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A Co-evolutionary Strategy of AI Technology for Expanding Regional Industrial Value Chains

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Abstract

This study introduces a co-evolution framework designed to substantively expand the value chains of regional industries through organic integration with artificial intelligence (AI) technologies. While AI continues to advance rapidly, regional small and medium-sized enterprises(SMEs) consistently face significant barriers to tech adoption, primarily driven by critical shortages in both infrastructure and specialized personnel. Moving beyond the limitations of unidirectional technology transfers, this research constructs a bidirectional growth model by leveraging hub cities with established manufacturing infrastructures as optimal testbeds. Specifically, the paper examines mechanisms through which regional strategic sectors—namely, materials, components, equipment (MCE) and mobility—can deploy data analytics and machine learning models to maximize operational efficiency across the entire spectrum of the value chain, from initial planning to production and distribution. Concurrently, it outlines a virtuous technical cycle wherein empirical data generated directly from industrial sites serves to continuously refine and advance the AI algorithms themselves. To ensure successful technological internalization, we propose an industry-academia matching platform as a core governance structure, dedicated to cultivating practical AI talent and integrating them directly into real-world corporate projects. Ultimately, the proposed co-evolution strategy not only generates new economic value for regional industries but also establishes a highly scalable and adaptable standard innovation model applicable to other municipalities and industrial clusters.

Keywords: Regional Industry, Artificial Intelligence, Value Chain Expansion, Co-evolutionary Strategy, Machine Learning

1. Introduction

Artificial intelligence (AI) has recently transcended mere technological progress to establish itself as a core driving force that fundamentally transforms paradigms across entire industries. Furthermore, the widespread adoption of Python-based machine learning and open-source AI algorithms is significantly enhancing the efficiency of corporate manufacturing processes, thereby driving the creation of new added value[1]. However, the benefits of such technological advancements and innovative outcomes tend to be disproportionately concentrated within metropolitan areas and large enterprises. Consequently, this trend exacerbates the divide in AI adoption and digital transformation for regional small and medium-sized enterprises (SMEs) operating with relatively inadequate infrastructure. In particular, the materials, components, and equipment (MCE) as well as the future mobility sectors—which serve as the central pillars of national strategic industries—are facing profound external pressures driven by the restructuring of global supply chains and rapid technological advancement. Consequently, due to insufficient capabilities in utilizing field data and a critical shortage of specialized personnel, these regionally based enterprises are currently struggling to achieve innovation across their entire value chains, from initial product planning through to production and distribution[2]. Therefore, to secure the self-sustaining viability of regional industries and foster sustainable growth, there is an urgent need for a novel approach that organically integrates advanced AI technologies in alignment with the specific characteristics of the regional industrial ecosystem.

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To date, local government-led technology support initiatives and vendor-driven AI adoption models have predominantly leaned toward unidirectional "technology transplantation." The approach of indiscriminately deploying externally developed, general-purpose AI solutions or merely matching hardware to regional enterprises has failed to account for the unique manufacturing processes and operational characteristics of the field, ultimately resulting in substantial underutilization and the obsolescence of the introduced technologies[3]. Furthermore, in the absence of internal personnel capable of sustainably operating and refining these technologies, the digital transformation (DX) of supply chains has frequently devolved into one-off pilot initiatives. This has created a fundamental disconnect between two essential pillars: the axis of innovation, where technology transforms the industry, and the axis of development, where empirical field data and human capital mature the technology itself. Consequently, this fragmentation has manifested in a clear limitation—an inability to achieve a substantive expansion of the value chain relative to the resources invested.

To overcome the limitations inherent in this unidirectional technology transplantation, this study proposes a "co-evolution" strategy wherein AI technologies and the regional industrial ecosystem interact bidirectionally to foster mutual growth. By designating a hub city equipped with a manufacturing-based empirical infrastructure as a testbed, this research analyzes how Python-based data analytics and machine learning models can optimize efficiency across the entire value chain. Furthermore, to ensure successful technological internalization, we present a governance model centered on an industry-academia matching platform. This platform is designed to cultivate practical, AI-proficient talent and closely integrate them with the real-world projects of regional enterprises. Ultimately, the co-evolution strategy derived from this study aims not only to generate new added value for regional industries but also to provide a standardized framework that can be flexibly adapted across various municipalities and industrial clusters.

2. Theoretical Background

2.1 Regional Industrial Value Chain and Artificial Intelligence Transformation

The value chain refers to a series of value-adding activities through which a company plans, designs, produces, markets, and distributes its products or services[4]. Amid the rapid restructuring of global supply chains, the DX and integration of AI technologies across the entire value chain are essential for the survival of regional SMEs and the MCE industries. Previous studies have demonstrated that integrating machine learning and data analytics into traditional manufacturing-based clusters can substantially enhance productivity through process optimization and predictive maintenance[5]. However, the artificial intelligence transformation (AX) of regional industries is inherently limited if it remains confined to merely transplanting high-performance equipment or general-purpose solutions. A genuine expansion of the value chain is only fully realized when the unique domain knowledge of the industrial field is organically combined with flexible open-source AI algorithms, thereby enabling the autonomous derivation of enterprise-specific predictive models[6]. Therefore, moving beyond piecemeal technology adoption, a structural approach that organically integrates data across all stages of the value chain is required.

2.2 Techno-Social Co-evolution Theory

The concept of co-evolution has been extensively employed in the fields of macro-organizational theory and the sociology of technology to elucidate the dynamic interactions in which technology and the environment—or technology and organizations—continuously evolve together as mutually reciprocal causes and effects[7]. According to research in technological innovation, for a novel technological system to be successfully embedded within a society or a regional industrial cluster, the evolution of the technology itself must be accompanied by the simultaneous co-evolution of the surrounding institutions, infrastructure, and the capabilities of the adopting actors[8]. From the perspective of the regional industrial ecosystem, co-evolution with AI technology is predicated on a bidirectional virtuous cycle. The high-quality data generated from the specialized empirical infrastructure and manufacturing sites of hub cities serves as a vital resource for optimizing AI algorithms and advancing models (Region → Tech). In turn, these sophisticated, field-tested AI models drive innovation within the value chains of regional enterprises and generate high added value (Tech → Region) [9]. Consequently, this study proposes this co-evolutionary mechanism as the core framework for regional industrial innovation.

2.3 Cultivation of Practical AI Talent and Industry-Academia Collaboration

Ultimately, the critical bridge that sustains the co-evolution of AI technologies and regional industries is

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human capital. The primary reason many local governments fail in technology adoption lies in the absence of internal specialized personnel capable of sustainably operating, modifying, and advancing general-purpose solutions[10]. Furthermore, recent studies demonstrate that practical, application-oriented AI education—which focuses on solving real-world projects in the industrial field—is significantly more effective in achieving regional technological internalization than traditional, theory-centric higher education[11-12]. In particular, field-tailored AI training programs—encompassing everything from Python-based data manipulation to no-code automation tools—are gaining significant traction as a viable solution to rapidly elevate the AX capabilities of SME incumbents and young talent [13]. To prevent the outflow of these trained professionals from the region and ensure their skills directly contribute to expanding the value chains of local enterprises, it is imperative to establish a self-sustaining, regional university-led industry-academia matching governance. This governance structure must be capable of mediating, in real time, the identification of problems within the supply chain and the corresponding supply of specialized talent..

3. Proposed Framework

3.1 Bidirectional Co-evolution Framework

The co-evolution framework proposed in this study is designed as a bidirectional cyclical structure wherein the regional industrial value chain (planning, production, and distribution) and the AI technology ecosystem continuously interlock and interact. To break away from the limitations of unidirectional solution adoption, enterprises continuously feed empirical data—generated during the production processes and product planning stages—into data analytics pipelines. By training on this data, AI models provide actionable feedback to enterprises in the form of process optimization and demand forecasting, thereby expanding the value chain. For this technological cycle to be sustained autonomously, a practical, project-based industry-academia matching platform—which connects field-ready talent with enterprises—must be integrated as an essential governance mechanism.

3.2 Value Chain Optimization and Application in Manufacturing

The technological axis of this framework lies in directly embedding machine learning models into the practical operations of manufacturing-oriented enterprises, specifically within key regional strategic industries such as MCE and future mobility. For instance, at the R&D planning stage—the frontline of the value chain—chemical and materials companies developing novel metal oxide-based materials can leverage Python libraries like Scikit-learn or TensorFlow to analyze experimental data. By constructing predictive models that incorporate variables such as precursor mixing ratios and heat treatment temperatures, these enterprises can drastically reduce the costs associated with repetitive experiments and maximize efficiency during the new product planning phase. Furthermore, in the mobility sector, large-scale sensor and traffic data collected during the empirical testing of autonomous driving can be preprocessed using Pandas to refine driving anomaly detection models. This constitutes an empirical case wherein the infrastructure of regional enterprises serves directly as a testbed for AI algorithms.

3.3 Cultivation of Practical Talent and Matching Platform

To proactively secure the human resources that will serve as the core driving force to sustainably lead this framework, this study proposes a two-stage industry-academia collaboration governance led by regional universities. First, it is necessary to support incumbents and regional talent by introducing new curricula focused on the utilization of no-code platforms and AI agents, departing from conventional theory-centric education. This will empower them with the capabilities to perform task automation and data analytics even without prior software development knowledge. Second, regional universities must function as project-based matching platforms, enabling local talent to directly solve the immediate challenges faced by enterprises. This approach not only alleviates the labor shortages of these companies but also connects regional youth with high-quality jobs they may have otherwise overlooked, ultimately strengthening the foundational AI capacity of the entire regional industry.

When this process establishes an iterative virtuous cycle, this governance model emerges as the most viable solution to simultaneously address the dual challenges of preventing youth talent outflow and successfully establishing AX in SMEs. Furthermore, its significance extends beyond a localized success story; it possesses robust scalability as a "Region-Customized Technology-Talent Co-evolution Standard Model" that can be flexibly adapted to the specific on-site conditions of other municipalities and industrial clusters currently facing population decline and industrial stagnation.

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4. Conclusion

This study proposed a "Technology-Talent Co-evolution Framework" designed to overcome the concentration of AI technological benefits in metropolitan areas and large corporations, and to substantially expand the value chains of regional SMEs struggling with relatively fragile infrastructure. Recognizing the limitations of unidirectional technology transplantation traditionally led by local governments or supplier enterprises, we engineered a bidirectional virtuous cycle structure wherein empirical data from regional industrial sites and machine learning models continuously interact to foster mutual growth.

In particular, focusing on the region's key strategic industries—such as MCE and future mobility—this study presented a practical approach to minimize R&D costs and maximize process efficiency by applying data collected during enterprises' planning and production stages to AI predictive models and anomaly detection algorithms. Furthermore, the research elucidated that a novel industry-academia collaboration governance, with regional universities at its core, is essential to ensure that such technological innovations do not remain isolated, one-off projects but rather achieve self-sustainability within the region. A matching platform that cultivates field-ready talent through practical, application-oriented education based on no-code tools and AI agents—and subsequently connects them with the real-world data projects of enterprises—serves as the core driving force to simultaneously achieve technological internalization and human resource acquisition.

In conclusion, the co-evolutionary governance proposed in this study emerges as the most viable solution to prevent the outflow of trained youth talent and drive the successful AX of local SMEs. Its scalability and policy implications extend far beyond the infrastructure of any single hub city; it serves as a customized "Technology-Talent Co-evolution Standard Model" that can be flexibly adapted to the on-site conditions of various municipalities and industrial clusters currently grappling with the dual hardships of population decline and industrial stagnation. For future research, we plan to apply this framework to the actual operational challenges of regional enterprises, analyze the resulting quantitative performance metrics, and, based on these findings, verify the feasibility of expanding the framework's application to other industrial sectors.

Conflict of Interest

The authors declare that there are no potential conflicts of interest related to this paper.

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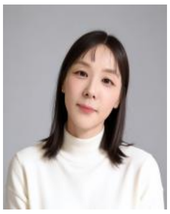

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