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Artificial Intelligence Enhancing Agricultural Total Factor Productivity in China: Mechanisms and Pathways

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Abstract: Against the dual backdrop of intensifying global food security challenges and increasingly tight resource and environmental constraints, enhancing agricultural Total Factor Productivity (TFP) has become a core driver for promoting high-quality agricultural development. Artificial Intelligence (AI), as a strategic technology leading the new round of scientific and technological revolution and industrial transformation, is profoundly reshaping agricultural production methods and industrial ecosystems. This paper systematically elucidates the driving effect of AI on agricultural TFP growth through three key mechanisms: enhancing technical efficiency, optimizing factor allocation, and fostering new business models. Simultaneously, it identifies the multiple challenges in the AI-enabled empowerment process, including underlying data deficiencies, technological application bottlenecks, institutional and talent lag, and regional disparities. To address these issues, this paper proposes systematic optimization pathways, including building a high-quality agricultural data resource system, developing adaptable AI technologies and equipment, cultivating interdisciplinary "AI + Agriculture" talent, and improving policy regulations and ethical governance frameworks. This research aims to provide a theoretical framework for understanding the intrinsic logic of AI-driven agricultural TFP growth and to offer decision-making references for formulating relevant industrial policies and promoting the practical implementation of smart agriculture.

Keywords: Artificial Intelligence; Agricultural Total Factor Productivity; Empowerment Mechanisms; Smart Agriculture; Optimization Pathways

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1.Introduction

President Xi of China emphasized: "Artificial Intelligence is a strategic technology leading the new round of scientific and technological revolution and industrial transformation, serving as a powerful bellwether with significant spillover and driving effects," and that "accelerating the development of next-generation artificial intelligence is a strategic issue concerning whether China can seize the opportunities presented by this new round of scientific and technological revolution and industrial transformation." This important discourse charts the course for China to grasp technological trends and promote industrial transformation and upgrading. Currently, a new generation of information technologies, such as 5G, AI, big data, the Internet of Things, cloud computing, and blockchain, is flourishing globally and accelerating its deep integration across various economic and social sectors. As a fundamental industry of the national economy, agriculture bears not only the crucial responsibility of ensuring national food security but also the vital mission of maintaining stable socio-economic development. Confronted with this new developmental context, the limitations of the agricultural growth model, which primarily relies on traditional factor inputs, have become apparent. Transitioning towards an intensive growth path driven by technological innovation and quality improvement has become an inevitable strategic choice.

Agricultural Total Factor Productivity (TFP) serves as a key metric for assessing the quality of agricultural development. It captures the output growth attributable to intangible factors like technological progress, organizational innovation, and specialized production, beyond the contributions of tangible inputs such as land, labor, and capital [1]. In this domain, Artificial Intelligence technology, leveraging its formidable capabilities in perception, learning, reasoning, and decision-making, demonstrates immense application potential. From precision seeding and smart irrigation to the intelligent identification and early warning of pests and diseases, and from autonomous agricultural machinery to data-driven decision-making based on market predictions, AI is facilitating the transformation of traditional agriculture from an experience-dependent, resource-intensive model towards a data-driven, intelligent, and efficient modern smart agriculture system. This transformation presents a new historic opportunity to overcome the bottlenecks constraining the improvement of agricultural TFP [2].

Nevertheless, the practical process of leveraging AI to enhance agricultural TFP faces numerous significant challenges. On the one hand, the complexity of agricultural production environments and the inherent uncertainties in crop growth cycles impose extremely high demands on the reliability and adaptability of AI technologies. On the other hand, the structure of China’s agricultural sector, where smallholder farmers constitute over 98% of all agricultural operators, creates a practical dilemma where advanced technologies encounter high application costs and significant diffusion difficulties. Furthermore, issues such as the inherent difficulties in agricultural data collection, the lack of unified quality standards and sharing mechanisms leading to “data silos” [3], the insufficient explainability and inclusivity of algorithmic models, and a severe shortage of interdisciplinary talent proficient in both agricultural science and AI collectively constrain the full realization of AI’s empowering effects [4]. If these deep-seated problems are not systematically addressed, the application of AI in agriculture risks remaining largely at the “demonstration project” stage, failing to achieve scaled, commercialized, and deep integration. This could potentially exacerbate development disparities among different types of agricultural operators due to technological barriers and cost issues.

Therefore, conducting an in-depth analysis of the intrinsic mechanisms through which AI empowers agricultural TFP, accurately identifying the key challenges it faces, and proposing forward-looking and actionable optimization pathways based on this analysis holds substantial theoretical value and practical significance. This research will undertake a systematic analysis across three critical dimensions, namely elucidating fundamental mechanisms, diagnosing practical challenges, and exploring viable pathways, to comprehensively investigate how AI can transform into a core engine driving the improvement of agricultural TFP. The ultimate aim is to provide valuable academic references and substantive policy insights that can contribute to accelerating the modernization of China’s agriculture sector and effectively supporting the full implementation of the Rural Revitalization Strategy.

2.The Mechanisms of AI in Enhancing Agricultural Total Factor Productivity

2.1 Enhancing Technical Efficiency

Artificial Intelligence significantly enhances agricultural technical efficiency by revolutionizing traditional decision-making models in agricultural production, representing the most direct pathway for enhancing Total Factor Productivity (TFP) growth. At the pre-production planning stage, AI algorithms can integrate multi-source data (including soil properties, meteorological conditions, market trends, and historical yields) to formulate optimal crop variety selection and sowing plans for farmers, thereby promoting the precise allocation of agricultural production resources from the outset [5]. During the production management phase, pest and disease identification systems based on computer vision technology utilize mobile applications or field monitoring equipment to enable real-time diagnosis of crop health. The accuracy and response speed of these systems far surpass traditional manual observation, significantly improving the precision and timeliness of pest and disease control, which in turn markedly reduces pesticide misuse [6]. Concurrently, smart irrigation systems employ sensors to monitor soil moisture in real time, integrating crop physiological water requirements and evapotranspiration models to achieve precise, on-demand water supply, effectively enhancing water use efficiency [7]. In the post-harvest handling stage, automated sorting equipment powered by AI technology can perform rapid and accurate grading of agricultural products based on multiple indicators such as appearance specifications, color, sugar content, and internal defects, substantially increasing product added value and market competitiveness. These concrete applications of "AI + Agriculture" collectively drive the transformation of agricultural decision-making mechanisms from fuzzy judgments reliant on traditional experience to scientific decisions based on data and algorithms, directly promoting the improvement of output efficiency per unit input and serving as a crucial source of agricultural TFP growth [8].

2.2 Optimizing Factor Allocation

AI profoundly optimizes the efficiency of factor allocation in agriculture by enhancing factor mobility, substituting scarce factors, and activating the value of potential factors [9]. First, AI platforms such as agricultural IoT platforms and intelligent agricultural machinery scheduling systems effectively break down information barriers, enabling key production factors, including land, agricultural machinery, and labor, to achieve efficient matching and shared utilization across temporal and spatial constraints. For instance, the "Didi Nongji" model, inspired by the sharing economy concept, can intelligently plan optimal operational routes and scheduling schemes based on real-time operational demands and the geographical locations of machinery, significantly improving the comprehensive utilization rate of high-value agricultural equipment [10]. Second, the application of AI equipment, such as agricultural robots and autonomous tractors, can substantially replace increasingly scarce and costly agricultural labor. These technologies undertake repetitive and labor-intensive tasks like crop picking, field weeding, and precision pesticide application, effectively mitigating the practical challenge of agricultural labor shortages in China [11]. Third, AI technology can fully exploit and activate the intrinsic value of "data" as a new production factor. Through in-depth mining and intelligent analysis of massive agricultural datasets, AI can uncover production patterns, market dynamics, and risk signals that were previously undetectable through experience alone. This transforms static data into digital assets capable of guiding production practices and generating economic benefits, further optimizing the input structure and developmental combination of traditional factors, ultimately achieving a Pareto improvement in overall agricultural factor allocation [12].

2.3 Fostering New Business Models

The penetration and integration of AI into agriculture extend beyond improving the efficiency of traditional production links; they also manifest in the generation of a series of new business models and formats through cross-industry integration, thereby opening up new value spaces for agricultural TFP growth. For example, at the intersection of "AI + Agriculture" and the financial insurance sector, agricultural insurance services based on remote sensing data and AI models have emerged. These services enable precise delineation of coverage areas and rapid claims processing, reducing on-site inspection costs and potential moral hazards for insurance institutions while enhancing the risk protection level for agricultural production and management [13]. In the agricultural product marketing domain, AI analyzes vast amounts of consumer preference and market behavior data, empowering the development of regional public brands for agricultural products and the formulation of precision marketing strategies. Furthermore, it facilitates the reverse transmission of market demand signals to the production end, guiding variety selection and standardized production processes, thereby achieving genuine "demand-driven production" [14]. Additionally, AI-driven new formats such as "immersive agricultural experiences" and "smart farm study tours," which integrate agriculture and tourism, successfully transform traditional agricultural production processes into perceivable, experiential, and consumable service-oriented products, greatly extending and expanding the agricultural industry value chain. The emergence and development of these new rural business models break down the traditionally relatively closed industrial boundaries of agriculture, facilitating the influx and recombination of high-level production factors such as technology, knowledge, and information. From the dimensions of industrial structure optimization and value addition, they inject more advanced and enduring growth momentum into the sustained improvement of agricultural TFP [15].

3.Practical Challenges in AI's Empowerment of Agricultural Total Factor Productivity

3.1 Inadequate Data Foundations and Data Silos

High-quality, large-scale data provides the foundation for training AI models. However, China's agricultural data infrastructure remains underdeveloped. The geographically dispersed nature and environmental complexity of agricultural production maintain high data collection costs and implementation challenges. Concurrently, hardware limitations, including insufficient sensor accuracy and environmental durability, result in inconsistent data quality [16]. More notably, pervasive “data silos” occur as agricultural data remains scattered across government departments, research institutions, agribusinesses, and smallholders, lacking unified standards and effective sharing mechanisms. The fragmentation among meteorological, soil, market, and production data prevents integration into complete, coherent datasets necessary for training AI models [17]. For example, AI models designed to predict regional grain yields often suffer significantly reduced accuracy due to unavailable field-level crop growth data or detailed meteorological information. This combination of a weak data foundation and circulation barriers creates a “no raw ingredients to cook with” dilemma for advanced AI algorithms, severely constraining their potential impact.

3.2 Technical Application Bottlenecks and Cost-Benefit Challenges

Implementing cutting-edge AI in complex agricultural environments presents dual technical and economic challenges. Technically, the unstructured characteristics of biological subjects (e.g., crop morphological diversity, variable pest manifestations) demand exceptional generalization capability and environmental adaptability from AI models. Algorithms performing well in controlled experiments may degrade significantly in field conditions due to factors like lighting variations, foliage occlusion, and background interference [18]. Economically, substantial initial investments required for AI solutions, including smart hardware, software development, deployment, and maintenance, create prohibitive cost barriers for small and medium-scale farmers who constitute most agricultural operators. The short-term benefits from yield increases or cost savings often cannot offset upfront costs, resulting in widespread “cannot afford and will not adopt” attitudes [19]. Additionally, the “black box” nature of most AI systems, with their opaque decision-making logic, prevents experience-dependent farmers from establishing necessary trust, posing another major barrier to adoption.

3.3 Institutional and Talent Gaps, and Regional Imbalances

Effective AI implementation in agriculture requires supportive institutions and adequate talent, yet both areas show significant deficiencies. Institutionally, clear rules defining agricultural AI data ownership, usage rights, and benefit distribution remain underdeveloped. The legal framework covering intelligent equipment certification, operational safety standards, and accident liability determination lacks maturity [20]. Effective ethical review and regulatory mechanisms are also absent for addressing potential algorithmic biases and discrimination risks. Regarding talent development, a severe shortage exists of interdisciplinary experts proficient in both AI technology and agricultural science. The higher education system maintains strong disciplinary boundaries, with agricultural institutions providing weak AI training while engineering programs produce AI specialists lacking agricultural domain knowledge [21]. This structural talent gap directly creates mismatches between AI solutions and agricultural needs. Meanwhile, regional disparities are intensifying. Economically advanced eastern regions and large-scale farms lead in capital investment, talent concentration, and technology application, while smallholders in central and western regions and hilly areas face increasing marginalization in terms of technology access and application capacity [22]. This widening “digital divide” not only hinders overall agricultural TFP growth but may also exacerbate regional development inequalities.

4.Optimization Pathways for AI’s Empowerment of Agricultural Total Factor Productivity

4.1 Strengthening Data Infrastructure and Promoting Technological Inclusiveness

Addressing data-related challenges requires establishing a high-quality, shareable agricultural data resource system as the priority. National-level initiatives should enhance top-level design and integrated planning, accelerating construction of integrated sky-air-ground remote sensing and IoT sensor infrastructure. Standardized national protocols and industry specifications for agricultural data collection, storage, and exchange need development and refinement. Diverse mechanisms like “data alliances” and data trading markets should be explored to facilitate orderly data sharing and integration among government agencies, enterprises, and research institutions while ensuring privacy and security. To address high application costs, multiple business models and implementation pathways require exploration. Governments can deploy policy tools like subsidies and tax incentives to reduce initial adoption costs. Technology firms should be encouraged to develop lightweight, modular, open-source AI solutions and "AI Model as a Service" cloud platforms, enabling smallholders to access these technologies with lower barriers. Concurrently, Explainable AI (XAI) research and application should be intensified to improve algorithmic transparency and interpretability. Demonstration projects allowing farmers to experience the benefits of AI firsthand can gradually build usage habits and trust in the technology.

4.2 Intensifying Technological Innovation and Fostering Industrial Integration

Targeted R&D on core AI technologies must address agricultural specificities. Key priorities include: developing low-cost, high-reliability sensors for complex environments; creating agile manipulation and control algorithms for agricultural robots adapting to crop variability and unstructured settings; and building vertical large language models with enhanced cognitive and reasoning capabilities for agricultural knowledge systems. Industrial integration efforts should establish a collaborative "AI + Agriculture" innovation ecosystem. Support should enable leading enterprises, universities, and research institutions to jointly create laboratories and demonstration bases, deepening AI integration with biobreeding, smart machinery, and green agriculture. AI-enabled modern service formats, such as intelligent supply chain management, smart logistics, and digital marketing platforms, deserve encouragement to facilitate the transition from "smart production" to a "smart entire industry chain." Establishing national smart agriculture demonstration zones and major scientific projects can concentrate resources to overcome key technological bottlenecks and generate replicable, scalable implementation models.

4.3 Improving Institutional Frameworks and Cultivating Interdisciplinary Talent

Robust institutional systems provide the foundation for sustainable AI integration in agriculture. The agricultural data legislation process requires acceleration to clarify data property rights attribution and circulation rules. Technical standards, testing specifications, and safety regulations for intelligent equipment like smart machinery and agricultural robots need formulation and refinement. Ethical guidelines and risk assessment frameworks for AI agricultural applications must address algorithmic discrimination and misuse risks. Local governments should strengthen digital governance capabilities, incorporating AI agriculture into Rural Revitalization Strategy planning while maintaining inclusive and prudent regulation. Talent cultivation demands deeper educational reform. Qualified institutions should establish "Smart Agriculture" majors offering AI-agriculture interdisciplinary courses. University-industry collaboration should intensify through joint internship and practice bases, enhancing students' problem-solving abilities in real application contexts. Implementing an "AI New Farmers" program can provide specialized training for new agricultural operators like family farms and cooperatives. Concurrently, competitive policies can attract AI innovators and entrepreneurs to agricultural development, establishing a talent mechanism that combines external recruitment with internal cultivation to provide continuous support for AI-enhanced agricultural TFP.

5.Conclusion

This paper systematically investigates the intrinsic mechanisms, practical constraints, and future directions of artificial intelligence in empowering agricultural Total Factor Productivity (TFP). The research demonstrates that AI provides robust momentum for the leapfrog development of agricultural TFP through three core mechanisms: enhancing technical efficiency, optimizing factor allocation, and fostering new business formats. Nevertheless, the empowerment process faces multiple practical constraints, including weak data foundations, insufficient technical adaptability, high application costs, inadequate institutional safeguards, and a shortage of interdisciplinary talent. If these issues remain unresolved, the empowering effects of AI will struggle to expand beyond isolated demonstration projects to achieve widespread application.

Looking ahead, promoting the deep integration of AI into agricultural TFP requires a systematic approach and coordinated strategies employing multiple measures. Technologically, persistent efforts are needed to develop specialized algorithmic models and intelligent equipment systems tailored for agriculture, thereby promoting the inclusive adoption of these technologies. Regarding data, the focus should be on establishing a unified, open, and shared agricultural big data resource system. Institutionally, it is crucial to accelerate the improvement of relevant laws and regulations, technical standards, and ethical governance frameworks. In terms of talent, significant efforts must be made to cultivate and attract interdisciplinary innovators proficient in both agriculture and artificial intelligence. Only through the synergistic coordination of technological innovation, data-driven approaches, institutional guarantees, and talent support can we effectively overcome the current development bottlenecks. This will fully unleash the immense potential of AI as a core engine of new quality productive forces, ultimately propelling Chinese agriculture toward the goals of high quality, high efficiency, enhanced resilience, and sustainability. Such progress will lay a solid foundation for ensuring national food security and comprehensively advancing the Rural Revitalization Strategy.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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