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Mechanisms and Pathways of Artificial Intelligence–Driven Rural Industrial Integration

-- An Analytical Framework of "Technological Penetration–Actor Empowerment–Network Restructuring–Value Co-creation"

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Abstract: The penetration of artificial intelligence (AI) into rural industries is reshaping the underlying logic of integration among the primary, secondary and tertiary sectors in rural areas. Based on a systematic review of the relevant literature, this paper develops a four-dimensional analytical framework—technological penetration, actor empowerment, network restructuring and value co-creation—to explain the micro-level mechanisms through which AI drives rural industrial integration. The analysis shows that AI reduces information asymmetry by embedding data as a production factor, alters the resource endowments and bargaining power of diverse business actors through tool-based empowerment and knowledge diffusion, reshapes the distribution of benefits by restructuring collaborative networks, and ultimately manifests itself in industrial chain extension, value chain upgrading and the sharing of value-added gains. Accordingly, drawing on resource endowments, industrial foundations and locational conditions, villages are classified into three types—peri-urban technology-integrated villages, specialty agriculture–empowered villages and eco-cultural tourism innovation villages—for which differentiated integration pathways are identified. A three-tier dynamic evaluation indicator system covering foundational support, integrative application, and impacts and benefits is then constructed. The paper argues that the extent to which smallholder farmers share in the gains should serve as the core criterion for assessing integration outcomes, and that progress should be advanced in a coordinated manner through precision-oriented technology supply, cultivation of actors' digital literacy, innovation in benefit-linkage mechanisms and optimization of institutional safeguards.

Keywords: Artificial intelligence, rural industrial integration, new quality productive forces, digital village, benefit linkage.

1. Introduction

The 15th Five-Year Plan period is a critical stage for advancing comprehensive rural revitalization. The 2026 No. 1 Central Document explicitly calls for "developing new quality productive forces in agriculture in light of local conditions and promoting the integration of artificial intelligence with agricultural development", providing a clear policy direction for the deep penetration of AI into rural industries. Industrial revitalization is the top priority of rural revitalization. In practice, however, rural industries in China still commonly face structural difficulties, including incomplete industrial chains, low value added, inefficient factor allocation, the continuous outflow of young and middle-aged labor, and a shortage of interdisciplinary talent. The traditional growth model, driven mainly by inputs of land, labor and other factors, has exhibited markedly diminishing marginal returns and urgently requires new drivers of growth.

AI is profoundly reshaping every stage of agricultural production, operation and management through its capabilities in perception, decision-making and coordination [1][2]. From the real-time sensing of production environments by intelligent sensors and the Internet of Things, to machine learning models that assist decisions on pest and disease identification, yield forecasting and market price assessment, and further to the cross-organizational coordination of production, supply and marketing enabled by big data platforms, AI is no longer merely an efficiency tool for individual stages. It is becoming a structural force that reorganizes industrial factors, reconstructs relationships among actors and reshapes value distribution [3]. This creates new possibilities for the deep integration of the primary, secondary and tertiary industries in rural areas, and offers a technological pathway for breaking the deadlock in rural industrial upgrading.

Nevertheless, a clear gap remains between existing research and practice. On the one hand, academic discussion of AI and rural industrial integration has largely stayed at the level of macro-level correlations concerning "whether the technology works", with insufficient attention to the intermediate process of "how the technology takes effect". On the other hand, when promoting digital village development, local governments often tend to replicate generic technological solutions while neglecting heterogeneity among villages in resource endowments, industrial foundations and locational conditions, resulting in projects that are left idle as soon as they are installed. Meanwhile, there is still no operational tool for scientifically quantifying the actual contribution of AI to industrial integration.

Against this background, the paper addresses three interrelated questions. First, through what micro-level mechanisms does AI change the behavioral choices and benefit linkages of multiple actors in the process of rural industrial integration? Second, how should different types of villages choose technology introduction strategies and integration pathways that match their intrinsic endowments? Third, how can an evaluation system be constructed that measures the technological contribution of AI dynamically

and scientifically?

The marginal contributions of this paper are threefold. First, in terms of research scale, it shifts the focus from macro-level effect evaluation to meso- and micro-level process analysis, opening the black box of technology-enabled industrial integration and remedying the literature's insufficient attention to the process mechanism of how it happens. Second, in terms of pathway design, it derives differentiated integration pathways through typological comparison, producing an adaptable toolkit of solutions rather than a generic checklist, thereby responding to the weak targeting of existing pathway designs. Third, in terms of evaluation tools, it attempts to build a three-tier dynamic evaluation indicator system that balances scientific rigor with applicability, and incorporates the degree of smallholders' benefit sharing as a core test criterion, filling the gap left by the absence of a dynamic evaluation system.

2. Literature Review

Scholars in China and abroad have actively explored AI-driven rural industrial integration from the perspectives of value orientation, mechanisms of action, practical pathways and real-world constraints, laying a solid foundation for this study.

Regarding value orientation, Wang [4] argues that during the 15th Five-Year Plan period, the upgrading of rural industries driven by new quality productive forces requires a logical shift from pure economic growth toward shared prosperity in people's livelihoods, the essence of which is to serve the fundamental goals of increasing farmers' incomes and achieving common prosperity. This dimension establishes the value coordinates for the present study: whether a technology genuinely promotes rural industrial integration should be judged not only by output and efficiency indicators, but also by whether the technological dividends are shared with smallholder farmers and translated into perceptible income improvements [5, 6].

Regarding mechanisms of action, existing studies have generally confirmed the effectiveness of digital technologies in enabling industrial integration, identifying technological innovation and rural human capital as key transmission channels. Chinese scholars have provided empirical evidence from several angles. Using a panel threshold model, Liu et al. [7] find a U-shaped relationship between digital village development and rural industrial integration, with a double threshold effect. Through spatial econometric modelling, Lin [8] confirms that AI exerts positive spatial spillover effects on rural industrial development, although siphon effects appear in some regions owing to unbalanced technological development. Using a coupling coordination degree model, Wei and Lu [9] characterize the spatiotemporal evolution of AI and rural industrial integration as high coupling, low coordination and steady improvement, and reveal a regional pattern in which the east leads, the central region catches up, and the west lags behind.

In terms of mechanism interpretation, Yu and Wen [1] systematically elaborate four channels through which AI operates: improving efficiency and optimizing allocation, coordinating industrial chains and enabling smart management, driving model innovation and expanding markets, and promoting green transformation. Du [10] emphasizes that new quality productive forces in rural industries are driven primarily by digital technologies, and that current difficulties involving talent, capital and quality must be resolved through digital empowerment. Drawing on the new development philosophy, Liu [3] proposes five enabling pathways—innovation, coordination, green development, openness and sharing. Taken together, these studies suggest that AI does not drive industrial integration directly, but indirectly through mediating variables such as technological innovation and human capital accumulation, which directly informs the mechanism framework constructed in this paper.

Regarding practical pathways, scholars have summarized various models of AI-enabled industrial integration on the basis of typical cases. Taking Zhanjiang in Guangdong as an example, Chen [11] points out that the application of smart agriculture technologies, the construction of agricultural big data platforms and the digital transformation of entire industrial chains can bring about data-driven industrial upgrading; however, bottlenecks remain in the autonomy of core technologies, the coordination of infrastructure and mechanisms for data circulation, requiring coordinated breakthroughs across technology, infrastructure and ecology. Wang et al. [12] argue that generative AI supports rural revitalization by promoting industrial intelligentization and reconstructing human capital, but faces difficulties such as weak digital infrastructure and an imbalanced talent structure, necessitating a collaborative innovation system spanning technology, institutions and culture. Focusing on DeepSeek-type generative AI, Huang [13] explores its internal mechanisms and pathway choices for promoting rural revitalization from the perspectives of knowledge supply and inclusive access to tools.

Regional and case studies provide further empirical evidence. First, in terms of mechanism extraction, Chen and Ren [14], taking Zhejiang Province as an example, summarize a three-dimensional mechanism of technological embedding, industrial linkage and institutional coordination. Based on the watermelon industry in Taizhou, Zhejiang, Xie and Mao [15] reveal the internal mechanism by which digital technologies drive the integration of entire agricultural industrial chains from the perspective of the co-construction of four chains, namely the innovation chain, supply chain, value chain and capital chain. Second, in terms of organization and actor relationships, Zhu et al. [16], using Daye in Hubei as a case and applying an industrial symbiosis model, show that farming households, demonstration bases together with cooperatives, and leading enterprises constitute respectively the main engine and the key organizational forces of integration. Jiao and Liu [17] further explain the emergence of industrial revitalization communities through the triple enabling logics of power, technology and rules. Third, in terms of scenario expansion, Hou et al. [18], drawing on the case of the Longji Terraced Fields scenic area in Guangxi, explain how AI restructures the value chain of rural tourism through intelligent services, data-driven decision-making and cultural innovation, while Zhang [2] supplements the practical constraints on technology implementation from the perspective of integrating AI with traditional agriculture. Overall, these studies cover diverse settings ranging from production to cultural tourism and from single actors to industrial communities; however, they rely mainly on inductive generalization from individual cases, and cross-type comparison of mechanisms remains insufficient.

In summary, existing research has clearly demonstrated the strategic value and overall effectiveness of AI-driven rural industrial integration, but three aspects still leave room for

deepening.

First, mechanism research needs to become more micro-oriented. Most existing work remains at the verification of macro-level correlations, and lacks in-depth discussion of such process-based questions as how AI specifically affects benefit linkages, trust building and risk sharing among different business actors. Second, pathway design needs to be better targeted. Systematic case comparison and model extraction for differentiated integration pathways across village types are still lacking, and one-size-fits-all promotion remains common in practice. Third, a dynamic evaluation system is still absent. Existing evaluations are largely qualitative descriptions or single economic indicators, making it difficult to quantify technological contributions scientifically and to optimize policies accordingly. On this basis, the paper focuses on the mechanisms and implementation pathways of AI-driven rural industrial integration and attempts to make marginal contributions in these three respects.

3. Conceptual Definitions and Theoretical Analytical Framework

Before proceeding with the analysis, three groups of core concepts need to be defined.

The AI technology cluster. The AI referred to in this paper is not a single technology but a cluster of technologies, principally machine learning, computer vision, natural language processing, intelligent sensing and the Internet of Things, and big data analytics. In rural industrial settings, these technologies are typically embedded in concrete forms such as intelligent decision-making platforms, automated equipment, data modelling services and smart contracts, constituting a supply of technologies that business actors can use directly.

Rural industrial integration. Rural industrial integration refers to the process by which, on the basis of agriculture, technological penetration, business form innovation and factor recombination bring about the cross-recombination of agriculture with secondary and tertiary industries such as processing and manufacturing, e-commerce and logistics, and cultural tourism and health care, giving rise to new business forms, new models and new value chains. Its essence is not the simple aggregation of industrial sectors, but the trinity of industrial chain extension, value chain upgrading and benefit chain restructuring.

New quality productive forces in rural areas. New quality productive forces are an advanced state of productivity generated jointly by revolutionary technological breakthroughs, the innovative allocation of production factors and the deep transformation and upgrading of industries. In rural settings they take the concrete form of factor combinations centered on data and intelligent technologies, and their salient feature is a substantial increase in total factor productivity [10, 5].

The analysis rests on four theoretical foundations. The theory of technological innovation diffusion explains how AI technologies are perceived, adopted and disseminated in rural society, indicating that the speed of adoption is influenced by attributes such as relative advantage, compatibility, complexity, trialability and observability; this provides a basis for analyzing the conditions of technological penetration and differences in adoption among actors. Industrial ecosystem theory regards rural industry as an ecosystem composed of multiple actors, factors and environments, emphasizing symbiotic relationships and value co-creation among actors. This is consistent with the industrial symbiosis logic employed by Zhu et al. [16] and corresponds to the network restructuring and value co-creation stages discussed later. Stakeholder theory provides tools for analyzing relationships among smallholders, cooperatives, enterprises, village collectives and governments, and is particularly useful for understanding benefit distribution, serving as the theoretical fulcrum for analyzing changes in data ownership and bargaining power. Transaction cost theory, in turn, offers a direct analytical logic for understanding how AI reduces information search costs, contracting costs and performance monitoring costs; the depiction by Xie and Mao [15] of changes in transaction costs within the co-construction of four chains also reflects this logic, constituting the mechanistic basis for the technological penetration and network restructuring stages.

On the basis of these concepts and theories, the paper proposes a four-stage, progressive analytical framework of micro-level mechanisms.

The basic logic of the framework is as follows. AI first penetrates all stages of rural industries in the form of data as a production factor, changing the ways in which information is generated, collected and circulated. It then empowers diverse business actors through the two channels of tools and knowledge, altering their resource endowments and capability structures. Changes in actors' capabilities necessarily entail adjustments to collaborative relationships, driving the restructuring of existing organizational networks. Finally, on the basis of the joint evolution of technology, actors and networks, value co-creation is realized through industrial chain extension and value chain upgrading. The four stages do not constitute a simple linear causal chain but involve feedback and iteration: the outcomes of value co-creation in turn affect actors' willingness to adopt technology and the depth of technological penetration in the next round.

4. Micro-level Mechanisms of AI-Driven Rural Industrial Integration

4.1. Technological Penetration: Embedding Data as a Factor and Reshaping the Information Structure

Technological penetration is the starting point of the mechanism chain. In traditional rural industries, production, market and business information is highly fragmented and asymmetric: farmers can hardly grasp soil moisture conditions and the patterns of pest and disease outbreaks with accuracy; processing enterprises find it difficult to anticipate the quality and yield of raw materials; and sellers struggle to convey credible quality signals to consumers. This information structure directly leads to inefficient factor allocation and to the failure of high-quality products to command high prices.

AI's intervention changes this information structure first of all. Intelligent sensors and IoT devices continuously convert physical information on soil, weather and crop growth into computable data streams. Computer vision shifts judgments in pest and disease identification, fruit grading and livestock health monitoring from experience-based assessment to model-based assessment. Big data platforms aggregate and connect information dispersed across production, supply and

marketing. As a result, information that was previously invisible or incomparable becomes visible, comparable and traceable, and information asymmetry within and between industries is markedly reduced. The analysis by Xie and Mao [15] of Taizhou's Guaguo Tianxia cloud platform shows that the integration and backflow of data systems across departments is precisely the key to resolving information asymmetry among melon growers, business actors and government departments. It should be stressed that technological penetration does not occur automatically; its depth depends on the coverage and quality of digital infrastructure and on actors' actual ability to use the equipment, which also explains why the same technological solution yields markedly different results across regions [11, 2].

4.2. Actor Empowerment: Improved Resource Endowments and Reconstructed Capabilities

The key stage following technological penetration is how technology changes the resource endowments and behavioral capabilities of multiple actors.

For smallholder farmers, the value of AI lies mainly in tool-based empowerment and knowledge diffusion. On the one hand, intelligent decision-making platforms convert production judgments that once depended on experience into visualized and actionable recommendations, lowering technological thresholds and enabling smallholders to approach the decision quality of large-scale operators. On the other hand, the operating guidance and online training attached to technology service platforms in effect constitute a low-cost channel of human capital accumulation, helping to ease the constraint that rural talent shortages impose on industrial upgrading. Existing research has confirmed the mediating role of human capital accumulation in technology empowerment, which means that Du's [10] emphasis on using digital technology as the core driver to resolve the talent dilemma holds precisely in this sense.

For family farms and farmers' specialized cooperatives, AI mainly improves their management capabilities and bargaining positions. Accurate forecasts of yield and quality provide them with fuller information when engaging with processing enterprises and sales channels, thereby changing their previously passive position in price negotiations. For agribusinesses, intelligent production scheduling, quality control and traceability systems enable them to supply standardized products of stable quality, laying the foundation for branded operation.

It should be noted that empowerment effects are not evenly distributed. Actors with higher digital literacy and larger operating scales tend to absorb technological dividends more quickly, while elderly farmers and small-scale operators benefit to a more limited extent. Without targeted intervention, technological penetration may instead intensify capability differentiation among actors. This corroborates, at the micro level, the regional differentiation pattern revealed by Wei and Lu [9], and warrants full attention in policy design.

4.3. Network Restructuring: Reorganizing Collaborative Relationships and Benefit Linkages

Changes in actors' capabilities are necessarily transmitted to the relational structure among them. In traditional farmer–cooperative–enterprise linkages, difficulties in building trust, high costs of monitoring contractual performance and opaque benefit distribution have long been pain points. The introduction of AI reshapes this network in three directions.

First, it reduces contracting and monitoring costs. Real-time sharing of production data allows enterprises and cooperatives to monitor planting and breeding processes remotely, reducing the need for frequent on-site verification. Logically, if smart contract technology is further introduced, agreed conditions can be written into executable code so that payments and revenue division are triggered automatically once the conditions are met, thereby reducing transaction costs and disputes in contract performance. This is consistent with the direction of change in agricultural credit models depicted by Xie and Mao [15].

Second, it reconstructs the basis of trust. It can be expected that when quality information shifts from third-party experiential judgment to traceable data records, trust among actors will partly move from interpersonal trust to systemic trust, allowing cooperation previously confined to acquaintance circles to extend to a wider scope and providing the organizational conditions for longer industrial chains.

Third, it alters power structures and bargaining power. Whoever controls the data occupies a more favorable position in the network. If data are controlled mainly by leading enterprises, smallholders may face new relations of dependence. Conversely, if shared data platforms are established at the level of village collectives or cooperatives, smallholders' degree of organization and bargaining position can be strengthened. Research by Jiao and Liu [17] on digitally enabled industrial revitalization communities shows that the joint operation of the triple logics of power empowerment, technological empowerment and rule empowerment can promote cooperative networks in which symbiotic relationships between smallholders and other actors are continuously strengthened. Institutional arrangements over data ownership therefore directly determine the direction of network restructuring and the pattern of benefit distribution.

4.4. Value Co-creation: Industrial Chain Extension and Value Chain Upgrading

The endpoint of the mechanism chain is the outcome at the value level. Through the cumulative effects of the preceding three stages, AI ultimately promotes value co-creation in three dimensions.

In terms of industrial chain extension, precise control and quality traceability enable agricultural products to enter processing and branding channels that demand greater quality stability, thereby opening up the chain from primary products to deeply processed goods, while e-commerce platforms and intelligent logistics further shorten the distance between producing areas and consumers.

In terms of value chain upgrading, AI contributes in two directions: cost savings through process optimization and loss reduction, and revenue growth through quality improvement and brand premiums. The analysis by Hou et al. [18] of the Longji Terraced Fields scenic area shows that the deployment of AI systems can increase villagers' incomes substantially while improving visitor experience and operational efficiency. Comparatively, the latter is more sustainable and better accords with the value orientation of shared prosperity in people's livelihoods emphasized by Wang [4].

In terms of value distribution, the key to value co-creation

lies in whether value-added gains can be reasonably shared among multiple actors. Zhu et al. [16] point out that rural cooperatives and leading enterprises play precisely the key organizational and constructive roles in the integration process. If technological application brings only growth in enterprise profits while farmers' incomes remain unchanged, integration has not genuinely occurred. Accordingly, this paper argues that the ultimate criterion for judging whether AI has truly driven rural industrial integration is not the area covered by technological applications or the number of devices installed, but whether farmers have obtained substantive income improvements and capability enhancement in the process.

5. Differentiated Integration Pathways: A Typological Comparison of Village Models

There is no universally optimal model of AI-driven rural industrial integration. The regional pattern revealed by Wei and Lu [9], in which the east leads, the central region catches up and the west lags behind, indicates that the effects of technological empowerment depend heavily on regional conditions. On the three dimensions of resource endowment, industrial foundation and locational conditions, this paper classifies villages into three typical types: peri-urban technology-integrated villages, specialty agriculture–empowered villages, and eco-cultural tourism innovation villages. The theoretical rationale for this classification is that the three types differ systematically in their capacity to absorb technology, in the dominant drivers of industrial integration and in their pathways of value realization, and therefore require different technology introduction strategies and modes of industrial linkage. This also echoes the logic of scenario adaptability emphasized by Chen and Ren [14].

5.1. Peri-Urban Technology-Integrated Villages: AI + R&D Innovation and Efficient Supply Chain Coordination

These villages are adjacent to large and medium-sized cities and can readily access urban spillovers of technology, capital and talent, and their digital infrastructure is relatively well developed; however, they also face high land costs and low comparative returns to agriculture. The initial driver of integration comes mainly from urban consumer demand for high-quality, quickly supplied agricultural products.

The appropriate pathway for such areas should center on AI + R&D innovation and efficient supply chain coordination. Specifically: first, leveraging proximity to research institutes and agri-technology enterprises, technologies such as intelligent breeding and intelligent environmental control in protected agriculture should be introduced to link R&D directly with production; second, data platforms should connect the supply chain running from production bases to central kitchens, urban distribution and retail terminals, reducing distribution losses through demand forecasting and intelligent scheduling; and third, new business forms such as deep processing of agricultural products and prepared dishes should be developed so that the value-added stages of the industrial chain remain local. The key supporting factors in such areas are technical talent and cold-chain logistics infrastructure, while the main obstacles are land-use constraints and homogeneous competition. Mechanistically, this pathway relies mainly on technological penetration and network restructuring, driving value co-creation through improved supply chain efficiency.

5.2. Specialty Agriculture–Empowered Villages: AI + Precise Whole-Chain Control and Brand Value Traceability

These villages possess unique varietal resources, traditional techniques or geographical indication products and have relatively strong industrial foundations, but they commonly face low standardization, unrealized brand premiums and the impact of counterfeit and substandard products. The smart agriculture and whole-chain digitalization pathway revealed by Chen [11] is most applicable in such areas, and the Taizhou watermelon industry analyzed by Xie and Mao [15] provides a complete practical example of this pathway.

The appropriate pathway should center on AI + precise control of the entire industrial chain and brand value traceability. First, a digital control system covering planting and breeding, harvesting, processing and storage should be established to parameterize and standardize traditional techniques and to address unstable quality. Second, a traceability system based on trusted data technologies should be constructed so that the quality information of geographical indication products is verifiable and presentable, providing technological support for brand building. Third, e-commerce big data should be used to identify consumer preferences and to guide varietal improvement and product grading, so that high quality commands high prices. The key supporting factors in such areas are quality control capability and brand operation capability, while the main obstacles are the tension between fragmented smallholder operation and standardization requirements, together with the absence of data sharing mechanisms. Mechanistically, this pathway starts with technological penetration, is supported by actor empowerment and network restructuring, and ultimately realizes value co-creation through quality improvement and brand premiums.

5.3. Eco-Cultural Tourism Innovation Villages: AI + Immersive Experience Design and a Smart Service Ecosystem

These villages rely on natural ecological and cultural resources to develop tourism, study tours and health and wellness industries, and have a relatively good foundation for integrating the primary, secondary and tertiary industries; however, they commonly face homogeneous experiences, large seasonal fluctuations and insufficient service standardization. The potential of generative AI in content generation and service reconstruction [12], together with practical experience of AI restructuring rural tourism value chains [18], points to the distinctive scope for AI in such settings.

The appropriate pathway should center on AI + immersive experience design and the construction of a smart service ecosystem. First, virtual reality, augmented reality and generative content technologies should be used to transform local cultural resources into experiential digital content, creating differentiated study tour and cultural tourism products. Second, smart service systems should be built that integrate guiding, booking, transport and safety warning functions, improving visitor experience and operational efficiency. Third, product design should be optimized through

the analysis of visitor flow and consumption data so as to ease seasonal imbalances. The experience summarized by Hou et al. [18]—technology implementation, cultural embedding and governance coordination—shows that the success of this pathway hinges on villagers' deep participation and the construction of pluralistic co-governance mechanisms. The key supporting factors in such areas are content creativity and service personnel, while the main obstacles are weak digital infrastructure and a shortage of interdisciplinary operational talent. Mechanistically, this pathway depends more on actor empowerment and network restructuring, transforming cultural resources into sustainable value co-creation through villagers' deep participation and pluralistic co-governance.

The three pathways differ in their integration drivers, dominant technologies, sources of value and supporting factors, and the differences can be summarized as follows. Peri-urban technology-integrated villages are pulled by urban demand, derive value mainly from supply chain efficiency, and suit areas with favorable locations and well-developed infrastructure. Specialty agriculture–empowered villages are driven by quality and branding, derive value mainly from premium-generating capacity, and suit areas with unique resources. Eco-cultural tourism innovation villages are driven by experience and services, derive value mainly from cultural value added and service efficiency, and suit areas with distinctive resources and a certain capacity to receive visitors.

It should be noted that this classification is an extraction of ideal types; real villages often combine several characteristics, and pathway selection should be combinational rather than exclusive. Nor are pathways static: as infrastructure improves and actors' capabilities rise, a village's dominant integration pathway may switch between stages. This paper therefore advocates adaptive generation in place of generic application—that is, providing different regions with a toolkit of solutions covering options for different scenarios and stages, rather than a single checklist of best practices.

6. Evaluating Integration Performance: Constructing a Three-Tier Dynamic Indicator System

Scientifically evaluating AI's actual contribution to industrial integration is a prerequisite for policy optimization and dynamic correction.

Constructing an evaluation indicator system must satisfy three requirements. First, scientific validity: indicators should genuinely reflect AI's technological contribution rather than a general level of digitalization. Second, dynamism: the indicator system should capture trends in the integration process and support intertemporal comparison. Third, applicability: while keeping the core framework unified, it should leave room for adjustment across regions, balancing scientific universality with local adaptability. The approach of Liu et al. [7], who measure digital village development and rural industrial integration using an evaluation indicator system, together with the technical route commonly used in the literature of indicator construction, entropy-weight TOPSIS measurement and obstacle degree diagnosis, provides a methodological reference for the indicator design in this paper.

Following these principles, the paper constructs a three-tier indicator system.

The foundational support tier measures the preconditions for technology implementation, including the coverage and quality of digital infrastructure (such as 5G and fiber-optic access rates in administrative villages and the density of sensing devices in agricultural production areas), actors' digital literacy (such as the share of business actors receiving digital technology training and their practical ability to operate intelligent equipment), and the level of institutional and financial support (such as dedicated investment in digital village development and the soundness of data management institutions). This tier reflects whether integration is possible.

The integrative application tier measures the breadth and depth of technology application, including breadth of application (such as the number of industrial stages using AI and the share of adopting actors), depth of application (such as whether application has moved from isolated points to whole-process data integration, and whether cross-actor data sharing has been achieved), and the degree of business form innovation (such as the number of newly created integrative business forms, the conversion rate of agricultural processing and e-commerce penetration). This tier reflects how far integration has gone.

The impacts and benefits tier measures the overall outcomes of integration, including economic benefits (such as the value-added rate of industrial chains, the growth rate of farmers' per capita disposable income and village collective economic income), social benefits (such as the number of local jobs created, the number of returning entrepreneurs, and the share of smallholders participating in integration together with their degree of benefit sharing), and ecological benefits (such as the reduction in fertilizer and pesticide use and resource use efficiency). This tier reflects how well integration performs, and the degree of smallholders' benefit sharing is the core indicator for testing whether value co-creation has been achieved.

As regards measurement methods, the paper recommends determining indicator weights through a combination of subjective and objective weighting—for example, using the entropy weight method to determine objective weights and expert consultation to determine subjective weights, and then synthesizing them—so as to avoid the bias of any single weighting approach. On this basis, a coupling coordination degree model can be used to measure the coordinated development of the three subsystems of technology application, industrial integration and comprehensive benefits, and to identify weak links [9]. An obstacle degree model can also be introduced to diagnose key constraints, or social network analysis can be applied to characterize the density and structure of linkages among multiple actors during integration, thereby testing the actual effects of network restructuring.

In terms of data sources, four types of data should be integrated: routine statistics from statistical yearbooks and agricultural and rural affairs departments; digital village development data from government platforms; business data from e-commerce and industrial internet platforms; and survey data obtained through questionnaires and in-depth interviews. It must be acknowledged that obtaining first-hand micro-level data is practically difficult, as it involves sensitive matters such as benefit distribution agreements and data ownership arrangements; this requires building trust through long-term fieldwork and triangulation with multiple methods. This is also a key direction for future empirical research. Overall, this chapter designs only the indicator framework and measurement approach; the determination of specific weights and empirical estimation are left to future research.

7. Discussion: Practical Constraints and Policy Recommendations

Judging from practice across regions, the advancement of AI-driven rural industrial integration still faces four practical constraints.

First, digital infrastructure remains weak and unevenly distributed. In some remote villages, the quality and stability of network coverage are inadequate, directly limiting the practical usability of sensing devices and cloud-based models. The studies of Chen [11], Wang et al. [12] and Zhang [2] all identify digital infrastructure as the foremost obstacle.

Second, there is a severe shortage of interdisciplinary talent. Professionals who understand both agriculture and digital technology are extremely scarce in rural areas, so that equipment can be installed but not well used, and technological dividends cannot be fully released. Du [10] emphasizes the mediating role of human capital in this process: insufficient human capital obstructs the mediating channel. Yu and Wen [1] likewise identify talent shortages and skill gaps as key bottlenecks.

Third, rules on data ownership and benefit distribution remain unclear. There are as yet no explicit rules governing who collects production data, who owns it and how the resulting value-added gains are distributed. If data rights are monopolized by a single actor, AI may strengthen rather than alleviate the disadvantaged position of smallholders.

Fourth, the coupling between technological logic and rural social logic is insufficient. AI pursues standardization, scale and efficiency maximization, whereas rural society operates on personal ties, trust and long-term relationships. There is tension between the two, and if technological design neglects local socio-cultural contexts, it often encounters covert resistance [18][13].

In response to these constraints, coordinated efforts should be made in four areas: precision-oriented technology supply, cultivation of actors' digital literacy, innovation in benefit linkage mechanisms and optimization of the institutional safeguard system.

First, shifting from generic supply to precision-oriented technology supply. The practice of assessing progress by the number of devices installed should be changed; technological solutions and application scenarios should be matched to differences among village types, priority should be given to projects closely linked to local leading industries, and mechanisms for tracking, evaluating and dynamically correcting technology application effects should be established.

Second, cultivating actors' digital literacy by tier and category. Differentiated training content should be designed for smallholders, cooperative leaders, enterprise technical managers and grassroots officials, with an emphasis on practical operating ability rather than conceptual awareness. The growth of local digital leaders should be supported so that demonstration effects can drive adoption by neighboring farmers.

Third, innovating benefit linkage and data rights distribution mechanisms. Rules on the ownership of agricultural production data should be clarified, and shared data platforms led by village collectives or cooperatives should be encouraged so as to strengthen smallholders' organization and bargaining position. Contract farming models based on smart contracts should be promoted to ensure transparent and enforceable benefit distribution through technological means, thereby advancing the formation of industrial revitalization communities [17].

Fourth, improving institutional safeguards and collaborative governance. Cross-departmental data sharing and coordination mechanisms should be established to break down data silos, and investment in digital infrastructure in remote areas should be increased. Local socio-cultural contexts should be fully respected in technology design and promotion, so as to foster adaptive coupling between technological logic and rural social logic and to build a collaborative system spanning technology, institutions and culture [12].

8. Conclusions and Outlook

Focusing on the mechanisms and pathways of AI-driven rural industrial integration, this paper draws three main conclusions.

First, AI's driving of rural industrial integration is a progressive process running from technological penetration through actor empowerment and network restructuring to value co-creation, with feedback and iteration among the four stages. The reshaping of the information structure by data as a production factor is the starting point, the reshaping of actors' capabilities is the pivot, and improvements in benefit linkages and value distribution constitute the ultimate criterion for judging whether integration has genuinely occurred.

Second, there is no universally applicable integration model. The three village types—peri-urban technology-integrated, specialty agriculture–empowered and eco-cultural tourism innovation—differ markedly in integration drivers, dominant technologies and sources of value, and should respectively adopt the differentiated pathways of AI + R&D innovation and supply chain coordination, AI + precise whole-chain control and brand value traceability, and AI + immersive experience and a smart service ecosystem. Policy-making should shift from generic application to adaptive generation.

Third, evaluating AI's technological contribution requires moving beyond single economic indicators to construct a dynamic indicator system across the three tiers of foundational support, integrative application, and impacts and benefits, with the degree of smallholders' benefit sharing as the core test criterion.

The limitations of this paper lie in its reliance on theoretical construction and typological comparison: large-sample empirical testing has not yet been conducted, and the proposed indicator system remains to be piloted and refined with actual data. Future research can proceed in two directions. First, typical villages can be selected for in-depth participatory observation and multi-case comparison to obtain first-hand micro-level evidence and to test and refine the mechanism framework proposed here. Second, multi-source data can be used to estimate the evaluation indicator system empirically, and to further examine regional differences and spatial spillover effects in AI-driven rural industrial integration.

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