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Simulation and Optimization of Pathway for Artificial Intelligence-Enabled Industrial Integration and Symbiotic Development

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Abstract

Artificial intelligence (AI) provides a new impetus for the integrated and symbiotic development of industries, yet the pathways through which it empowers and evolves dynamically remain unclear. This paper constructs a system dynamics model for AI-enabled industrial integration and symbiotic development, simulates and analyzes the corresponding pathways and dynamic evolution trends. The results show that: (i) In the baseline scenario, which represents the continuation of the current development model, the overall trend of AI-enabled industrial integration and symbiotic development is positive; (ii) In scenarios involving dynamic changes in influencing factors, AI development levels exert a positive feedback effect on industrial integration and symbiotic development trends, though the pathways may vary; (iii) AI fosters industrial integration and symbiotic development by promoting the three-industry integration in rural areas and the two-industry integration in urban areas. Finally, the paper proposes recommendations for deepening the application and integration of AI and promoting the coordinated development of AI applications and regional industrial development, tailored to local conditions.

Keywords

Artificial Intelligence (AI), Industrial Integration and Symbiotic Development, Pathway Simulation and Optimization

1. Introduction

Industrial development is essential to economic progress. President Xi Jinping has emphasized the necessity of seizing opportunities, strengthening innovation, and accelerating the establishment of a modern industrial system in the context of the new technological revolution. This process encompasses the transformation of traditional industries, the rapid advancement of emerging sectors, and the modernization of the industrial system. Industrial integration serves as a fundamental aspect of this transformation, reflecting global economic trends and the profound influence of technological advancements.

The "Recommendations of the Central Committee of the Communist Party of China for the 14th Five-Year Plan for Economic and Social Development and the Long-Range Goals Through 2035" explicitly advocate promoting the deep integration of modern services with advanced manufacturing and modern agriculture, alongside accelerating the digitalization of services. The report of the 20th National Congress further underscores the importance of building a high-quality, efficient new service system and advancing the integration of modern services with advanced manufacturing and agriculture. Despite observable progress, challenges persist, including limited integration points, weak stakeholder connections, and a lack of leading enterprises. Addressing these issues is crucial for constructing a modern industrial system.

The current wave of technological revolution is progressing rapidly, characterized by an unprecedentedly dynamic phase of innovation. President Xi has underscored the significance of integrating technological and industrial innovation. As a pivotal driver of this revolution, next-generation artificial intelligence (AI) has emerged as a core force in China's pursuit of high-quality economic development. The Third Plenary Session of the 20th Central Committee has emphasized the necessity of enhancing mechanisms to support strategic industries, including AI.

AI is now extensively permeating various industries, bridging traditional and emerging sectors, and integrating technology with society. Elucidating the pathways of AI-enabled industrial integration is vital for fostering cross-industry development, amplifying the compounded effects of digitalization, and establishing new competitive advantages. This study investigates the evolution, pathways, and optimization of AI-driven industrial integration, offering insights to accelerate the formation of a modern industrial system.

2. Literature Review

2.1. Industrial Integration

The concept of industrial integration was initially introduced by Marshall, though its economic implications were not immediately recognized. By the 20th century, scholars increasingly concurred that industrial integration is predominantly driven by technological convergence, with technological innovation serving as the primary internal catalyst. Rosenberg (1963) posited that products with distinct functions and characteristics can nonetheless adopt common technologies, establishing the basis for industrial integration. Sahal (1985) further argued that a specific technological paradigm can be broadly deployed across multiple industries, facilitating cross-sectoral diffusion and stimulating innovation, thereby advancing technological integration. Subsequently, research on industrial integration gradually expanded into the field of industrial economics. Yoffie (1996) defined industrial integration as the process of integrating independent products following the adoption of digital technologies. The European Commission reported that industrial integration involves a fusion of three key aspects: technology network platforms, market and industry alliances, and mergers. Steiner (2003) described industrial integration as a new type of industry, brought about by the development of information technology, which has altered the characteristics of traditional industrial products and market demands, resulting in changes to the competitive and cooperative dynamics between enterprises within the industry. Uson et al. (2012) argued that industrial integration is a phenomenon where the established economic activity of one industry intersects with that of another, often as industrial boundaries become blurred in the real economy. While expressions of industrial integration may vary, they generally refer to the economic phenomenon in which the boundaries between different industries become increasingly indistinct due to mutual integration, intersection, and overlap.

In terms of industrial integration models, Shane et al. (1997) classified industrial integration into two types: alternative integration and complementary integration. Building on this framework, Pennings and Puranam (2001) proposed a new "alternative-complementary" model, which they divided into demand integration (product integration) and supply integration (technology integration). Further extending this model, Stieglitz (2003) developed a "2 × 2" industrial integration matrix, which includes four categories: technology substitution, technology complementation, product substitution, and product complementation. The specific forms of industrial integration include three-industry integration (Li et al., 2024), agricultural industry integration (Chen et al., 2024) manufacturing and services integration (Yao et al., 2024), and digital-real integration (Meng et al., 2023), among others.

Regarding the impact of industrial integration on industrial development, Englmaier and Reisinger (2008) argued that strengthening the use of information industry resources helps improve the production efficiency and overall performance of the manufacturing sector. However, Colombo et al. (2013) found that information technology has not significantly improved the performance of the manufacturing industry due to the low level of informatization and the lag in the effects of industrial integration on industrial performance. Forero (2013) suggested that information technology could significantly enhance technical efficiency and help companies gain a competitive advantage. Brock et al. (2014) observed that when spatial externalities are not internalized by firms, industrial integration may occur endogenously in a competitive equilibrium, with the externalities of information technology positively impacting total factor productivity (TFP). Anderson and Toffolo (2013) discovered that technology integration had a positive impact on plant performance. Industrial integration offers considerable momentum for development across industries. Lozada (2019) proposed that the integration of traditional industries with the Internet of Things (IoT) could accelerate the differentiation and reorganization of these industries, with vertical integration helping to revitalize traditional sectors. Nathan (2017) suggested that the coupling degree and coordination between China's information industry and manufacturing industry are positively correlated with the optimization and upgrading of the industrial structure.

Extensive research has examined the concept, models, and implications of industrial integration. It represents the internalization of inter-industry specialization, initially rooted in technological advancements before evolving into a focal area of industrial economics. The diversification of integration models is pivotal to economic and social development. However, most existing studies tend to focus on isolated integration models, such as rural-industrial convergence or manufacturing-service integration. While these studies allow for a detailed exploration of specific mechanisms, they fail to offer a holistic perspective on the overarching patterns and principles governing industrial integration. Moreover, studies on the influencing factors and development paths of industrial integration remain relatively limited, especially in the context of digitization and informatization. The role and mechanisms through which modern information technologies, particularly artificial intelligence, influence industrial integration are still unclear. Clarifying the intrinsic connection between AI and industrial integration is of great practical significance for building a modernized industrial system and achieving high-quality industrial development.

2.2. Effects of Artificial Intelligence

As a novel factor of production, AI leverages emerging technologies to reshape productivity dynamics and drive the transformation of production relations (Bogachov et al., 2020). The continuous advancement and deepening application of AI play a pivotal role in driving economic growth and social progress

From a macroeconomic perspective, AI enhances managerial efficiency and optimizes resource allocation, thereby improving labor division and expanding production frontiers (Wu et al., 2020). AI is capable of performing human mental work and creative tasks, granting it the ability to analyze, make decisions, and drive innovation (Galaz et al., 2021). Additionally, intelligent technology facilitates the rational flow and efficient agglomeration of highly skilled talent, while improving R&D efficiency by reducing development cycles and cutting costs, ultimately fostering technological innovation (Alrowwad et al., 2020). Moreover, AI accelerates the process of technological innovation and performance improvement. By promoting complementary innovations, it significantly impacts technological progress and economic development, creating a multiplier effect (Kromann et al., 2020).

From the perspective of meso industry, AI transforms production modes and drives the development of manufacturing towards flexibility and sustainability (Wang et al., 2020). AI facilitates the intelligent upgrading and transformation of the entire industrial chain-upstream, midstream, and downstream-creating incremental output through its continuous penetration into industrial development (Ge et al., 2020). Additionally, AI promotes the extension of industries into higher-value chains by improving the efficiency of scarce industrial resources and enhancing the sharing of high-quality resources (Chen, 2020). AI influences both the industrial supply side and the consumer demand side. On the supply side, AI leverages technologies like big data and cloud computing to gather information and accurately predict market supply and demand shifts (Ruiz-Real et al., 2021). This enables continuous upgrades on the supply side to meet demand-side changes, fostering the intellectualization of production processes. As a result, industrial operations are enhanced, helping to resolve issues such as inventory backlog and difficulties in capital turnover (Acemoglu & Restrepo, 2018). On the demand side, AI enables the seamless integration of information flow, capital flow, and logistics, optimizing the consumer development environment and efficiently matching market demand (Feizabadi, 2022).

Existing studies have shown that the deepening application of artificial intelligence (AI) can further promote industrial development, help optimize and upgrade traditional industrial structures, enhance the resilience and security of industrial chains, and drive the transformation of traditional industries while nurturing new industries and business models, thereby fostering high-quality industrial development. However, there is limited research on the integration of AI with industry, and the practical pathways for AI-enabled industrial integration and development remain unclear. Clarifying these pathways and understanding their dynamic evolution is of great practical significance for advancing the further integration and development of industries in China. Therefore, this paper uses system dynamics methodology to construct a model of AI-enabled industrial integration and symbiotic development, simulating and analyzing the dynamic driving effects and long-term evolution trends of AI on industrial integration and symbiosis.

This paper differentiates itself from previous research in three key aspects. First, it introduces the concept of symbiotic industrial development, shifting the research focus from conventional industrial integration to industrial integration and symbiosis. This perspective highlights the mutual reinforcement, coupled growth, and co-evolutionary dynamics among industries, unveiling the dynamic equilibrium and synergistic evolution mechanisms inherent in industrial integration. Unlike prior studies that predominantly examined static integration outcomes, this paper provides a more comprehensive and systematic perspective on the fundamental nature of industrial integration and its broader socio-economic implications. Second, this paper conceptualizes industrial integration and symbiosis as a two-tiered system, comprising the integration of rural primary, secondary, and tertiary industries and the integration of manufacturing and service industries. This framework not only reflects the realities of China's economic development but also consolidates and extends previous research on single-mode industrial integration. By facilitating comparative analyses across rural and urban dimensions, this paper identifies the regional heterogeneity of industrial integration and symbiosis, thereby providing a theoretical foundation for developing differentiated industrial policies. Third, employing a system dynamics approach, this paper develops a model of AI-enabled industrial integration and symbiotic development, with artificial intelligence serving as a key driving force. Through simulation analysis, the model investigates the pathways and dynamic evolutionary trends of AI-driven industrial integration and symbiotic development. By addressing the existing research gap in the influencing factors of industrial integration, this paper deepens the understanding of AI's role in fostering industrial symbiosis and provides valuable insights and decision-making support for the practical implementation of AI-driven industrial integration and co-evolution.

The remainder of this paper is structured as follows: Chapter 3 delves into the underlying mechanisms by which AI facilitates industrial integration and symbiotic development. Chapter 4 develops a system dynamics model to systematically explore the role of AI in enabling industrial integration and symbiosis. Chapter 5 conducts model simulations and presents a detailed analysis of the results, offering insights into the dynamic impacts of AI on industrial synergy. Chapter 6 summarizes the key findings and provides policy recommendations to guide the practical implementation of AI-driven industrial integration and symbiosis.

3. Analysis of The System Structure and Action Mechanism

Figure 1 illustrates the system structure of AI-enabled industrial integration and symbiotic development. Initially, Industries A and B maintain distinct boundaries, operating independently with limited product offerings. However, technological advancements and the digital economy gradually blur these boundaries, fostering industrial integration—A transition from inter-industry division to a more interconnected model. This integration enhances supply quality and drives the emergence of new products and services. Three forms of integration emerge: (i) Deep Integration: Industries A and B fully merge, experiencing extensive knowledge spillovers and technological synergies, leading to a highly innovative ecosystem. (ii) Partial Integration: Industries overlap without complete fusion, prompting competitive and cooperative interactions. Firms must innovate to avoid homogeneous competition and maintain growth. (iii) Emergence of New Industries: Technological advancements create entirely new sectors or business models, enriching the industrial system through resource recombination and structural transformation.

Industrial integration is characterized by the progressive blurring of boundaries among sectors, leading to cohesive entities and new industries. In China, this convergence is driven by digitalization, integrating primary, secondary, and tertiary sectors. Agriculture benefits from enhanced productivity, manufacturing adopts service-oriented functions, and services integrate production capabilities, reflecting mutual reinforcement. Regionally, rural areas leverage technology to boost agricultural productivity and diversify economic structures, while manufacturing-service convergence in urban areas enhances innovation. This multi-dimensional process is driven by technology, market demand, and policy support.

To systematically analyze this process, this paper categorizes industrial integration and symbiotic development into two dimensions: (i) Rural industrial integration, encompassing primary, secondary, and tertiary sectors; and (ii) the integration of manufacturing and services. This framework captures the diverse pathways of industrial convergence in China's economic landscape.

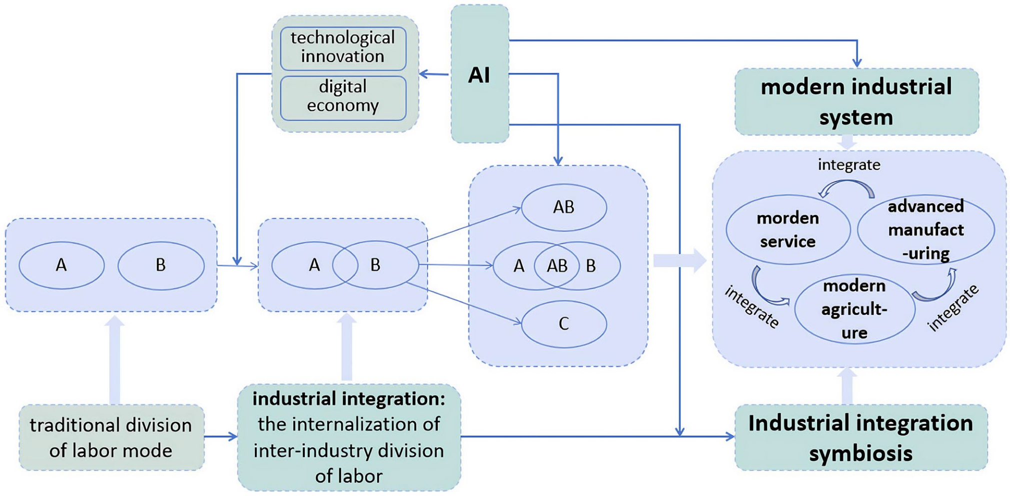

Figure 1. System structure of AI-enabled industrial integration and symbiotic development.

3.1. The Mechanism of Rural Three-Industry Integration and Symbiosis

Figure 2 illustrates the structural framework of rural three-industry integration. Centered on agriculture, the integrated industrial chain of the primary, secondary, and tertiary sectors encompasses three phases: pre-production, production, and post-production. (i) Pre-production involves activities preceding agricultural production, mainly in the secondary and tertiary industries. AI facilitates intelligent transformation of agricultural inputs and enhances data-driven decision-making through big data analytics and machine learning, optimizing supply and forecasting demand. AI applications in agricultural finance, technical consulting, and information services improve decision accuracy and efficiency. (ii) Production focuses on the agricultural phase, primarily involving the primary and tertiary sectors. AI supports intelligent full-process management by employing IoT, real-time sensors, and precision systems for accurate data. AI-driven scheduling optimizes equipment leasing and technical extension services. Furthermore, AI fosters new business models like leisure agriculture and agritourism by improving service quality via recommendation systems and virtual tours. (iii) Post-production covers activities after harvest, mainly in the secondary and tertiary industries. AI optimizes processing, storage, transportation, and marketing. Algorithms enable precise quality detection and classification, enhancing processing efficiency. Intelligent forecasting and scheduling improve logistics, reducing losses. AI-driven big data analysis and personalized recommendations enable targeted marketing, boosting product competitiveness. Additionally, AI enhances personalized services in catering and entertainment, enriching consumer experiences.

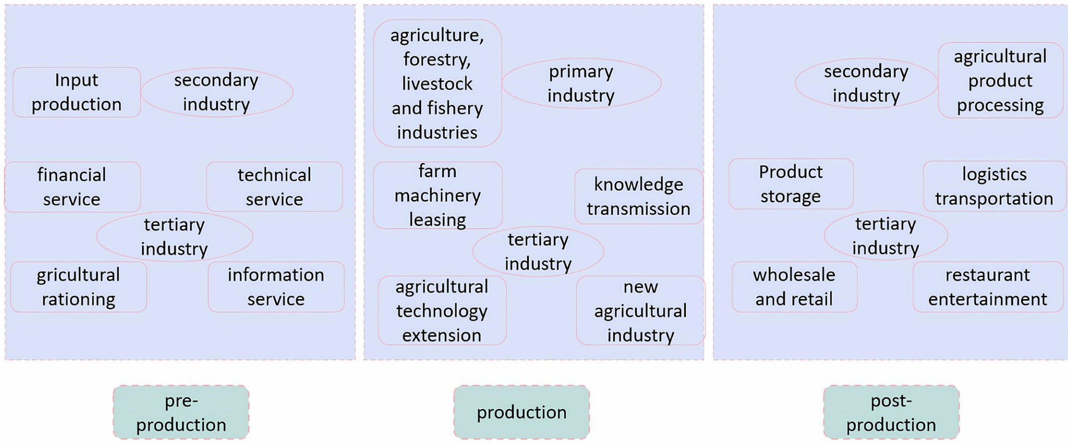

Figure 2. The system structure of the rural three-industry integration.

3.2. The Mechanism of Urban Two-Industry Integration and Symbiosis

Figure 3 illustrates the structural framework of two-industry integration. Technological integration is a fundamental pillar of this process. Innovation at industry boundaries and inter-industry technology diffusion create essential conditions for integration. Driven by these technological advances, advanced manufacturing and information services engage in frequent technological interactions, promoting inter-industry integration and enabling deeper industrial convergence. Technological integration facilitates the fusion of products across industries throughout the product lifecycle, including design, production, sales, and after-sales service. This process goes beyond simple product and service combination to form "manufacturing + service" hybrid products that provide higher added value and comprehensive solutions. These fusion products combine the tangible aspects of advanced manufacturing with the intelligent capabilities of information services. As product and technological integration deepens, market recognition and demand for hybrid products increase, accelerating the convergence of the original markets. The repeated transactions of these hybrid products refine market mechanisms, leading to the formation of concentrated industrial clusters. These clusters drive industrial upgrading and coordinated development along upstream and downstream value chains, intensifying market convergence. Furthermore, technology exchange and sharing catalyze further integration between advanced manufacturing and information services. This integration not only redefines products but reshapes market dynamics, with composite "manufacturing + service" solutions meeting rising demand for value-added offerings. As the demand for hybrid products grows, the market converges rapidly and transaction mechanisms mature, establishing a robust foundation for continued industrial integration. Through the interconnected evolution of technology, products, and markets, advanced manufacturing and information services achieve synergistic growth. Information services supply technology, services, and knowledge to support advanced manufacturing's high-quality development. Conversely, advanced manufacturing introduces cutting-edge technologies to information services, stimulating its innovation. This mutually reinforcing dynamic deepens integration and promotes sustainable co-evolution of both industries.

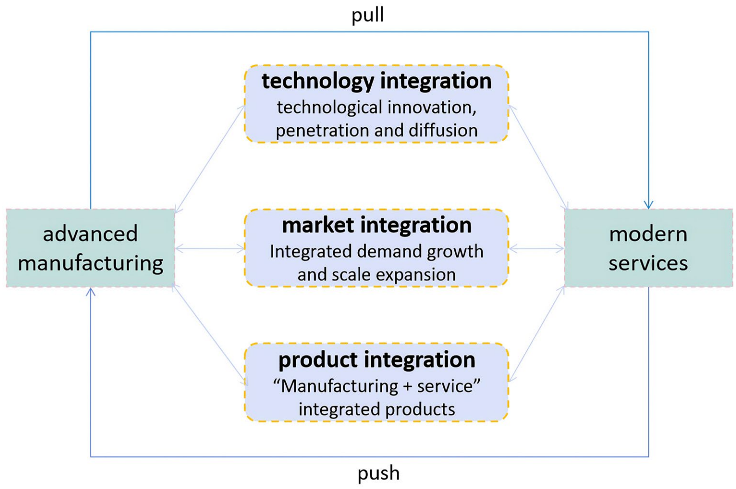

Figure 3. The system structure of the two-industry integration.

4. System Dynamics Model Construction

4.1. Model Applicability and Underlying Assumptions

4.1.1. System Dynamics Applicability Analysis

System dynamics is a well-established method based on cybernetics, system theory, and information theory, aiming to simulate, emulate and predict the development of complex systems by constructing a dynamic model of the system. It is an effective method for analyzing complex systems by establishing mathematical models such as the system of differential equations to describe the functional relationship between system variables, and describing the dynamic changes of the system through simulation, Specifically, the use of system dynamics to analyze the path of AI-enabled industrial integration and symbiotic development is mainly manifested in the following two aspects:

(i) The symbiotic system of industrial integration has a complex structure and path of action, which involves many influencing factors and has a complex relationship with each other. System dynamics emphasizes holistic thinking and systematic consideration of the relationship between various elements. The structured approach of system dynamics helps to decompose the symbiotic path of AI-enabled industrial integration and analyze the complex interaction and feedback relationship of each subsystem, which is conducive to a systematic and comprehensive analysis of the symbiotic path of AI-enabled industrial integration.

(ii) The path of symbiosis of AI-enabled industrial integration involves various feedback mechanisms, and the system dynamics approach helps to analyze how these feedback mechanisms affect the evolution of the whole path. The system dynamics-based model can also be used for simulation and prediction, and by adjusting its parameters, the effects of different strategies can be assessed, thereby facilitating the analysis of AI's dynamic impact on industrial integration and enabling policymakers to formulate more forward-looking strategies to optimize AI-enabled development pathways.

4.1.2. System Division and Basic Assumptions

Based on the previous analysis, this paper divides the system dynamics model of industrial integration symbiosis into two sub-systems: the rural three-industry integration symbiosis development and the two-industry integration symbiosis development. The aim is to study the AI-enabled paths and the effectiveness of their impact. In order to simplify the real-world industrial integration symbiosis system reasonably and ensure that the construction of the system dynamics model maintains scientific integrity, the following basic assumptions are proposed:

H1: The influencing factors of AI-enabled industrial integration symbiosis arise from within the system itself, and external interactions are not considered at this stage.

H2: During the simulation period, the system undergoes no significant changes, and the development of system elements remains in a relatively stable state.

H3: The level of industrial integration symbiosis development can be comprehensively measured by the two subsystems: the level of rural three-industry integration symbiosis development and the level of two-industry integration symbiosis development.

H4: Moderate simplification of the measurement of industrial integration and symbiotic development will not affect the effectiveness of the system's operation.

4.2. Identification of Subsystem Variables and Construction of Causality Diagrams

4.2.1. Determination of Subsystem System Variables

This paper divides the industrial integration symbiosis system into two subsystems: the rural three-industry integration symbiosis subsystem and the urban two-industry integration symbiosis subsystem. The rural three-industry integration symbiosis focuses on the deep integration of agriculture and its related industries, emphasizing the extension of the agricultural industry chain and the expansion of its multifunctionality to achieve increased agricultural efficiency, higher incomes for farmers, and rural prosperity. On the other hand, the manufacturing-service two-industry integration symbiosis focuses on the deep integration of manufacturing and service industries, stressing upstream and downstream synergies within the industry chain and the optimal allocation of resources to enhance the core competitiveness of the manufacturing sector and the added value of the service industry. Both subsystems differ in their integration paths, policy support, and contributions to economic development. Rural three-industry integration symbiosis is an essential practical approach for advancing rural industrial development, as well as a critical driver for rural revitalization and common prosperity. This paper measures the level of rural three-industry integration in six dimensions: agricultural industry chain extension, multifunctional expansion of agriculture, integration of agricultural services, cultivation of new agricultural business models, agricultural technology penetration, and benefit linkage. The relevant data were obtained from sources including the *China Statistical Yearbook*, the *China Agricultural Products Processing Industry Development Report*, provincial statistical yearbooks, the *China Leisure Agriculture Yearbook*, the *China Rural Statistical Yearbook*, the *China Population and Employment Statistical Yearbook*, as well as the Zhejiang University Carter-Enterprise Research China Agriculture-related Research Database, covering the period from 2010 to 2022. The urban two-industry integration symbiosis is a key component in building a modern industrial system and realizing industrial integration. This paper assesses the level of two-industry integration in two dimensions: upgrading the advanced manufacturing industry and upgrading the modern service industry. The upgrading of the advanced manufacturing industry is evaluated through four dimensions: economic benefits, social benefits, innovation benefits, green benefits, and value-added benefits. The upgrading of the modern service industry is measured by the process of productivization and the advancement of the internal structure of the service industry, which reflects the structural upgrading of the sector. The relevant data were drawn from sources such as the *China Statistical Yearbook*, the *China Industrial Statistical Yearbook*, the *China Labor Statistical Yearbook*, provincial statistical yearbooks, the *China Urban Statistical Yearbook*, and the *China Tertiary Industry Statistical Yearbook*, covering the period from 2010 to 2022. The system structure variables of the subsystems are presented in **Table 1**. The level of AI development was measured by identifying AI enterprises through keyword searches in the "Tianyancha" enterprise database, with the indicator constructed as the natural logarithm of the number of AI enterprises in each city plus one, covering the period from 2010 to 2022.

Table 1. System structure variables.

subsystem	primary index	secondary index
rural three-industry integration and symbiosis	agricultural chain extension	proportion of the total output value of the primary industry
		per capita total output value of agricultural and sideline products processing industry
	agricultural multifunctional expansion	annual operating income of leisure agriculture
		the proportion of rural non-agricultural employment
	integration of agricultural services	per capita output value of agriculture, forestry, animal husbandry and fishery service industry
	cultivation of new agriculture formats	the proportion of facility agriculture area
	penetration of agricultural technology	degree of agricultural mechanization
	benefit linkage	the number of farmers' professional cooperatives per 10,000 people

Continued

two-industry integration and symbiosis	economic benefits	contribution rate of economic growth
		sales profit margin
	innovation benefits	innovation investment level
		innovation commercialization level
	green benefits	comprehensive utilization rate of solid waste
		unit exhaust gas emissions
	value added benefits	proportion of high-tech industries
	productivisation of the internal structure of services	the proportion of producer services employees in the tertiary industry employees
	advanced internal structure of services	the proportion of modern services employees in the tertiary industry employees

After identifying the variables of each subsystem, the entropy method was employed for data processing, and the resulting indicator weights are presented in the following Table 2.

Table 2. Indicator weights.

subsystem	indicator	weight	attribute
rural three-industry integration and symbiosis	proportion of the total output value of the primary industry	0.150997292	negative
	per capita total output value of agricultural and sideline products processing industry	0.0743564	positive
	annual operating income of leisure agriculture	0.163190889	positive
	the proportion of rural non-agricultural employment	0.087634975	positive
	per capita output value of agriculture, forestry, animal husbandry and fishery service industry	0.171474446	positive
	the proportion of facility agriculture area	0.09695871	positive
	degree of agricultural mechanization	0.111240193	positive
	the number of farmers' professional cooperatives per 10,000 people	0.144147095	positive
two-industry integration and symbiosis	contribution rate of economic growth	0.17025557	positive
	sales profit margin	0.229091699	positive
	innovation investment level	0.084411187	negative
	innovation commercialization level	0.072527741	positive
	comprehensive utilization rate of solid waste	0.172479627	positive
	unit exhaust gas emissions	0.21280347	negative
	proportion of high-tech industries	0.058430706	positive

4.2.2. Analysis of Subsystem Causality Diagrams

In the AI-enabled industrial integration symbiosis development system, the rural three-industry integration symbiosis subsystem and the two-industry integration symbiosis subsystem have distinct focuses and include different system variables. Therefore, it is essential to clarify the causality relationships among the elements within the subsystems and to further analyze the interconnections between them. A commonly used method for qualitatively analyzing the elements within the subsystems is the construction of a causality diagram. In this section, the naming of the variables is based on the previous analysis, and a causality diagram is created using Vensim software to depict the main feedback loops present within the system.

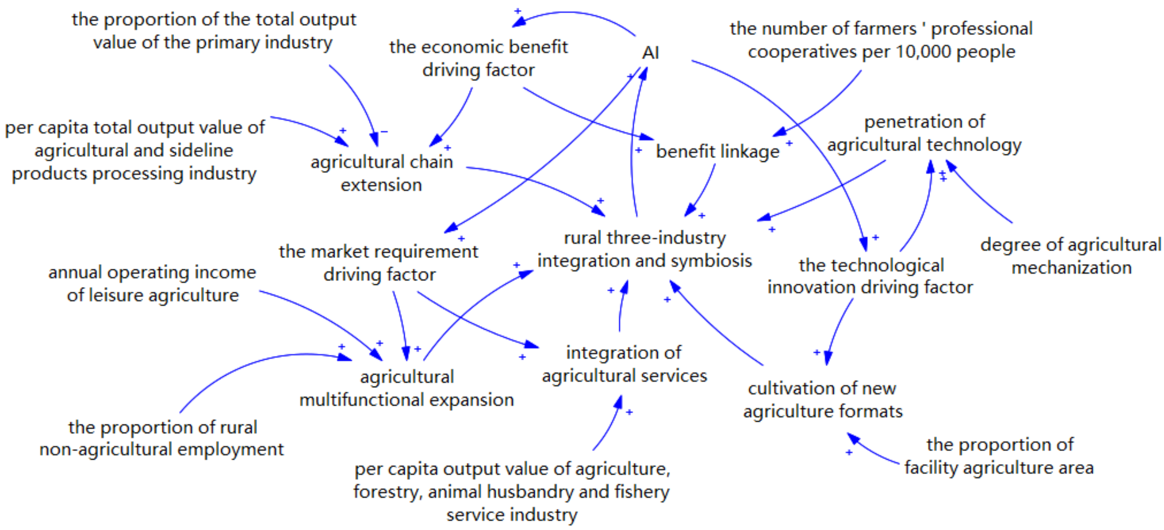

Figure 4. Causality diagram of the subsystem of rural three-industry integration and symbiosis.

The causality diagram of the rural three-industry integration and symbiosis subsystem is shown in Figure 4. In this system, the extension of the agricultural chain refers to the vertical extension of the agricultural industry chain, extending into both the pre-production and post-production stages, through the integration of agricultural product production, processing, and sales. The multi-functional expansion of agriculture refers to the continuous broadening-of agriculture's economic, social, cultural, and ecological functions, and the promotion of deep integration between agriculture and industries such as tourism, culture, and health care, thereby creating new forms of rural industry integration and development. The integration of agricultural services refers to the coordination and collaborative development between agriculture and the agricultural service industry, which provides essential services across all stages of agricultural production and sales. The cultivation of new agricultural business formats involves transforming traditional agriculture using new thinking, technologies, and models, resulting in diversified new forms of agriculture. The penetration of agricultural technology refers to introducing modern agricultural machinery, IoT, Big Data, and other information technologies into agricultural production to accelerate the digitalization, intelligence, and standardization of agricultural operations, thereby enhancing agricultural production efficiency. The linkage of interests involves improving the interest linkage mechanisms between various agricultural stakeholders to foster connections between agriculture and the broader rural economy, ultimately promoting sustained income growth for farmers.

The causality diagram of the subsystem of two-industry integration and symbiosis is shown in Figure 5, in which the upgrading of the advanced manufacturing industry is measured by four dimensions: economic benefits, innovation benefits, green benefits, and value-added benefits. Economic benefits measure the effectiveness of AI in improving labor efficiency, enhancing industry productivity, providing new products and services, innovating business models, and promoting the formation of new industries. This cultivates new momentum for economic growth and achieves high-quality development in the manufacturing industry. Innovation benefits evaluate the application and penetration of AI in the manufacturing field, leading to the gradual formation of a high-quality development model driven by innovation and knowledge. Green benefits assess AI's role in reducing carbon emission intensity, improving energy efficiency, enhancing industrial green development, and generating green economic benefits. Value-added benefits measure AI's effectiveness in driving and accelerating smart consumption, upgrading consumption structures, and promoting enterprise product research and development and quality improvements. The upgrading of the modern service industry is measured by two dimensions: the productivisation and advancement of the service industry's internal structure. The structural upgrading of the service industry is characterized by the continuous development of modern, knowledge-intensive, and technology intensive service industries (or productive service industries). The structural change in human capital, or the advancement of human capital structure, not only directly influences the service industry's structure but also indirectly affects this upgrading by improving labor efficiency, promoting technological innovation, and other channels and mechanisms.

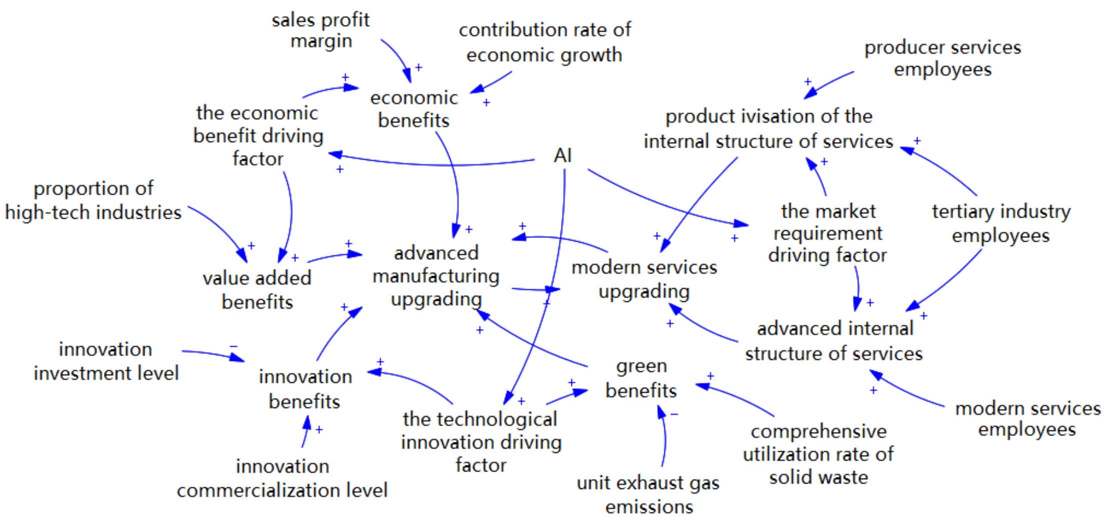

Figure 5. Causality diagram of the subsystem of two-industry integration and symbiosis.

4.2.3. System Flow Diagram Construction and Variable Equation Expression

Based on the analysis of the system structure variables and causality diagrams presented earlier, the stock-flow diagram for AI-enabled industrial integration and symbiotic development is constructed, as shown in Figure 6.

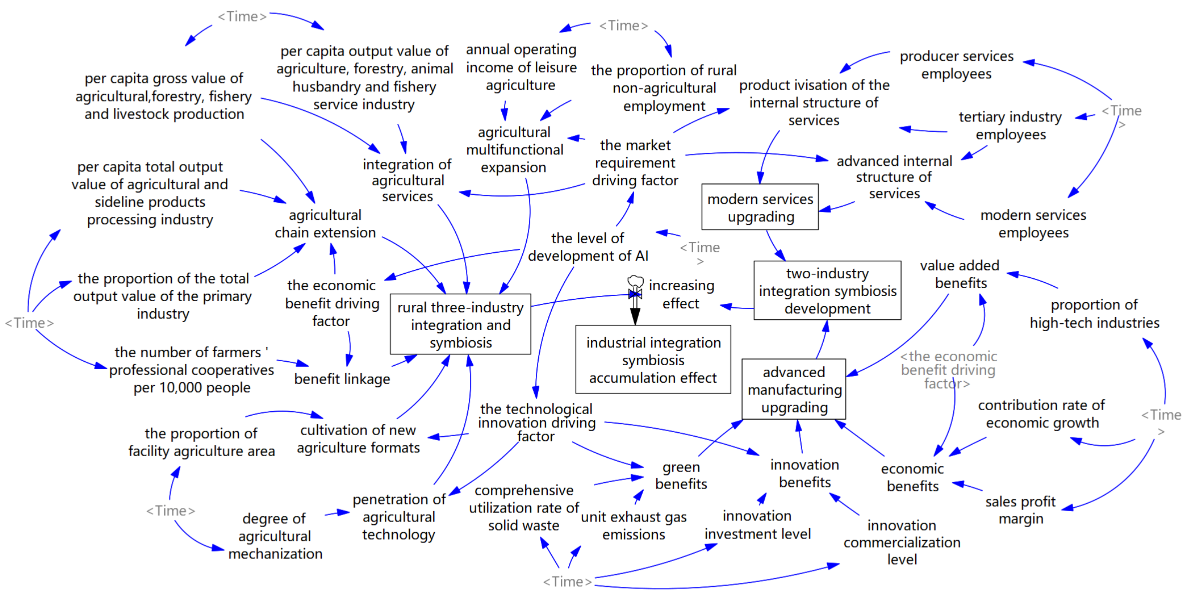

Figure 6. Stock flow map of AI-enabled industry integration and symbiotic development.

The model consists of a total of 41 variables, which include 5 state variables, 1 rate variable, 31 auxiliary variables, and 4 constants. Specifically, the 5 state variables are the industrial integration symbiosis accumulation effect, rural three-industry integration symbiosis development, two-industry integration symbiosis development, modern service industry upgrading, and advanced manufacturing upgrading. The rate of change of the integral variables is calculated from the rural three-industry integration symbiosis development and the two-industry integration symbiosis development, with the rate variable representing the increasing effect. The 31 auxiliary variables include agricultural chain extension, agricultural multifunctional expansion, integration of agricultural services, cultivation of new agricultural formats, penetration of agricultural technology and benefit linkage, economic benefits, social benefits, innovation benefits, green benefits, value-added benefits, productivisation of the internal structure of services, advancement of service industry structure, and others. The 4 constants are the level of AI development, economic benefit driving factor, technological innovation driving factor, and market demand driving factor.

This paper primarily investigates the role path and dynamic evolution trends of AI-enabled industrial integration and symbiotic development. Based on the aforementioned basic assumptions and historical data of the variables, the table function method is employed to establish mathematical formulas that define the functional relationships between the variables. The weights of the relevant variables are calculated using the entropy method. The representative equations in the model are as follows:

(i) *industry integration symbiosis cumulative effect* = *increasing effect*/4

(ii) *increasing effect* = (1/3 * *rural three-industry integration symbiosis development* + 2/3 * *two-industry integration symbiosis development*) * 0.7

(iii) *rural three-industry integration symbiosis development* = *agricultural chain extension* * 0.225353692 + *agricultural multifunctional expansion* * 0.250825864 + *penetration of agricultural technology* * 0.111240193 + *cultivation of new agriculture formats* * 0.09695871 + *integration of agricultural services* * 0.171474446 + *benefit linkage* * 0.144147095

(iv) *two-industry integration symbiosis development* = *advanced manufacturing upgrading* * 0.704842 + *modern services upgrading* * 0.295158

(v) *modern services upgrading* = 0.5 * *productivisation of the internal structure of services*+ 0.5 * *advanced structure of services*

(vi) *modern services upgrading* = *economic benefit* * 0.399347 + *innovation benefit* * 0.156939 + *green benefit* * 0.385283 + *value added benefit* * 0.0584307

Among the three driving factors, AI can be transformed into drivers of technological innovation, economic benefits, and market demand, thereby influencing different dimensions of industrial integration and symbiosis. In this study, we assume that the market responds instantaneously, whereas technological innovation and economic benefits are subject to time lags. Innovation is a multi-stage value chain transmission process, and its value does not emerge immediately; the transformation of innovation inputs into outputs may be delayed (Wang et al., 2016). The progression from technological innovation to knowledge development, technology transfer, and industrialization also entails delays (Song et al., 2022). In particular, the conversion of technological effects into measurable economic benefits requires additional time, and thus the lag in economic benefits is often longer than that of technological prototyping (Hall et al., 2010). Given that the time span of AI development in this study is one year, we adopt a compromise in lag settings: the technological innovation driver is specified as DELAY1 (AI development level, 0.5), and the economic benefits driver as DELAY1 (AI development level, 0.75).

Furthermore, in system dynamics models, stock variables are often subject to depreciation effects, meaning that accumulations may experience certain degrees of decay or irreversible loss over time. This phenomenon has been extensively examined in studies on innovation diffusion, industrial upgrading, and collaborative development (Nelson & Winter 1985; Teece et al., 1997). Technological iteration can render existing organizational models and modes of industrial integration obsolete or marginalized (McAfee & Brynjolfsson, 2017). Similarly, prior knowledge accumulation, resource allocation logics, and institutional frameworks tend to exhibit "depreciation" effects over time. Regarding the magnitude of depreciation rates, the depreciation of knowledge capital is estimated to be around 20% - 40% (Griliches, 1990), while that of firm-level R&D stock is approximately 25% - 35% (Hall, 2007), indicating that technology and knowledge-related stocks generally display depreciation characteristics. Since industrial integration and symbiotic development fundamentally rely on inter-industry knowledge sharing, technological innovation, and organizational collaboration, the depreciation effect may be further exacerbated in such contexts due to cross-organizational coordination costs, heterogeneous technology adaptation cycles across industries, and other factors. Nevertheless, considering that part of the depreciation risk can be offset at the industrial level through resource integration and policy coordination, this study assumes that the cumulative effects of industrial integration and symbiosis depreciate annually at a rate of 0.3.

As defined in the function, the cumulative effect of industrial integration and symbiosis comprehensively incorporates the level of rural three-sector integration and symbiosis as well as the degree of integration between advanced manufacturing and modern services in urban areas, thereby providing a consolidated reflection of the overall level of industrial integration and symbiotic development.

4.3. Model Testing and Simulation Scenario Design

4.3.1. Model Testing

To ensure that the model can operate properly and accurately reflect the system's state, it is necessary to test the reasonableness and applicability of the model, focusing on whether the test results can effectively describe the current situation and address the research problem. This paper conducts verification through system boundary testing and extreme case testing. The boundary appropriateness test and model structure test have been implemented through subsystem delineation and the determination of relationships between variables. The extreme case test is outlined as follows.

Extreme case testing is used to assess whether the system model behaves realistically under extreme conditions, with the simulation results reflecting the actual changes observed in reality. By placing one or more variables in the model under extreme conditions, the system's response is observed to determine whether it conflicts with real-world logic. In this paper, the driving factor is artificial intelligence, and given the complexity of industrial economic development, three driving factors-market demand, economic efficiency, and technological innovation-are set, each influencing industrial integration and symbiotic development from different dimensions. Therefore, this paper examines the impact of setting the extreme value of these three driving factors to 0 on other variables within the model. As the pathways of influence for the different driving factors are numerous, three system variables were randomly selected for analysis, as shown in **Figure 7**. "Current" represents the baseline scenario, and "current1" represents the extreme scenario where the values are set to 0. When the market driving factor is set to 0, the trend line of agricultural multifunctional expansion remains relatively flat, with no significant growth observed. When the economic efficiency driving factor is set to 0, the economic efficiency trend line remains flat in the early stage, with a growth trend emerging later but subsequently declining. When the technological innovation driving factor is set to 0, the innovation efficiency trend line exhibits a general downward trend. It can be observed that when the driving factors are set to their extreme value of 0, the remaining variables within the system experience negative effects, and this trend aligns well with real-world observations.

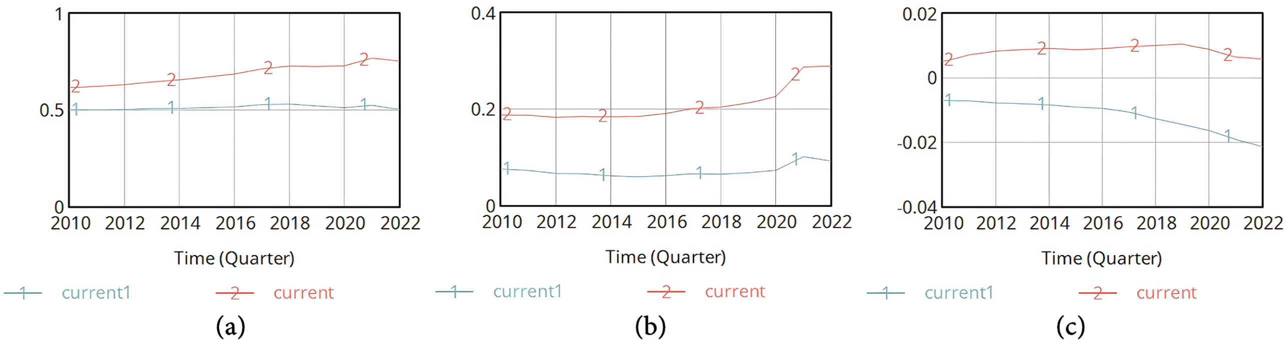

Figure 7. Extreme case test. (a) agricultural multifunctional expansion; (b) economic benefits; (c) innovation benefits.

The results of the two tests mentioned above have been validated. In addition, the model has successively passed both the intuitive and operational tests, demonstrating that the system dynamics model is both valid and reliable, and capable of reflecting the complex drivers and mechanisms underlying the symbiotic development of industrial integration.

4.3.2. Simulation Scenario Design

In this paper, the simulation scenarios are categorized into two types. The first type is the baseline scenario, where the model's initial state is maintained without altering any parameters or values. The second type is the dynamic scenario of driving factors, where only the level of AI development is modified, while other parameters remain unchanged. This scenario is designed to observe the changes in the values of other variables resulting from the variation in the level of AI development.

5. Model Simulation and Result Analysis

According to the causality and correlation function relationship, the simulation of AI-enabled industrial integration symbiosis system is simulated by Vensim-PLE10, and the initial values of the model are set as follows: INITIAL TIME = 1, FINAL TIME = 10, TIME STEP = 0.25, Units for Time = Year, the model is assumed to be for 13 years and the system is dynamics of each variable was analyzed in the simulation.

5.1. Analysis of the Results of the Baseline Scenario System's Operation

Under the condition of maintaining the initial state of the system dynamics model without changing any functional relationships or values, the simulation of the AI-enabled industrial integration symbiosis system was carried out. The simulation results of the cumulative effect of industrial integration symbiosis, the symbiotic development of rural three-industry integration, and the symbiotic development of two-industry integration in the baseline scenario (status quo continuation model) are shown in Figure 8. As seen in Figure 8, during the simulation period, the overall trend of the industrial integration symbiosis system, as well as the development of rural three-industry integration and two-industry integration, exhibits a positive and favorable trajectory.

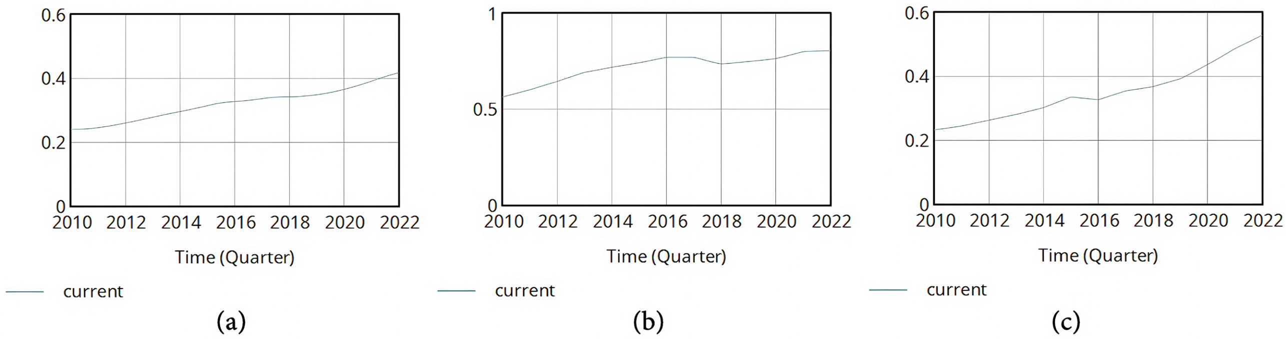

Figure 8. Simulation results of the baseline scenario. (a) industrial integration symbiosis accumulation effect; (b) rural three-industry integration symbiosis development; (c) two-industry integration symbiosis development.

In terms of rural three-industry integration, the in-depth application of artificial intelligence has accelerated the intelligent transformation of agricultural production models. By integrating advanced technologies such as the Internet of Things, big data, and cloud computing, AI provides agricultural producers with precise, scientific guidance on planting and management decision-making support. This not only significantly enhances agricultural production efficiency but also effectively reduces resource consumption and environmental burden, thus promoting the green and sustainable development of agriculture. Furthermore, the deeper application of AI has also advanced the extension and diversification of the agricultural industry chain, including intelligent processing of agricultural products, quality testing, packaging optimization, and other processes. This, in turn, enhances the added value and market competitiveness of agricultural products. Additionally, AI has spurred the growth of emerging rural service industries, such as rural e-commerce and rural tourism, enriching the rural industrial structure, promoting employment, increasing farmers' incomes, and accelerating the diversified transformation and development of the rural economy.

In terms of the integration of the two-industry, the widespread application of artificial intelligence in the manufacturing sector has accelerated the rapid development of intelligent manufacturing, achieving the automation, intelligence, and flexible transformation of production processes. By integrating advanced technologies such as sensors, robotics, and big data, manufacturing enterprises can track production status in real time, optimize production workflows, and significantly enhance production efficiency and product quality. This intelligent production model not only meets the market's demand for personalization and customization but also reduces production costs and operational risks, thereby boosting the competitiveness of enterprises. In the service industry, the application of artificial intelligence has fostered the innovation and upgrading of service models, such as intelligent customer service and intelligent recommendation systems, offering consumers more convenient and personalized service experiences that cater to their diverse needs. Furthermore, AI promotes deep collaboration and integration between the manufacturing and service industries, strengthening the close ties and collaborative development between upstream and downstream enterprises in the industry chain. This enhances the overall efficiency and quality of the industry chain, driving innovative transformation and development in economic models.

5.2. Scenario Analysis of Dynamics of Drivers

Power factor-driven scenario analysis builds upon baseline scenario analysis by keeping all other parameters constant and only altering the value of a specific factor to examine its impact on the symbiotic development of industrial integration. In this paper, we explore the effect of varying the level of AI development on industrial integration.

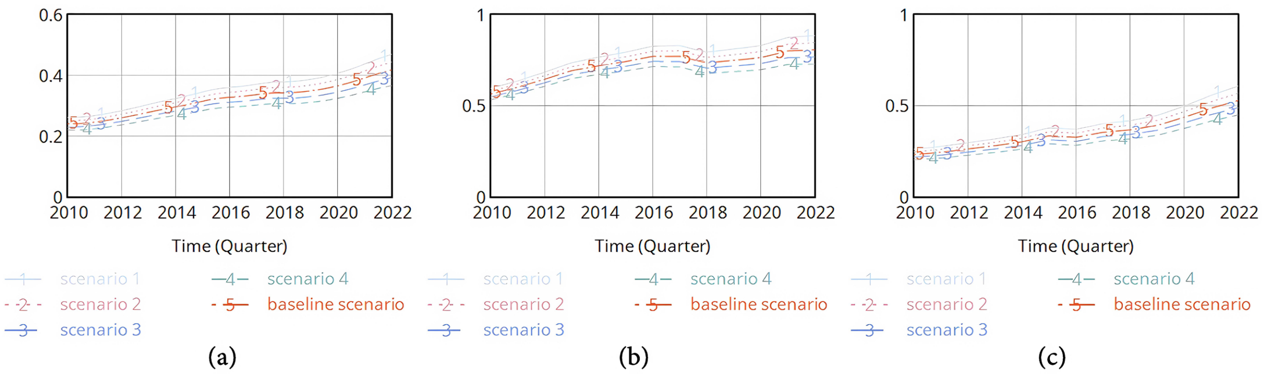

Figure 9. Simulation results under the scenario of change in driver assignment. (a) industrial integration symbiosis accumulation effect; (b) rural three-industry integration symbiosis development; (c) two-industry integration symbiosis development.

By maintaining all other factors unchanged and adjusting the original value of the key variable the level of AI development, we set four different scenarios: an increase of 30%, 15%, and a decrease of 15%, 30%, respectively, corresponding to Scenario 1, Scenario 2, Scenario 3, and Scenario 4. The simulation results are shown in the **Figure 9**. It is evident that the distribution of the five trend lines corresponds to the AI development levels, and the changes become increasingly significant over time. This indicates that AI can positively drive the symbiotic development of industrial integration. Altering the level of AI development generates a positive feedback effect across the overall industrial integration system, promoting an increase in the values of relevant variables in the subsystems. As a result, the overall development of industrial integration exhibits a clear upward trend, with notable changes. Specifically, within this model, AI plays a positive role in fostering the symbiotic development of rural three-industry integration and two-industry integration, thereby further advancing industrial integration symbiosis.

From the perspective of rural three-industry integration and symbiotic development, the deepening application of AI has further advanced the symbiotic development of the integration of the three rural industries. First, AI has enabled precision management of agricultural production and the intelligent transformation of agricultural product processing through technologies such as precision agriculture and intelligent agricultural machinery, significantly improving production efficiency and product quality. This, in turn, has fostered the extension and expansion of the agricultural industry chain. Second, the application of AI has enhanced the added value of agriculture. Data analysis and machine learning techniques have uncovered the value and quality characteristics of agricultural products, promoting the development of specialized agricultural industries and the branding of unique agricultural products. This has increased the economic added value of agricultural products and enhanced their commercialization and marketability. Furthermore, AI has facilitated the deep integration of agriculture with modern services. The emergence of new professions, such as intelligent customer service agents and agricultural big data analysts, has provided agriculture with more convenient and personalized services. The construction of agricultural IoT platforms has strengthened the interactive relationships between new agricultural management entities and farmers, fostering the sharing and joint use of agricultural resources. This has further promoted the innovation and upgrading of agricultural service models. Additionally, AI applications have given rise to a range of emerging agricultural business models, such as intelligent agriculture, precision agriculture, and smart farms. The rise of these new business forms has significantly improved agricultural production efficiency, enriched the agricultural industry landscape, and injected new vitality and growth opportunities into the agricultural economy. The widespread adoption of AI technology has also accelerated the penetration and diffusion of new technologies, driving innovation and upgrading in agricultural practices. By integrating sensors, drones, big data analytics, and other advanced technologies, AI has enabled comprehensive monitoring and optimization of agricultural production processes, thereby improving the intelligence of agricultural production. Finally, the application of AI has strengthened the interest linkages between agriculture-related entities, further reinforcing the connections between the upstream and downstream sectors of the agricultural industry chain, as well as between producers and consumers. Through the IoT platform, agricultural producers can access real-time market demand and consumer preference data, enabling them to adjust production plans flexibly and enhance the market competitiveness of agricultural products. Meanwhile, consumers can track the production process and quality of agricultural products through traceability systems, which enhances their trust in and satisfaction with the products.

From the perspective of two-industry integration and symbiotic development, the application of AI has further promoted the development level of two-industry integration, which is primarily reflected in the following two aspects:

First, the deepened application of AI can drive the upgrading of advanced manufacturing. The widespread adoption of AI technology significantly improves production efficiency and cost control in advanced manufacturing. By introducing intelligent production lines and automated equipment, precise control over production processes and optimized resource allocation have been achieved, effectively reducing production costs and significantly enhancing production efficiency. Furthermore, with the aid of big data analysis, enterprises can accurately forecast market demand, enabling flexible adjustments to production and further boosting the economic efficiency and market responsiveness of the manufacturing industry. Second, AI applications promote technological innovation and industrial upgrading. By utilizing advanced technologies such as deep learning and machine learning, businesses can support product design, process optimization, and quality control, thus steering the manufacturing industry toward higher technological content and greater value-added products. This process also stimulates the innovation capacity of enterprises, further encouraging the research, development, and application of new technologies and processes, thereby providing strong support for the continuous upgrading of the manufacturing sector. Additionally, AI facilitates the green transformation of advanced manufacturing. Energy-saving, emission reduction, and resource recycling are achieved through real-time monitoring and optimization of energy consumption, thus mitigating the environmental impact. By strengthening green supply chain management, the entire industrial chain is guided toward greener, low-carbon, and more sustainable development. Finally, AI technology also enhances product value by improving product quality and enabling personalized customization. With intelligent production and big data analysis, businesses can precisely capture consumer demands and market trends, offering tailored products and services that align with market needs, thereby enhancing both market competitiveness and product value and providing new growth opportunities for the manufacturing industry's transformation.

Second, the deepened application of AI can also promote the upgrading of the modern service industry. First, AI technology drives the productive transformation of the internal structure of the service sector. On one hand, automating complex processes and optimizing operational management strategies significantly improves both the production efficiency and service quality of the service industry. On the other hand, AI's application in data analysis and decision support enables enterprises to gain precise market insights and improve risk management capabilities, which, in turn, strengthens the competitiveness and profitability of the service industry.

Furthermore, the application of AI technology also promotes the advanced transformation of the service industry's internal structure. On one hand, the widespread adoption of AI has spurred the emergence of new service models such as intelligent customer service and smart finance, which have driven the service sector to higher levels of development by demanding advanced technological and data capabilities. On the other hand, AI has facilitated the optimization and upgrading of the internal structures of the service industry, promoting the transformation of traditional services toward greater intelligence and higher-end offerings. By constructing intelligent service platforms and enhancing data analytics capabilities, the modern service industry is better positioned to capture changes in consumer demand, achieving more personalized and customized services that meet the diverse and differentiated needs of the market.

6. Conclusions and Recommendations

AI-enabled industrial integration and symbiotic development is a holistic, systematic, complex, and organic operational system that evolves continuously and functions in an orderly manner. In this paper, a system dynamics model for AI-enabled industrial integration symbiosis is constructed using the system dynamics approach. The dynamic evolution characteristics of the various dimensions and the overall development level of AI-enabled industrial integration symbiosis are simulated and analyzed under two major driving scenarios (including the baseline scenario and the dynamic scenario of motivational factors). The paper discusses the impact of changes in the level of AI development on industrial integration and symbiotic development. The main conclusions are as follows: (i) Under the baseline scenario, which represents a continuation of the current development model, the overall trend of AI-enabled industrial integration symbiosis development is positive; (ii) Under the dynamic scenario of motivational factors, the development level of AI plays a positive feedback role in the trend of change for industrial integration symbiosis, rural three-industry integration symbiosis, and two-industry integration symbiosis. However, the pathways of influence differ; (iii) AI promotes industrial integration symbiosis development through its impact on the rural three-industry integration symbiosis and two-industry integration symbiosis. Specifically, AI promotes the symbiotic development of rural three-industry integration by influencing agricultural chain extension, multifunctional agricultural expansion, integration of agricultural services, cultivation of new agricultural formats, agricultural technology penetration, and benefit linkage. It promotes the integration and symbiotic development of the two industries by facilitating the upgrading of advanced manufacturing and modern services. Additionally, AI fosters the upgrading of advanced manufacturing by enhancing economic, social, innovation, green, and value-added benefits, and promotes the upgrading of modern services by driving the productive and advanced transformation of the service sector's internal structure.

The deepening application of AI contributes to the advancement of industrial integration and symbiotic development, ultimately promoting the construction of a modern industrial system. This paper proposes the following recommendations for further advancing the development and application of AI.

First, it is crucial to vigorously develop the AI industry and deepen the application and integration of AI across sectors. This includes actively advancing the construction of intelligent infrastructure, further enhancing public service platforms for intelligent manufacturing, and creating a favorable development environment by lowering industry barriers and reducing enterprise development costs. Such efforts will drive the high-quality growth of the manufacturing sector. Moreover, AI-driven industrial development is a complex, systemic process that cannot rely solely on the resources of manufacturing enterprises. Therefore, the government must implement effective industrial policies. By strategically designing policy frameworks, the government can promote the optimization and upgrading of industrial structures, actively support emerging strategic industries, and effectively facilitate industrial integration and symbiotic development.

Second, promote the coordinated development of AI applications and industry in line with local conditions. Compared to the central and western regions, the eastern region has more pronounced comparative advantages in both factor endowments and institutional support, making the scale of AI development and its impact on industrial integration significantly more evident. Therefore, each region should design AI and industry integration policies and plans that align with its own economic development status, AI adoption level, and industrial needs. This will help create a development strategy that leverages regional strengths and fosters complementary advantages across regions. Furthermore, the central and western regions should capitalize on their resource endowments, improve the business environment, facilitate the efficient movement of resources in the market, and enable local governments to play a guiding role. These efforts will help promote high-quality industrial development at the regional level.

Third, further harness technological innovation, optimize human capital structures, and foster industrial agglomeration to promote high-quality industry development. Strengthen capabilities in technological innovation, vigorously promote collaboration between industry, universities, and research institutions, accelerate the commercialization of scientific and technological achievements, and drive the transition from traditional to new growth engines. At the same time, focus on attracting and nurturing multi-disciplinary, innovative, and application-oriented professionals to meet the key demands of industries, while establishing a sound talent evaluation and incentive system. Additionally, expedite the development of industrial clusters by establishing innovation demonstration zones, nurturing new business forms and models, advancing modern agriculture, facilitating the service-oriented transformation of manufacturing industries, and promoting the integration of manufacturing with modern services.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Acemoglu, D., & Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review, 108,* 1488-1542. https://doi.org/10.1257/aer.20160696

Alrowwad, A., Abualoush, S. H., & Masa'deh, R. (2020). Innovation and Intellectual Capital as Intermediary Variables among Transformational Leadership, Transactional Leadership, and Organizational Performance. *Journal of Management Development, 39,* 196-222. https://doi.org/10.1108/jmd-02-2019-0062

Anderson, J., & Toffolo, A. (2013). Improving Energy Efficiency of Sawmill Industrial Sites by Integration with Pellet and CHP Plants. *Applied Energy, 111,* 791-800. https://doi.org/10.1016/j.apenergy.2013.05.066

Baquero Forero, M. d. P. (2013). Mobile Communication Networks and Internet Technologies as Drivers of Technical Efficiency Improvement. *Information Economics and Policy, 25,* 126-141. https://doi.org/10.1016/j.infoecopol.2012.11.004

Bogachov, S., Kwilinski, A., Miethlich, B., Bartosova, V., & Gurnak, A. (2020). Artificial Intelligence Components and Fuzzy Regulators in Entrepreneurship Development. *Entrepreneurship and Sustainability Issues, 8,* 487-499. https://doi.org/10.9770/jesi.2020.8.2(29)

Brock, W. A., Xepapadeas, A., & Yannacopoulos, A. N. (2014). Spatial Externalities and Agglomeration in a Competitive Industry. *Journal of Economic Dynamics and Control, 42,* 143-174. https://doi.org/10.1016/j.jedc.2014.03.010

Chen, X., Huang, Z., Luo, C., & Hu, Z. (2024). Can Agricultural Industry Integration Reduce the Rural-Urban Income Gap? Evidence from County-Level Data in China. *Land, 13,* Article No. 332. https://doi.org/10.3390/land13030332

Chen, Y. (2020). Improving Market Performance in the Digital Economy. *China Economic Review, 62,* Article ID: 101482. https://doi.org/10.1016/j.chieco.2020.101482

Colombo, M. G., Croce, A., & Grilli, L. (2013). ICT Services and Small Businesses' Productivity Gains: An Analysis of the Adoption of Broadband Internet Technology. *Information Economics and Policy, 25,* 171-189. https://doi.org/10.1016/j.infoecopol.2012.11.001

Englmaier, F., & Reisinger, M. (2008). Information, Coordination and the Industrialization of Countries. *CESifo Economic Studies, 54,* 534-550. https://doi.org/10.1093/cesifo/ifn006

Feizabadi, J. (2022). Machine Learning Demand Forecasting and Supply Chain Performance. *International Journal of Logistics Research and Applications, 25,* 119-142. https://doi.org/10.1080/13675567.2020.1803246

Galaz, V., Centeno, M. A., Callahan, P. W., Causevic, A., Patterson, T., Brass, I. et al. (2021). Artificial Intelligence, Systemic Risks, and Sustainability. *Technology in Society, 67,* Article ID: 101741. https://doi.org/10.1016/j.techsoc.2021.101741

Ge, J., Wang, F., Sun, H., Fu, L., & Sun, M. (2020). Research on the Maturity of Big Data Management Capability of Intelligent Manufacturing Enterprise. *Systems Research and Behavioral Science, 37,* 646-662. https://doi.org/10.1002/sres.2707

Griliches, Z. (1990). *Patent Statistics as Economic Indicators: A Survey Part I.* NBER.

Hall, B. H. (2007). Measuring the Returns to R&D: The Depreciation Problem. *Economics* *of Innovation and New Technology, 16,* 301-328.

Hall, B. H., Mairesse, J., & Mohnen, P. (2010). Measuring the Returns to R&D. In *Handbook of the Economics of Innovation* (Vol. 2, pp. 1033-1082). Elsevier. https://doi.org/10.1016/s0169-7218(10)02008-3

Kromann, L., Malchow-Møller, N., Skaksen, J. R., & Sørensen, A. (2020). Automation and Productivity—A Cross-Country, Cross-Industry Comparison. *Industrial and Corporate Change, 29,* 265-287. https://doi.org/10.1093/icc/dtz039

Li, J., Liu, H., & Chang, W. (2024). Evaluating the Effect of Fiscal Support for Agriculture on Three-Industry Integration in Rural China. *Agriculture, 14,* Article No. 912. https://doi.org/10.3390/agriculture14060912

Lozada, M. C. (2019). Industry 4.0: The Era of Digitalization, Generation and Integration of Industrial Knowledge. *Ingenius-Revista de Ciencia Y Tecnologia, No. 21,* 7.

McAfee, A., & Brynjolfsson, E. (2017). *Machine, Platform, Crowd: Harnessing Our Digital Future*. WW Norton & Company.

Meng, X. N., Xu, S. C., & Hao, M. G. (2023). Can Digital-Real Integration Promote Industrial Green Transformation: Fresh Evidence from China's Industrial Sector. *Journal of Cleaner Production, 426,* Article ID: 139116. https://doi.org/10.1016/j.jclepro.2023.139116

Nathan, A. J. (2017). *Strategic Coupling: East Asian Industrial Transformation in the New Global Economy*.

Nelson, R. R., & Winter, S. G. (1985). *An Evolutionary Theory of Economic Change*. Harvard University Press.

Pennings, J. M., & Puranam, P. (2001). Market Convergence & Firm Strategy: New Directions for Theory and Research. In *ECIS Conference, The Future of Innovation Studies*, Eindhoven, Netherlands (Vol. 20).

Rosenberg, N. (1963). Technological Change in the Machine Tool Industry, 1840-1910. *The Journal of Economic History, 23,* 414-443. https://doi.org/10.1017/s0022050700109155

Ruiz-Real, J. L., Uribe-Toril, J., Torres, J. A., & De Pablo, J. (2021). Artificial Intelligence in Business and Economics Research: Trends and Future. *Journal of Business Economics and Management, 22,* 98-117. https://doi.org/10.3846/jbem.2020.13641

Sahal, D. (1985). Foundations of Technometrics. *Technological Forecasting and Social Change, 27,* 1-37. https://doi.org/10.1016/0040-1625(85)90002-2

Shane, G., Khanna, T., & Yoffie, D. B. (1997). What Does Industry Convergence Mean? *In Competing in an Age of Digital Convergence* (pp. 201-226). Harvard Business Press.

Song, Y. Q. et al. (2022). An Empirical Study of Establishment of the Time-Lag Effect Model of Innovation Value Transformation. *Science Research Management, 43,* 192.

Steiner, M. (2003). Restructuring Industrial Areas: Lessons in Support of Regional Convergence in an Enlarging Europe. In *Economic Convergence and Divergence in Europe: Growth and Regional Development in an Enlarged European Union* (pp. 86-107). Edward Elgar Publishing. https://doi.org/10.4337/9781781951286.00013

Stieglitz, N. (2003). Digital Dynamics and Types of Industry Convergence: The Evolution of the Handheld Computers Market. In *The Industrial Dynamics of the New Digital Economy* (pp. 179-208). Edward Elgar Publishing. https://doi.org/10.4337/9781781957547.00018

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal, 18,* 509-533. https://doi.org/10.1002/(sici)1097-0266(199708)18:7<509::aid-smj882>3.0.co;2-z

Usón, S., Valero, A., & Agudelo, A. (2012). Thermoeconomics and Industrial Symbiosis. Effect of By-Product Integration in Cost Assessment. *Energy, 45,* 43-51. https://doi.org/10.1016/j.energy.2012.04.016

Wang, D., Zhao, X., & Zhang, Z. (2016). The Time Lags Effects of Innovation Input on Output in National Innovation Systems: The Case of China. *Discrete Dynamics in Nature and Society, 2016,* Article ID: 1963815. https://doi.org/10.1155/2016/1963815

Wang, L., Luo, G., Sari, A., & Shao, X. (2020). What Nurtures Fourth Industrial Revolution? An Investigation of Economic and Social Determinants of Technological Innovation in Advanced Economies. *Technological Forecasting and Social Change, 161,* Article ID: 120305. https://doi.org/10.1016/j.techfore.2020.120305

Wu, F., Lu, C., Zhu, M., Chen, H., Zhu, J., Yu, K. et al. (2020). Towards a New Generation of Artificial Intelligence in China. *Nature Machine Intelligence, 2,* 312-316. https://doi.org/10.1038/s42256-020-0183-4

Yao, Y., Cai, W., Zhou, Z., & Zheng, Y. (2024). Integration of Manufacturing and Services: Examining Its Effect on Resource Allocation and Manufacturing Labor Productivity. *International Review of Financial Analysis, 96,* Article ID: 103708. https://doi.org/10.1016/j.irfa.2024.103708

Yoffie, D. B. (1996). Competing in the Age of Digital Convergence. *California Management Review, 38,* 31-53. https://doi.org/10.2307/41165853