

The Impact of Artificial Intelligence on Agricultural Supply Chains: A Case Study of Pinduoduo's Agricultural Land Cloud Group Buying Project

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Abstract. Against the backdrop of domestic and international dual circulation and rural revitalization, artificial intelligence (AI) serves as the core impetus driving the digital transformation of the agricultural product supply chain. Existing research mostly focuses on the application of AI in a single link of the agricultural supply chain, lacking studies from the perspective of e-commerce platforms on how to solve the problem of dispersed supply chain entities and achieve full-chain collaboration. This paper takes the Pinduoduo's Agricultural Land Cloud Group Buying Project as the research object and uses the case study method to analyze the empowerment practice of AI in the entire process of agricultural supply chain production, circulation, and sales, and explores the impact of macro and micro factors on the empowerment effect of AI. The research finds that the project has achieved the compression of supply chain links, reduction of losses, and increase in sales through AI, but it faces bottlenecks such as the low digital literacy of elderly farmers and the tilt of platform R&D resources towards the sales end. Based on this, this paper designs optimization paths from three dimensions: e-commerce platforms, government departments, and research institutions, providing theoretical and practical references for e-commerce platforms to empower the digital transformation of the agricultural supply chain.

Keywords: artificial intelligence, agricultural supply chain, e-commerce platform, Pinduoduo's Agricultural Land Cloud Group Buying Project, digital literacy

1. Introduction

Under the dual circulation development pattern of domestic and global markets, the digitalization of the agricultural product supply chain has become an important approach for rural revitalization. The "14th Five-Year Plan for Agricultural and Rural Informatization Development" issued by the Ministry of Agriculture and Rural Affairs in 2022 clearly set a target of achieving a 27% rate of agricultural production informatization by 2025, providing policy support for the application of artificial intelligence (AI) technology in the agricultural product supply chain. Currently, benefiting from capabilities in big data mining and intelligent decision-making, AI has been integrated into every segment of agricultural production, circulation, and sales. Han et al. pointed out that it has

achieved remarkable results in areas such as pest and disease control and cold chain scheduling [1]. Waqas et al. also confirmed that machine learning and deep learning can effectively enhance agricultural production efficiency and sustainability [2].

Although existing research has accumulated certain achievements, there are still obvious gaps. From the perspective of research, Birner et al. [3] and Wang Xintian et al. [4] have conducted studies from the supply side and the industrial chain perspective respectively, but there are few studies focusing on e-commerce platforms and analyzing the path through which AI solves the problem of scattered supply chain subjects and achieves full-chain collaboration. From the perspective of research content, Pallottino et al. [5] and Waqas et al. [2] have focused on the application of single-link technologies, but have paid insufficient attention to key influencing factors and practical bottlenecks such as the AI full-chain collaboration mechanism, farmers' digital literacy [6], and platform resource allocation.

Based on this, this paper takes the Pinduoduo Agricultural Cloud Group Buying Project as the research object and adopts the case study method. It deeply integrates the theories of agricultural supply chain, technology adoption, and digital divide with the project case. Through case analysis, it interprets the theoretical application scenarios, deconstructs the project's production and sales collaboration model with the agricultural supply chain theory, analyzes farmers' AI usage behavior with the technology adoption theory, and reveals the technology adaptation problems of elderly farmers with the digital divide theory. On this basis, it systematically sorts out the project model characteristics and the current status of AI application, and combines macro factors such as policies, technologies, and industrial environments with micro factors such as farmers' digital literacy and platform R&D strategies to systematically analyze the impact mechanism of AI empowerment. Finally, it designs optimization paths from three dimensions: e-commerce platforms, government departments, and research institutions, not only achieving in-depth mutual verification between theory and cases and enriching applied research in the digital agriculture domain, but also providing practical solutions for the digital upgrading of agricultural supply chains, theoretical references and practical references for similar models, and assisting in the advancement of the rural revitalization strategy.

2. Theoretical framework of Pinduoduo's Agricultural Cloud Group Buying Project

2.1. Agricultural supply chain theory

The core of agricultural supply chain theory emphasizes the coordinated integration of all supply chain segments, advocating for the optimization of resource allocation in production, circulation, and sales links to enhance the overall efficiency and resilience of the supply chain [7]. The Agricultural Land Cloud-Pooling project, by integrating production and sales resources through AI technology, is a practical application of agricultural supply chain theory in the digital age. Its core objective is to achieve coordinated optimization of the entire agricultural supply chain through technological means, addressing the pain points of traditional models.

2.2. Technology adoption theory

Technology adoption theory posits that users' technology adoption behavior is influenced by multiple dimensions such as individual characteristics, technology features, and environmental factors [6]. In the agricultural context, farmers, as the end users of AI technology, their digital

literacy levels, trust in technology, and willingness to accept it directly determine the implementation effect and application depth of the technology.

2.3. Abbreviations and acronyms

Digital divide theory points out that there are significant disparities among different groups in terms of access to, use of, and benefits from digital technology. If these disparities are not effectively alleviated, they will further exacerbate social inequality [8]. Within the digital transformation of the agricultural supply chain, the digital divide is mainly manifested as the digital literacy gap between farmers of varying ages and educational levels.

3. Analysis of influencing factors of AI empowerment in Pinduoduo's Agricultural Cloud Group Buying Project

3.1. Macro influencing factors analysis

3.1.1. Policy support: institutional guarantee for agricultural digitalization

The national digital agriculture policy provides a clear development orientation and financial support for the Agricultural Land Cloud-Purchasing Project. The "14th Five-Year Plan for Agricultural and Rural Informatization Development" issued by the Ministry of Agriculture and Rural Affairs in 2022 clearly states the goal of achieving a 27% rate of agricultural production informatization by 2025, and promotes the application of emerging digital tools including artificial intelligence in the agricultural product supply chain through various policy and financial support measures. The research by Pan et al. [9] confirmed that the full-scope pilot policy for e-commerce in rural areas increased the registration numbers of farmers' professional cooperatives and rural collective enterprises by 7.9% and 8.2% respectively, effectively boosting the upstream circulation of agricultural products and infrastructure development. Driven by relevant policies, the rural e-commerce sector has witnessed robust growth. According to official statistics issued by the Ministry of Commerce in 2025, rural online retail sales exceeded 3 trillion yuan for the first time, posting a year-on-year increase of 6.7%, laying a sound industrial foundation for the development of the Agricultural Land Cloud-Purchasing Project. However, there is a lack of specific policies for the application of AI technology in the agricultural production end and the improvement of farmers' digital literacy. Policy support is biased towards the macro level, and the precision and targeting of policy implementation need to be strengthened.

3.1.2. Industrial environment: the overall prosperity of rural e-commerce

The rapid development of the rural e-commerce industry lays a solid industrial groundwork for the Agricultural Land Cloud-Purchasing Project. On the one hand, the steady advancement of rural network infrastructure has achieved wide coverage of high-speed broadband and 5G, providing network support for the rural application of AI technology. Additionally, the continuous expansion of the rural online commerce market has cultivated farmers' online sales habits, reducing the difficulty of promoting the Agricultural Land Cloud-Purchasing Project. Furthermore, rural digital commerce ecosystem has propelled the growth of supporting industries such as cold chain logistics and packaging design, providing hardware support for the application of AI technology in the circulation link. According to Pinduoduo's "2025 Semi-Annual Report on Agricultural Products Upward Movement", the project covers hundreds of agricultural specialty production areas across

the country, with a 54% increase in high-quality product SKUs. This achievement is closely tied to the comprehensive backing of the rural e-commerce industrial environment. However, there are still gaps in digital infrastructure in remote agricultural production areas, and the integration of technologies such as agricultural computing power facilities and the Internet of Things with agricultural infrastructure is insufficient. The intelligence level of cold chain logistics needs to be improved to meet the full-chain application requirements of AI technology.

3.2. Micro influencing factors

3.2.1. Farmers' digital literacy: the key individual factor for technology implementation

Farmers' digital literacy is the core factor determining the implementation effect of AI technology in the production end, and its influence is mainly reflected in three dimensions: basic knowledge, professional skills, and awareness and attitude [6]. In terms of basic knowledge, 62% of elderly farmers in the project coverage area lack basic knowledge of operating digital devices and understanding interfaces. In terms of professional skills, farmers lack the skills to use AI planting guidance tools. In terms of awareness and attitude, elderly farmers lack trust and internal motivation for new technologies. These factors have led to an overall usage rate of AI tools in the production end of only 31%, far lower than 78% for middle aged and young farmers. Zhang et al. [8] empirical research shows that the level of digital literacy directly and significantly affects the income level and relative poverty status of rural households. The specific AI tool usage rate differences between different age groups of farmers are shown in Figure 1.

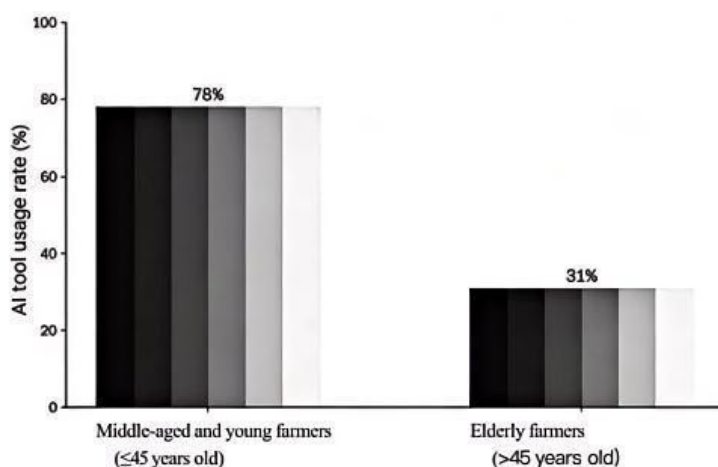


Figure 1. Framework diagram of influencing factors of AI empowerment in the Pinduoduo Agricultural Land Cloud Grouping Project

3.2.2. Platform R&D strategy: the orienting impact of resource allocation

The R&D strategy and resource allocation of the platform directly determine the intensity of AI technology empowerment in each link of the agricultural supply chain. In terms of R&D investment, in 2024, the proportion of Pinduoduo's AI technology R&D investment to its revenue was only 3.2%, and the overall insufficient investment has restricted the in-depth R&D and application of AI technology. This resource misallocation has brought about two impacts: on the one hand, the precise matching ability at the sales end has been continuously enhanced, and agricultural product sales have continued to rise steadily; on the other hand, the insufficient AI empowerment at the

production end has led to a low degree of standardization in the production process and limited improvement in production efficiency. The specific structure of the platform's AI R&D resource allocation is presented in Figure 2.

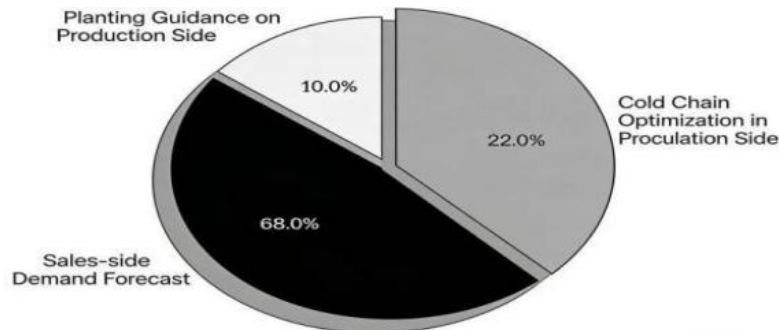


Figure 2. Schematic diagram of platform AI R&D resource allocation structure

3.3. Integration framework and chart analysis of influencing factors

The influencing factors of the AI empowerment in the project can be divided into two levels: macro and micro. The macro level includes policy support and industrial environment, which provide external guarantees for AI empowerment. The micro level includes two factors: farmers' digital literacy and platform development strategies, which directly determine the implementation effect and empowerment depth of AI technology. These factors interact and influence each other, jointly forming the influencing factor system of AI empowerment in the agricultural supply chain: policy support promotes the optimization of the industrial environment, the industrial environment provides the basic conditions for the improvement of farmers' digital literacy, and the platform development strategy needs to be dynamically adjusted in combination with the macro environment and the characteristics of farmers. The cross-analysis results of farmers' digital literacy and AI tool usage rate are detailed in Table 1.

Table 1. Cross-analysis of farmers' digital literacy and AI tool usage rate

Age groups of farmers	Digital literacy level (high/medium/low)	The usage rate of AI tools	Main obstacles
Young and middle-aged farmers (≤ 45 years old)	High: 38.2%; Medium: 49.5%; Low: 12.3%	56.8%	Insufficient operational proficiency; lack of systematic training
Elderly farmers (over 45 years old)	High: 12.1%; Medium: 27.4%; Low: 60.5%	12.3%	The interface is hard to understand, there is no trust in the technology, and there is a lack of skills.

4. Optimization path design for AI-enabled agricultural supply chain

4.1. Optimization measures at the e-commerce platform level

4.1.1. Technology adaptation: development of AI tools friendly to farmers

Develop simple interaction tools considering the cognitive characteristics and operational habits of elderly farmers. Simplify the design of the AI guidance interface, adopt intuitive forms such as combining text and images, and voice broadcasts to reduce operational difficulty. Customize

personalized AI guidance modules based on the agricultural production characteristics and crop types of different regions to enhance the adaptability of the technology.

4.1.2. User empowerment: conduct diversified digital skills training

Promote through both government-enterprise cooperation and self-training: for elderly farmers, rely on village cadres and rural experts to carry out mutual learning; provide advanced training for middle-aged and young farmers. Build a linked system of online short videos, live broadcasts, and offline training sites to strengthen the effectiveness of guidance.

4.1.3. R&D adjustment: optimize resource allocation and technological layout

Reassess the marginal benefits of R&D investment, increase overall investment in AI technology R&D, and direct more resources to R&D at the production end. At the same time, draw on the research conclusions of Liao et al. [10] to dynamically adjust the mixed development model led by enterprises and platforms based on AI development efficiency and supply chain demands.

4.1.4. R&D adjustment: optimize resource allocation and technological layout

Jointly formulate data standards for agricultural products with industry leaders to achieve interconnection and interoperability of data assets. Broaden data collection, integrate production data and local knowledge from small-scale farmers and remote areas to avoid algorithmic bias. At the same time, strengthen data security guarantees, establish and improve data privacy protection mechanisms, and enhance the trust of farmers and partners.

4.2. Support policies at the government department level

4.2.1. Strengthen policy support and guidance

Further improve the policy system for agricultural digitalization, increase subsidies for AI technology R&D among e-commerce platforms, and prioritize supporting R&D and application of AI technology at the production end; formulate special plans for improving farmers' digital literacy, incorporate digital skills training into key tasks of rural revitalization, and set up special training funds; establish a digital evaluation system to guide the coordinated optimization of the entire chain.

4.2.2. Improve digital infrastructure construction

Increase investment in rural digital infrastructure, achieve full coverage of high-speed broadband and 5G, and focus on improving network quality in remote areas; build supporting agricultural computing power facilities to provide hardware support for AI training and big data analysis; promote the integration of Internet of Things, blockchain, and emerging digital technologies with agricultural infrastructure to build a digital infrastructure network covering the entire production, circulation, and sales process [7].

4.2.3. Promote talent cultivation and introduction

Establish a mechanism for cooperation among industry, academia, and research, support universities in setting up agricultural digitalization majors, and cultivate technical and management talents in a targeted manner; introduce policies to incentivize rural digital talents, encourage return to the

countryside for entrepreneurship and employment; organize exchanges between urban and rural digital talents to enhance the technical level of local rural talents.

4.3. Research directions at the research institution level

4.3.1. Focus on core technology R&D

Target key technologies based on actual agricultural needs, develop low-cost and easy-to-operate AI devices suitable for small-scale farmers; optimize the application of machine learning and deep learning in agricultural scenarios, and improve the accuracy of models for pest and disease identification and yield prediction [2].

4.3.2. Deepen theoretical and empirical research

Integrate multi-disciplinary knowledge, build a cross-disciplinary research framework; expand case studies and data samples, analyze the digital transformation paths of different types of agricultural supply chains; focus on bottlenecks such as the digital divide and resource misallocation, and provide targeted theoretical guidance.

4.3.3. Promote the transformation of scientific research achievements

Establish a mechanism for connecting scientific research with industrial demands, and strengthen cooperation with e-commerce platforms and agricultural enterprises; Build a collaborative innovation platform integrating industry, academia and research, simplify the process of technology transfer, and promote the rapid application of technologies to serve the transformation of the agricultural supply chain.

5. Conclusion

This paper takes the Pinduoduo's Agricultural Land Cloud-Purchasing Project as a case study, and analyzes the empowerment effect and influencing factors of AI on the agricultural supply chain by integrating three major theories: agricultural supply chain, technology adoption, and digital divide. It also proposes optimization paths. The research finds that the empowerment of AI is influenced by both macro and micro factors. At the macro level, policies and industrial environments provide a basic guarantee. At the micro level, the imbalance between farmers' digital literacy and platform R&D resources constitutes the core bottleneck. The former is prominently manifested as the digital divide among elderly farmers, while the latter is reflected in the emphasis on the sales end and the weakness of the production end. The interplay of these two factors affects the fairness and sustainability of empowerment.

This study has certain limitations: the single case selection may affect the universality of the conclusion, some data rely on platform reports and existing research, and lack first-hand research. It also does not fully consider the influence of various moderating factors and has not empirically tested the feasibility of the optimization paths. Future research can be targeted: expand the case range to conduct multi-case studies, collect first-hand data through questionnaires and in-depth interviews, explore the deep integration path of the agricultural supply chain, and provide more advanced theoretical and practical references for digital transformation.

Authors contribution

All the authors contributed equally and their names were listed in alphabetical order.

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