural knowledge may face the risk of elimination, and advanced knowledge will also be concentrated in the hands of minorities, further expanding the knowledge gap[10]. Only by ensuring fairness in knowledge acquisition through policies can we achieve the goal of ‚artificial intelligence assisting the public in absorbing agricultural knowledge‘.

7. Conclusion

Currently, it is not in the stage of agriculture being „eliminated“, but undergoing a „Renaissance“ of the agricultural knowledge system. Artificial intelligence is not simply an automated tool, but a new cognitive system and knowledge carrier for agriculture. Data has replaced land as the core carrier of agricultural knowledge and the primary element of agricultural production. But this intelligent technology needs to be rooted in the „pragmatic soil“, and policies need to ensure the universality of technology, so that small farmers can also absorb advanced knowledge at low cost; Algorithms need to integrate traditional farming wisdom and transform farmers‘ implicit experiences into systematic knowledge. Silicon-based technology needs to serve all agricultural practitioners, not minority groups. When „technological innovation“ meets „knowledge equity“, humanity can obtain dual guarantees of food security and ecological security during the harvest season. The future farm will no longer be a ‚cold laboratory‘, but a ‚digitally enhanced fertile ground‘, where the buzzing of drones and the chirping of cicadas intertwine. The knowledge transmitted by artificial intelligence will coexist with the practical experience of farmers, and humanity will nourish the earth in a ‚technology knowledge ecology synergy‘ manner, achieving sustainable development of agriculture.

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